A Method for Classification of Power Quality Disturbance Exploiting Higher Order Statistics in the EMD Domain

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Abstract—This paper presents a new approach for the classification of power quality disturbances based on Empirical mode decomposition (EMD) and \(k\)-Nearest Neighbor (\(k\)-NN). A disturbed power signal is first analyzed in terms of intrinsic mode functions (IMF) by EMD. Considering the first three IMFs, the Higher Order Statistics (HOS) is then applied to them to obtain the feature vector. The obtained feature vector thus fed to a \(k\)-NN classifier which shows effective classification of various classes of power quality (PQ) disturbances. Simulation results through training and testing show that the proposed method using \(k\)-NN classifier is superior in performance in comparison to the methods using S-Transform and probabilistic neural network (PNN) and radial basis function (RBF) neural network. It is also shown that the proposed method outperforms some of the state-of-the-art methods in detection and classification.

Index Terms—Power quality, Empirical mode decomposition, Higher order statistics, \(k\)-NN classifier, Probabilistic neural network, Radial basis function neural network.

I. INTRODUCTION

Power quality has become a major concern in recent times because of increasing number of sensitive loads being connected to the power system. Degradation in quality of electric power is normally caused by power-line disturbances, malfunctions, instabilities, short lifetime, failure of electrical equipment, inclusion of distributed energy resources, and so on. Among the variety of power quality (PQ) disturbance events, voltage sag, swell, harmonics, fluctuation, interruption, spike, notch, transients, sag with harmonics, swell with harmonics are profoundly detected. Fig. 1 shows signal of these corresponding PQ disturbances [1].

In an electric distribution network faults may cause voltage sag or momentary interruption whereas switching off large load or energization of a large capacitor bank may lead to voltage swell. On the other hand, use of solid-state switching devices and nonlinear and power electronically switched loads such as rectifiers or inverters may cause harmonic distortion and notchings in the voltage and current. Use of arc furnaces may lead to flickers. Ferroresonance, transformer energization, or capacitor switching may cause transients and lightning strikes may lead to spikes [2].

In order to improve power quality, the sources and causes of such disturbances must be known before appropriate mitigating actions can be taken. However, to determine the causes and sources of disturbances, it is important to detect and localize them. Recently, for the detection, localization and classification of PQ disturbances, researchers become interested to use efficient and appropriate signal processing methods that always try to model all information into a set of feature from where decision making becomes easier and more accurate than the conventional methods. In general, the identification of PQ disturbances involves three processes, which are: 1) signal analysis; 2) features selection; and 3) disturbance classification [3].

For power system disturbance signal analysis, the available time series data is processed through different signal processing approaches. Fourier transform (FT) is commonly used [4] among them. But the effectiveness of FT is limited to stationary signals only. Brief time frequency information related to disturbance waveforms can be obtained by using the short time fourier transform (STFT) [5]–[7]. However, the transient signals cannot be adequately described using STFT due to a fixed window size. Other developed methods for the feature extraction of power system disturbance signals were based on wavelet transform, wavelet packet transform, and wavelet multiresolution analysis [8]–[14]. But these methods tend to be over sensitive to noise signals. Also, proper selection of mother wavelet and the level of decomposition are crucial for effective recognition of disturbance signals in the wavelet domain. The Stockwel transform produces a time-frequency representation of a signal that uniquely combines a frequency dependent resolution and simultaneously localizes the real and imaginary spectra. In this method, the modulating sinusoids are fixed with respect to time axis while the Gaussian window scales and moves. But it requires the selection of a suitable window to match with the specific frequency content of the signal [15], [16]. In [17], authors used Hilbert transform for feature extraction of distorted waveforms to generate a quadrature signal and an analytical signal. From these signals, the instantaneous amplitude and phase can be easily evaluated. But Hilbert Transformer gives a better approximate of a quadrature signal only if the signal approaches a narrow band condition. A combination of Prony analysis and Hilbert transform [18] was also proposed where a signal was reconstructed using linear combination of damped complex exponential. A prediction model was developed in this work to estimates the different modes of a signal. The estimated signal best fits with the original signal only if condition of minimization of least square error between the original signal and estimated signal is satisfied. The Hilbert transform applied on the estimated signal derives the envelope of the voltage waveform which is informative about the severity of voltage flicker. The technique employed was well capable of detecting a voltage envelope of distorted waveform. One limitation that the Prony technique suffers with, in the selection of number of modes. The accuracy of the estimation depends upon the number of modes, based on which a prediction model was developed. There are...
no rules which can guide in the selection of this number and generally it is chosen randomly.

As a multi-resolution signal decomposition technique, empirical mode decomposition (EMD) has the ability to denoise signals and detect PQ disturbances [19], [20]. The key task here is to identify the intrinsic oscillatory modes of a signal in time scales empirically, and then decompose it into intrinsic mode functions (IMFs) accordingly. Unlike FT or wavelet, EMD is intuitive and adaptive, with basic functions derived fully from the data. The computation of EMD does not require any previously known value of the signal. As a result, EMD is especially applicable for nonlinear and non-stationary signals, such as PQ disturbances. Feature selection is always the key element among the process. Previous studies may have overlooked some essential features and some nonessential features may be inappropriately regarded [21]–[23], [28]. Any resulting combination of inappropriate attributes add difficulty to the classification. In this study, we endeavored to develop the appropriate features selection to improve the efficiency of classification. Higher order statistics (HOS) of the extracted IMFs, such as variance, skewness and kurtosis are utilized to form the feature vector. The discriminatory attributes of the HOS for different PQ disturbance signals are more prominent in the EMD domain as seen from the shape of the histograms of the IMFs and the values of the corresponding HOS [24], [25]. Thus, it is expected that these HOS would be more effective if computed in the EMD domain rather than in the time domain. Recently reported works applied different machine learning algorithms to classify PQ disturbances after defining the feature vectors from the disturbance waveform. Probabilistic neural network [9], radial basis function neural network [23], k-nearest neighbour [26], support vector machines [27] and decision tree [29] are mostly utilized classifiers for PQ disturbance signals.

In this research, IMFs of the PQ disturbance signals are obtained by using EMD operation. As most frequency content of the PQ disturbance signals lies in the first three IMFs, they are selected for further analysis [30]. HOS of the extracted IMFs, such as variance, skewness and kurtosis are utilized to form the feature vector. The feature set obtained is fed to the radial basis function (RBF), probabilistic neural network (PNN) and k-nearest neighbor (k-NN) classifiers for classifying the multi-class PQ disturbance signals. For the characterization of PQ disturbance signals, mathematical models of eleven classes of disturbances are used. In comparison to the other methods, k-NN classifiers shows superior performance for the proposed feature vector. Simulation results reveal the effectiveness of the proposed method for classifying multi-class PQ disturbance signals.

II. PROPOSED METHOD

Let us consider a pure power system signal represented by

\[ v(t) = E \sin \omega_c t \]  

here, \( E \) represents the amplitude, with \( f \) symbolizes fundamental frequency of 50 Hz. Different types of power quality signal sag, swell, fluctuation, interruption, transient, harmonics, sag with harmonics, swell with harmonics, spike and notch are considered. The mathematical models that are used to characterize different types of PQ disturbances to the power signal \( v(t) \) are presented in Table I. Hereafter, the PQ disturbance signal is also symbolized as \( v(t) \).

The proposed method consists of two major steps, namely, feature extraction and classification. Details of these steps are discussed below.

A. Feature Extraction

1) Empirical Mode Decomposition: A function is considered to be an IMF if it satisfies two conditions; first, in the whole data set, the number of local extrema and that of zero crossings must be equal to each other or different by at most one and second, at any point, the mean value of the envelope defined by the local maxima and that defined by the local minima should be zero. The systematic way to decompose the data into IMFs, known as the as sifting process, is described as follows:
### TABLE I: Models of power quality disturbance signals

| Disturbance | Equations | Parameters |
|-------------|-----------|------------|
| Normal      | \( v(t) = E \sin \omega_c t \) | \( u(t) \) is the unit function |
| Sag         | \( v(t) = E[1 - \beta \{u(t - t_1) - u(t - t_2)\}] \sin \omega_c t \) | \( 0.1 \leq \beta \leq 0.9, \ T \leq (t_2 - t_1) \leq 9T \) |
| Swell       | \( v(t) = E[1 + \beta \{u(t - t_1) - u(t - t_2)\}] \sin \omega_c t \) | \( 0.1 \leq \beta \leq 0.9, \ T \leq (t_2 - t_1) \leq 9T \) |
| Flicker     | \( v(t) = E[1 + \sin(2\pi \alpha t)] \sin \omega_c t \) | \( 0.1 \leq \beta \leq 0.2, \ 5Hz \leq \alpha \leq 20Hz \) |
| Interruption| \( v(t) = E[1 - \beta \{u(t - t_1) - u(t - t_2)\}] \sin \omega_c t \) | \( 0.9 \leq \beta \leq 1, \ T \leq (t_2 - t_1) \leq 9T \) |
| Transient   | \( v(t) = E[\sin \omega_c t + \beta e^{(t/\tau)} \sin(2\pi f_n(t - t_1)) \{u(t_2) - u(t_1)\}] \) | \( 0.1 \leq \beta \leq 0.9, 0.5T \leq (t_2 - t_1) \leq 3T, 300Hz \leq f_n \leq 900Hz, 8ms \leq \tau \leq 40ms \) |
| Harmonics   | \( v(t) = E[\sin \omega_c t + \beta_3 \sin 3\omega_c t + \beta_5 \sin 5\omega_c t] \) | \( 0.1 \leq \beta \leq 0.9, \ T \leq (t_2 - t_1) \leq 9T, \ 0.05 \leq \beta_3, \beta_5 \leq 0.15 \) |
| Sag with Harmonics | \( v(t) = E[1 - \beta \{u(t - t_1) - u(t - t_2)\}] \ast [\sin \omega_c t + \beta_3 \sin 3\omega_c t + \beta_5 \sin 5\omega_c t] \) | \( 0.1 \leq \beta \leq 0.9, \ T \leq (t_2 - t_1) \leq 9T, \ 0.05 \leq \beta_3, \beta_5 \leq 0.15 \) |
| Swell with Harmonics | \( v(t) = E[1 + \beta \{u(t - t_1) - u(t - t_2)\}] \ast [\sin \omega_c t + \beta_3 \sin 3\omega_c t + \beta_5 \sin 5\omega_c t] \) | \( 0.1 \leq \beta \leq 0.9, \ T \leq (t_2 - t_1) \leq 9T, \ 0.05 \leq \beta_3, \beta_5 \leq 0.15 \) |
| Spike      | \( v(t) = E[\sin \omega_c t - \operatorname{sign}(\sin \omega_c t) \times \{\sum_{n=0}^{9} \kappa \times \{u(t - (t_1 + 0.02n)) - u(t - (t_2 + 0.02n))\}\}] \) | \( 0.1 \leq \kappa \leq 0.4, 0 \leq (t_2 - t_1) \leq 0.05T, 0.01T \leq (t_2 - t_1) \leq 0.05T \) |
| Notch      | \( v(t) = E[\sin \omega_c t + \operatorname{sign}(\sin \omega_c t) \times \{\sum_{n=0}^{9} \kappa \times \{u(t - (t_1 + 0.02n)) - u(t - (t_2 + 0.02n))\}\}] \) | \( 0.1 \leq \kappa \leq 0.4, 0 \leq (t_2 - t_1) \leq 0.05T, 0.01T \leq (t_2 - t_1) \leq 0.05T \) |

i. All the local maxima of the data are determined and joined by cubic spline line thus constructing an upper envelope.

ii. All the local minima of the data are found and connected by cubic spline line to obtain the lower envelope.

iii. The difference between the PQ disturbance signal, \( v(t) \) and the mean of both the envelopes, \( m_1 \) is computed as \( h_1(t) \).

\[
h_1(t) = v(t) - m_1
\]  

If \( h_1(t) \) satisfies the conditions of IMF, then it is the first frequency and amplitude modulated oscillatory mode of \( v(t) \).

iv. If \( h_1(t) \) dissatisfies the conditions to be an IMF, it is treated as the data in the second sifting process, where steps i, ii and iii are repeated on \( h_1(t) \) to derive the second component \( h_2(t) \) as:

\[
h_2(t) = h_1(t) - m_2
\]  
in which \( m_2 \) is the mean of upper and lower envelopes of \( h_1(t) \).

v. Let after \( w \) cycles of operation, if \( h_w(t) \), given by

\[
h_w(t) = h_{w-1}(t) - m_w
\]  
becomes an IMF, it is designated as \( c_1(t) = h_w(t) \), the first IMF component of the original signal.

vi. Subtracting \( c_1(t) \) from \( v(t) \), \( r_1(t) \) is calculated as

\[
r_1(t) = v(t) - c_1(t)
\]  

which is treated as the original data for the next cycle for calculating the next IMF.

vii. Repeating the above process for \( L \) times, \( L \) no. of IMFs is obtained along with the final residue \( r_L(t) \). A popular stopping criteria for the sifting process is to have the value of standard difference (SD) within a threshold as:

\[
SD = \sum_{n=1}^{N} \frac{|h_{w-1}(t) - h_w(t)|^2}{h_w(t)^2}
\]  

here, \( w \) and \( w-1 \) are index terms indicating two consecutive sifting processes. Thus the decomposition process is stopped since \( r_L(t) \) becomes a monotonic function from which no more IMF can be extracted. To this end, for \( L \) level of decomposition, the PQ disturbance signal \( x(t) \) can be reconstructed by the following formula,

\[
v(t) = \sum_{k=1}^{L} c_k(t) + r_L(t)
\]
2) IMF Selection: The PQ disturbance signals, namely sag and swell, each result in six IMFs through EMD analysis, whereas EMD decomposition of the other PQ disturbance signals, such as harmonics and fluctuation, each provide only one or two IMFs. Since, most of the frequency content of the PQ disturbance signal $x(t)$ lies in the first three IMFs, we are motivated to exploit the first three IMFs for feature extraction in this work. For the PQ disturbance signals that can be decomposed into one or two IMFs, we will consider the remaining IMFs as zero. Fig. 2 and Fig. 3 show sag and swell signals and their empirically decomposed IMFs. Note that as the level of an IMF increases, the corresponding data becomes smoother.

3) Higher Order Statistics: In this work, higher order statistics such as variance, skewness and kurtosis are utilized for classifying the EEG signals in the EMD domain. The use of these moments is motivated by the fact that distribution of the samples of a data set, is often characterized by its level of dispersion, asymmetry and concentration around the mean. For an $N$-point data, $X = x_1, x_2, ..., x_N$, the corresponding variance ($\sigma^2$), skewness ($\beta_1$) and kurtosis ($\beta_2$) are calculated as

$$\sigma^2 = \frac{1}{N} \sum_{n=1}^{N} (x_n - \mu)^2, \mu = \frac{1}{N} \sum_{n=1}^{N} x_n$$  \hspace{1cm} (8)

$$\beta_1 = \frac{1}{N} \sum_{n=1}^{N} \frac{(x_n - \mu)^3}{\sigma}$$ \hspace{1cm} (9)

$$\beta_2 = \frac{1}{N} \sum_{n=1}^{N} \frac{(x_n - \mu)^4}{\sigma^2}$$ \hspace{1cm} (10)

where, $\mu$ denotes the sample mean of the data. If skewness is negative, the data is spread out more to the left of the mean than to the right, while a positive skewness indicates spreading more to the right. For a perfectly symmetric distribution about mean, the skewness is zero. In histogram analysis, kurtosis of a data with a sharper peak have a fatter tails than a data having a more rounded peak. Notice that the variance itself is the 2nd order moment of the data, whereas the skewness and kurtosis are computed from the 2nd, 3rd and 4th order moments. Fig. 4 shows the histograms of pure signal and first IMF of PQ disturbances. From Fig. 4, it is observable that the shapes of the PQ disturbances are different from each other. It is expected since the values of the corresponding variance, skewness and kurtosis are different from each other and these quantities are representative of the dispersion, asymmetry and peakedness of a data. The discriminatory attributes of these quantities are more prominent in the EMD domain as seen from the shape of the corresponding histograms and the values of the corresponding variance, skewness and kurtosis. Thus, one may expect that these statistical measures would be more effective if computed in the EMD domain rather than in spatial domain for classifying the PQ disturbance signals. Thus, from the first three extracted IMFs, nine features are derived to form the feature vector. Fig. 5 shows the flow diagram for proposed extracted features from distorted waveform.

B. Classification

1) $k$-NN Classification: $k$-NN is the simple and robust classifier [26]. The classifier works by comparing a new sample (testing data) with the baseline data (training data). The classifier finds the $k$ neighborhood in the training data and assign class which appear more frequently in the neighborhood of $k$. The value of $k$ needs to be varied in order to find the match class between training and testing data. The default value of $k$ is 1. The default neighborhood setting is Euclidean and nearest. The Euclidean distance is used to find the object
In this paper, the value of $k$ is varied from 1 to 10. The $k$-NN classifier was also evaluated by changing the default setting of distance from Euclidean to cityblock, cosine and correlation. Meanwhile, the $k$-NN classifier rule was changed from the default setting of nearest to random and consensus.

2) Probabilistic Neural Network: Probabilistic neural networks (PNNs) are a kind of radial basis network suitable for classification problems [9]. The PNN model belongs to the family of supervised learning networks, but it is distinct from others in the following manner.

i. It is implemented using the probabilistic model with a Gaussian mapping function.

ii. No requirement of setting initial weights of the network. Only the spread of the Gaussian function needs to be specified.

iii. No relationship between learning processes and recalling processes.

iv. The difference between the inference vector and the target vector are not used to modify the weights of the network.

High learning speed of PNN model makes it suitable for diagnosing PQ disturbances. Fig. 6 shows architecture of PNN model composed of radial basis layer and the competitive layer. For a classification application, the training data is classified according to their distribution values of probabilistic density function (PDF). A simple PDF is shown as

$$f_r(x) = \frac{1}{N_r} \sum_{j=1}^{N_r} \exp\left(-\frac{\|X - X_{rj}\|^2}{2\sigma^2}\right)$$  \hspace{1cm} (12)

Modifying and applying eq. (12) to the output vector $H$ of the hidden layer in the PNN is as

$$H_h = \exp\left(-\sum_i (X_j - W_{ih})^2\right)$$  \hspace{1cm} (13)

$$net_j = \frac{1}{N_r} \sum_h W_{hj}^y H_h \text{ and } net_j = \max_r(\text{net}_r)$$  \hspace{1cm} (14)

then $y_j = 1$ or $y_r = 0$, where

- $i$ = number of input layers;
- $h_j$ = number of hidden layers;
- $j$ = number of output layers;
- $r$ = number of training examples;
- $N$ = number of classifications (clusters);
- $\sigma$ = smoothing parameter (standard deviation);
### TABLE II: Values of Pure Signals

| Classes          | Variance | Skewness | Kurtosis |
|------------------|----------|----------|----------|
| Normal Signal    | 0.5      | -2.77E-16 | 0.375    |
| Sag              | 0.167    | 1.11E-18  | 0.304    |
| Swell            | 0.6594   | 9.36E-04  | -0.6358  |
| Flicker          | 0.2147   | 9.36E-04  | -0.7302  |
| Interruption     | 0.45     | -1.78E-17 | 0.27     |
| Transient        | 0.5275   | -0.152    | -0.3586  |
| Harmonics        | 0.2      | 2.56E-16  | 0.4453   |
| Sag with Harmonics | 0.3734 | -7.84E-18 | -0.189   |
| Swell with Harmonics | 0.0186 | -1.81E-16 | -0.0304  |
| Spike            | 0.0114   | -0.0027   | -0.1997  |
| Notch            | 0.4781   | -0.0039   | -0.3391  |

X = input vector; 

\[||X - X_{ri}|| = \text{Euclidean distance between the vectors } X \text{ and } X_{ri} :\]

i.e. \(||X - X_{ri}|| = \sum_{i}(X - X_{ri})^2\)

\(W_{ik}\) = connection weight between the input layer X and and the hidden layer H

\(W_{kj}\) = connection weight between the hidden layer H and the output layer Y

3) Radial Basis Neural Network: The schematic diagram of RBF neural network is shown in Fig. 7. The RBF network has an input layer, a hidden layer consisting of Gaussian node function, a set of weights \(W\), to connect the hidden layer and output layer. The transfer functions in the nodes are similar to the multivariate Gaussian density function:

\[
\Phi_j(x) = \exp\left(\frac{||x - \mu_j||^2}{2\sigma_j^2}\right)
\]

(15)

Where \(x\) is the input vector, \(\mu_j\) and \(\sigma_j\) are the center and spread of the corresponding Gaussian function. Each RBF unit has a significant activation over a specific region determined by \(\mu_j\) and \(\sigma_j\). Thus each RBF represents a unique local neighborhood in the input space. The connections in the second layer are weighted and the output nodes are linear summation units. The value of \(k^{th}\) output node \(y_k\) is given by:

\[
y_k(x) = \sum_{j=1}^{h} w_{kj} \Phi_j(x) + w_{k0}
\]

(16)

where \(w_{kj}\) is the connection weight between the \(k^{th}\) output and the \(j^{th}\) hidden node and \(w_{k0}\) is the basis term.

### III. SIMULATION RESULT AND ANALYSIS

In the proposed method, PQ disturbance signals were generated using MATLAB based on the equations in Table I with a sampling frequency of 2 kHz. Eleven types of PQ disturbance signals are termed as:

1) C1 - Normal,
2) C2 - Sag,
3) C3 - Swell,
4) C4 - Flicker,
5) C5 - Interruption,
6) C6 - Transient,
7) C7 - Harmonics,
8) C7 - Sag with harmonics,
9) C8 - Swell with harmonics,
10) C10 - Spike,
11) C11 - Notch.

A. Statistical Analysis

For the purpose of signal analysis, each PQ disturbance signals were decomposed into IMFs using the algorithm described in Section II. Their HOS were calculated. For comparison, HOS values were also calculated for the PQ disturbance signals. Tables II, III, IV and V show the values obtained for the different sets of PQ disturbance signals as well as their IMFs. It is clear that the values are distinguishable for the different sets of PQ signals. Also, note that the difference becomes larger in the EMD domain as compared to that of real signal. It is also seen that kurtosis shows significant statistical difference.

### TABLE III: Values of IMF1

| Classes                     | Variance | Skewness | Kurtosis |
|-----------------------------|----------|----------|----------|
| Normal Signal               | 0        | 0        | 0        |
| Sag                         | 0.0018   | -3.60E-03| 0.148    |
| Swell                       | -0.0925  | 0.0922   | 0.66     |
| Flicker                     | -0.0999  | -3.93E-04| 0.523    |
| Interruption                | -0.0043  | 0.0111   | 0.417    |
| Transient                   | -7.25E-04| 0.0053   | 0.8284   |
| Harmonics                   | -8.74E-04| 2.75E-04 | 0.0184   |
| Sag with Harmonics          | -1.20E-03| -0.0012  | 7.40E-03 |
| Swell with Harmonics        | 1.38E-03 | -0.0053  | 0.0187   |
| Spike                       | 3.7E-04  | -8.74E-04| 0.0174   |
| Notch                       | -3.403E-03| 3.25E-05| 0.149    |

### TABLE IV: Values of IMF2

| Classes                     | Variance | Skewness | Kurtosis |
|-----------------------------|----------|----------|----------|
| Normal Signal               | 0        | -2.78E-16| 0        |
| Sag                         | 0.0057   | 7.80E-03 | 5.44E-05 |
| Swell                       | 4.38E-04 | 3.29E-04 | 1.49E-06 |
| Flicker                     | 9.44E-05 | 3.47E-03 | 1.01E-04 |
| Interruption                | 0.0176   | -8.90E-03| -2.72E-05|
| Transient                   | 0.2426   | 0.0309   | -0.0011  |
| Harmonics                   | 1.17E-05 | -2.01E-05| 4.20E-04 |
| Sag with Harmonics          | 8.96E-04 | -2.38E-06| 2.47E-04 |
| Swell with Harmonics        | 1.38E-03 | -1.32E-05| 5.30E-05 |
| Spike                       | 1.92E-04 | 1.66E-04 | -4.04E-04|
| Notch                       | 5.803E-06| 2.92E-04 | 6.77E-04 |

### TABLE V: Values of IMF3

| Classes                     | Variance | Skewness | Kurtosis |
|-----------------------------|----------|----------|----------|
| Normal Signal               | -0.375   | 0        | 0        |
| Sag                         | 0.0188   | -6.34E-05| -1.98E-05|
| Swell                       | -0.64    | -3.97E-07| -2.89E-07|
| Flicker                     | 0.1907   | -1.19E-03| 1.98E-04 |
| Interruption                | -0.2277  | -1.19E-03| -4.61E-04|
| Transient                   | 0.0767   | -0.0013  | 0.0741   |
| Harmonics                   | -3.89E-04| -0.4124  | -1.86E-10|
| Sag with Harmonics          | -7.21E-05| -0.1831  | -1.98E-06|
| Swell with Harmonics        | -4.01E-04| -0.0012  | 1.28E-06 |
| Spike                       | -4.08E-04| -0.3125  | -1.29E-10|
| Notch                       | -3.38E-04| -0.1807  | -4.74E-11|
among eleven groups for EMD based PQ signals as well as the first three IMFs. Variance and skewness do the same work.

B. Efficiency Analysis

For each of the above classes, 135 signals are considered, 35 signals are selected for training and the rest of the signals are left for testing and validation. The performance evaluation criteria considered are: 1) confusion matrix and 2) overall efficiency in percentage (%). Confusion matrix is a form of representing the result from a classification exercise. Overall efficiency for the methodology is calculated using the formula given as in

\[
\text{Overall Efficiency} = \frac{\text{No. of correctly classified events}}{\text{Total no. of events}} \quad (17)
\]

For same type of training and testing data a comparative study between S-transform [31], Empirical Mode Decomposition with Hilbert transform [32], and proposed HOS based analysis in EMD domain is made. Confusion matrix resulting from the proposed feature set and compared methods set via \(k\)-NN classifier are presented in Tables VI, VII and VIII.

It can be seen from the diagonal entries of confusion matrix in Table VI that S-transform is unable to distinguish among PQ disturbance signals, such as swell (C3), flicker (C4), harmonics (C7), swell with harmonics (C9), spike (C10) and notch (C11). It is vivid from Table VII that HHT based \(k\)-NN classification misclassifies some sag (C2), interruption (C5), harmonics (C7) and sag with harmonics (C7) signals. It is demonstrated from Table VIII that HOS based EMD domain features are able to identify all of the signals almost perfectly. Classification performance in terms of overall efficiency (%). resulting from the proposed feature set when fed to RBF, PNN and \(k\)-NN classifiers are calculated over all classes and are presented in Tables IX.

Classification accuracy can be further enhanced by training the \(k\)-NN by higher number of events. Table X shows the testing results when training and testing events are made double (70 events of each class for training and 200 events of each class for testing). From Table X, it is seen that testing accuracy enhances to 99.6% for our proposed method.

### TABLE VI: Confusion matrix of S-transform

| Input Cases | Detected Cases |
|-------------|----------------|
| C1          | 100            |
| C2          | 97             |
| C3          | 60             |
| C4          | 90             |
| C5          | 3              |
| C6          | 99             |
| C7          | 69             |
| C8          | 0              |
| C9          | 40             |
| C10         | 19             |
| C11         | 31             |

Classification Efficiency(%) = 100 - Classification Error(%) = 81.2

### TABLE VII: Confusion matrix of HH-transform

| Input Cases | Detected Cases |
|-------------|----------------|
| C1          | 100            |
| C2          | 95             |
| C3          | 100            |
| C4          | 5              |
| C5          | 92             |
| C6          | 100            |
| C7          | 94             |
| C8          | 2              |
| C9          | 100            |
| C10         | 6              |
| C11         | 16             |

Classification Efficiency(%) = 100 - Classification Error(%) = 96

### TABLE VIII: Confusion matrix of HOS in EMD domain

| Input Cases | Detected Cases |
|-------------|----------------|
| C1          | 100            |
| C2          | 97             |
| C3          | 100            |
| C4          | 3              |
| C5          | 98             |
| C6          | 99             |
| C7          | 97             |
| C8          | 3              |
| C9          | 100            |
| C10         | 100            |

Classification Efficiency(%) = 100 - Classification Error(%) = 99

| Method | Overall Classification Accuracy (%) |
|--------|------------------------------------|
| S-transform | RBF | 87.1 | 74.5 |
|         | PNN | 74.5 | 91.2 |
|         | k-NN | 81.2 | 96 |
| HHT    | RBF | 94.5 | 95.6 |
|         | PNN | 95.6 | 96 |
|         | k-NN | 96.2 | 98.8 |

### TABLE IX: Classification results for RBF, PNN and \(k\)-NN

### TABLE X: Classification results for increased training and testing events (%)

| Method | Overall Classification Accuracy (%) |
|--------|------------------------------------|
| C1     | RBF | 95.1 | 78.6 |
|        | PNN | 96.9 | 84.4 |
|        | k-NN | 98.2 | 97.2 |
| C2     | RBF | 98.2 | 98.3 |
|        | PNN | 98.5 | 99.6 |
|        | k-NN | 98.8 | 99.9 |

C. Computational Performance

It should be noted that the structure of \(k\)-NN is simple and it requires less training numbers and less learning time compared to PNN and RBF. The time requirement for training and testing are specified in Table XI. It is clarified that with the nine features resulting from HOS based-EMD domain with \(k\)-NN classifier can effectively classify different kinds of PQ disturbances.
TABLE XI: Comparative time requirement to perform of k-NN, PNN and RBF

|                | k-NN | PNN | RBF |
|----------------|------|-----|-----|
| CPU time (s)   | 53   | 82  | 449 |

TABLE XII: Confusion matrix after inclusion of noise

| Input Cases | Detected Cases |
|-------------|----------------|
| C1          | 87             |
| C2          | 88             |
| C3          | 100            |
| C4          | 97             |
| C5          | 88             |
| C6          | 98             |
| C7          | 87             |
| C8          | 83             |
| C9          | 88             |
| C10         | 95             |
| C11         | 78             |

| Classification Efficiency(%) | 86 | 88 | 97 | 88 | 98 | 88 | 87 | 83 | 88 | 95 | 78 |
| Classification Error(%)      | 14 | 12 | 3  | 12 | 2  | 12 | 15 | 17 | 12 | 5  | 22 |
| Overall Efficiency(%)        | 90 |

D. Performance of k-NN under Noisy Environment

In an electrical power distribution network, the practical data consists of noise; therefore, the proposed approach has to be analyzed under noisy environment. Gaussian noise is widely considered in the research of power quality issues. In actual practice, since noise is a random parameter, the noise with which k-NN is trained may not be same when k-NN classifier is installed for testing. Hence, k-NN is trained and tested with different noise level signals.

Noise is added with pure signals and operated with EMD-Transform for the feature extraction. Then with these features k-NN is trained and subsequently tested for automatic classification. k-NN classifier was trained with signal to noise ratio (SNR) 20, 30 and 40 dB levels and tested with the inclusion of 20,25,30,35 and 40 dB levels of noise. Corresponding confusion matrix is shown on Table XII. The classification results show that the accuracy level decreases with the inclusion of noise. Hence, classification results of k-NN are quite satisfactory even if noise levels are added.

IV. CONCLUSION

In this paper, HOS based EMD transform and k-NN are employed to extract distinguishable features to classify different PQ disturbance signals. Only the first three IMFs are considered to derive the outcomes from which variance, skewness and kurtosis are extracted to form an effective feature set. The work here is formulated as a eleven class problem which is solved using the proposed feature set in conjunction with the k-NN as a classifier. The proposed method when compared to the methods using S-transform and Hilbert Huang transform along with PNN and RBF classifiers. It is found that the proposed method is superior in performance in classifying different PQ disturbance signals in terms of higher overall efficiency in percentage.

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