ELECTRIC POWER QUALITY EVENTS DETECTION AND CLASSIFICATION USING HILBERT TRANSFORM AND MLP NETWORK

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ABSTRACT

This paper shows a new technique for the detection and classification of various power quality events using Hilbert transform. The Hilbert transform has been introduced as a powerful tool for input features exaction such as mean, peak value and standard deviation from the distorted voltage waveforms using Matlab simulation for disturbance of various classes in the test system. The MLP based neural network has been chosen as the classifier of several types of power quality events and the neural network has been trained using 900 number of test data at the rate of 100 samples for each class of disturbance. The algorithm has been tested with 900 number of test data and the outcomes are recorded.

Keywords: power quality, power quality disturbances, hilbert transform, neural network, MLP based neural network.

Nomenclature

$x(t)$ = Real signal
$x_{HT}(t)$ = Hilbert transform signal
λ = Shifting operator
$(-jsgn(\Omega))$ = Shifting the negative frequency of $x(t)$
$A(t)$ = Envelop signal of $x(t)$
$\theta(t)$ = Instantaneous phase signal of $x(t)$

1. INTRODUCTION

Now a day's power quality has become a main problem in the electric power system. The reason for the poor quality of electric power is caused by the power line disturbances such as sag, swell, interruption, harmonics, sag with harmonics, swell with harmonics, flicker and notches. The various types of power quality disturbances were detected and classified using wavelet transform analysis as illustrated in [1].The time and frequency of multi resolution wavelet has been presented in [2] to analyze the electromagnetic power system transients.

Another approach of wavelets to identify the various power system transient signals such as capacitor switching, lighting impulse, etc has been discussed in [3]. Comparison of various signal processing techniques such as Fourier transform, multi resolution analysis and the continuous wavelet transform forthe analysis of power quality disturbanceshas been explained in [4]. The Fourier and wavelet transform based fuzzy expert system for the detection and classification of PQ disturbances has been demonstrated in [5]. The wavelet based neural classifier has been discussed in [6] for the recognition of PQ disturbance waveform. The wavelet multi resolution analysishas been used for the online classification of power quality events along with pattern classifier in [7]. Discrete wavelet transform along with neural network for PQ disturbance classification has been explained [8]. As wavelet transforms cannot be applied for the analysis of non stationary signals, S-transforms were implemented due to their excellent frequency resolution characteristics. Application of s-transform for power quality analysis has been discussed in [9] and a fuzzy logic based pattern recognition system along with multi resolution S-transform for power quality event classification has been discussed in [10].

S-transform based neural network for the detection and classification of PQ disturbance signal has been implemented in [11]. A combination of wavelet transform along with Kalman filter has been presented in [12] for the detection and analysis of voltage event in power system. Discrete wavelet transform and wavelet coefficients based neural network classifier has been demonstrated for the classification of PQ disturbances in [13]. The S-transform and modular neural network based power quality classifier has been presented in [14] and this combines the frequency resolution characteristics of S transform with the pattern recognizing ability of a neural network. A hybrid method of adaptive filtering and discrete wavelet transform for detection and analysis of PQ events in [15]. The classification of the various types of power quality disturbances based on S-transform and Probabilistic neural network has been discussed in [16].

Wavelet transform support vector machines based power quality disturbance classifier is presented in [17] where the analysis takes into account the different noise conditions also. Hilbert transform has been used for the detection and classification of power quality events along with RBF network in [18]. A combination of kalman filter and fuzzy expert system for the characterization of power quality disturbances has been illustrated in [19]. The dual neural network as ADALINE and FFNN has been implemented for the classification of single and combined form power quality disturbance in [20].A Hilbert transform and MLP neural network based power quality analyzer in which features are extracted using Hilbert transform and disturbances are identified and classified using an MLP based neural network is presented in this paper.

2. PROPOSED METHOD

The classification technique proposed has two stages namely a feature extraction stage and a classification stage. In the feature extraction stage, Hilbert transform is used for extracting features such as amplitude, slope and standard deviation. The classification stage consists of a MLP based neural network with four hidden layers. Disturbance waveforms were generated using Matlab simulink.

2.1 Feature extraction stage using Hilbert transform

The Hilbert Transform is used to generate an analytical signal obtained by convolving the real signal with the function as shown below:

$$x_{HT}(t) = x(t)(\frac{1}{\pi t}) \quad (1)$$

$$x_{HT}(t) = \frac{1}{\pi}\int_{-\infty}^{\infty} x(\frac{\lambda}{(t-\lambda})d\lambda \quad (2)$$

$$x_{HT}(t) = -jsgn(\Omega)X(\Omega) \quad (3)$$

The output of the Hilbert transform is 90^0 phase shift of the original signal$x(t)$, a complex signal. It is defined as

$$x_C(t) = x(t) + jx_H(t) \quad (4)$$

$$x_C(t) = A(t)e^{j\theta(t)} \quad (5)$$

The analytical signal has the information about amplitude as well phase of the signal. It is clear that

$$A(t) = \sqrt{x^2(t) + x_{HT}^2(t)} \quad (6)$$

$$\theta(t) = tan^{-1}(\frac{x_{HT}(t)}{x(t)}) \quad (7)$$

2.2 Multi-layer perceptron (MLP) neural network

A multilayer perceptron neural network is a feed-forward artificial neural network that has an input layer, output layer and one or more hidden layers. A MLP based neural network consists of multiple layers of nodes in which each layer connected to the next one fully in a directed graph. Except for the input nodes, each node is a neuron with a nonlinear activation function. MLP based neural network utilizes a supervised learning technique called back propagation for training the network. MLP based neural network architecture diagram is shown as in the Figure-1. The training parameters of the MLP used in this work are shown in Table-1.

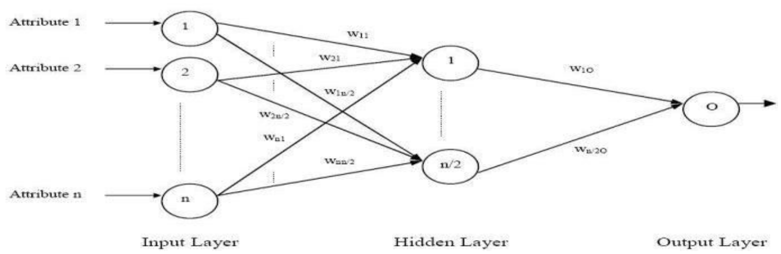

Figure-1. Architecture of MLP neural network.

Table-1. MLP architecture and training parameters.

Architecture	
The number of layers	3
The number of neuron on the layers	Input: 13, hidden: 10, output: 9
The initial weights and biases	Random
Activation functions	Tangent sigmoid
Training parameters	
Learning rule	Back-propagation
Learning rate	0.75
Mean-squared error	1E−08

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Back propagation learning algorithm

BP has two phases:

- **Forward pass phase:** Calculate the 'functional signal' and feed forward propagation of input pattern signals through network
- **Backward pass phase:** Calculate the 'error signal' and propagates the error backwards through network starting at output units (the difference between actual and desired output values).

The back-propagation network has an input layer, an output layer, and atleast one hidden layer. There is no limit on the number of hidden layers but typically there is just one or two. But in some case a minimum requirement of four layers (three hidden layers plus an output layer) are used to solve complex problems. Each layer is fully connected to the succeeding layer.

Recall is the process of setting input data into a trained network and receiving the answer. Back-propagation is not used during recall, but only when the network is learning a training set.

3. CLASSIFICATION STAGE

In this stage, Hilbert Transform extracted input features such as standard deviation, peak value, variances. The extracted input features are applied to the multi-layer perception based neural network in order to classify the disturbances. MLP networks are very useful for the classification of those input signals.

3.1 Flowchart of the proposed method

The flowchart for the Classification of Power Quality disturbances is shown in below. It has three different blocks.

- Block-(a)-Features extraction such as amplitude, slope andstandard deviation
- Block-(b) -Detection and classification of the power quality disturbances

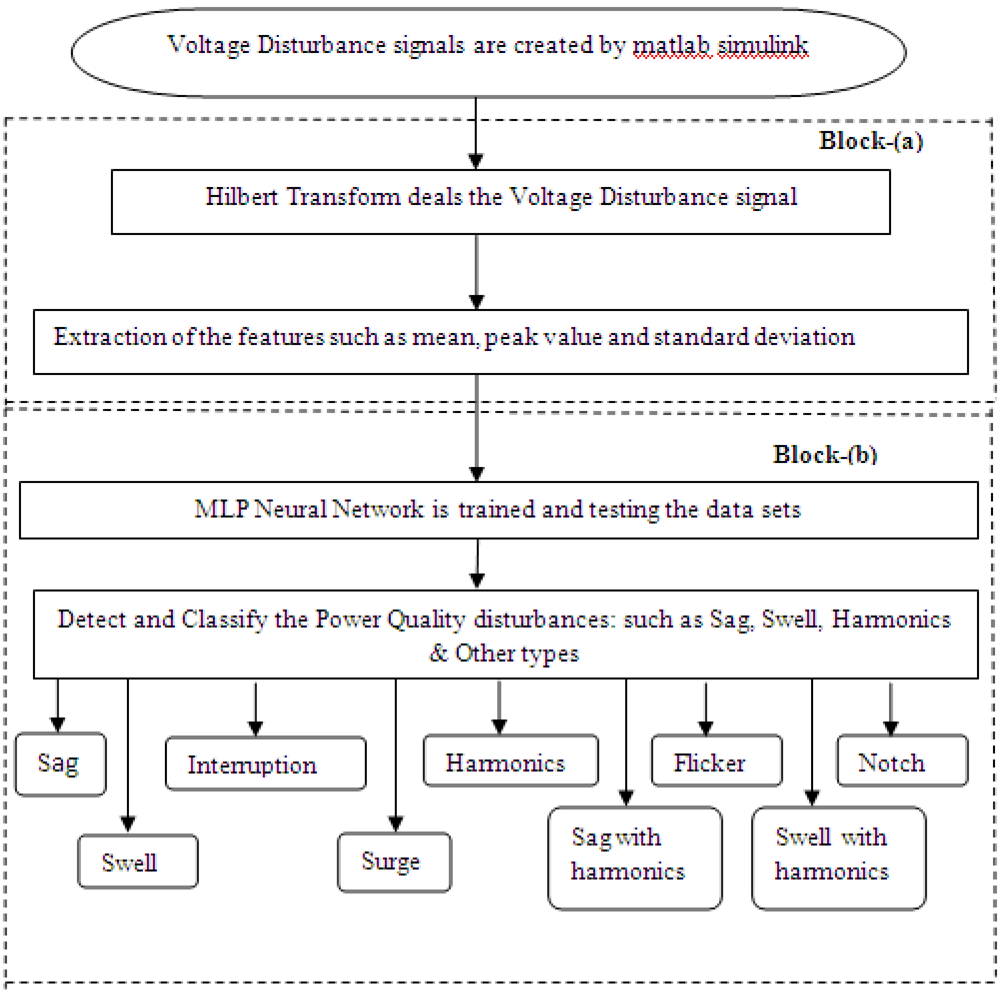

Figure-2. Flowchart for the classification of power quality disturbances.

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4. SIMULATION AND TEST RESULTS

Training and Test data were generated using Matlab simulink for various classes of disturbances .The signals closer to real situation can be simulated and different signals belonging to same class can be generated with ease so that the generalization ability of neural network based classifier could be improved. The single line diagram for the test system and the Matlab simulation block diagram are shown in Figure-3 and Figure-4.

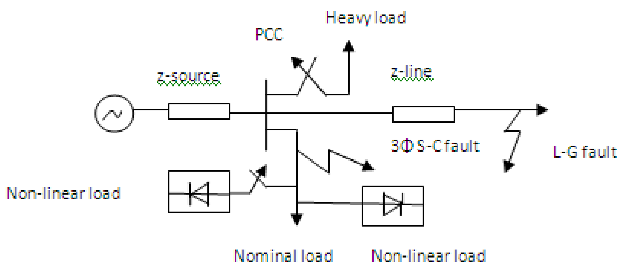

Figure-3. Single line diagram of test system model.

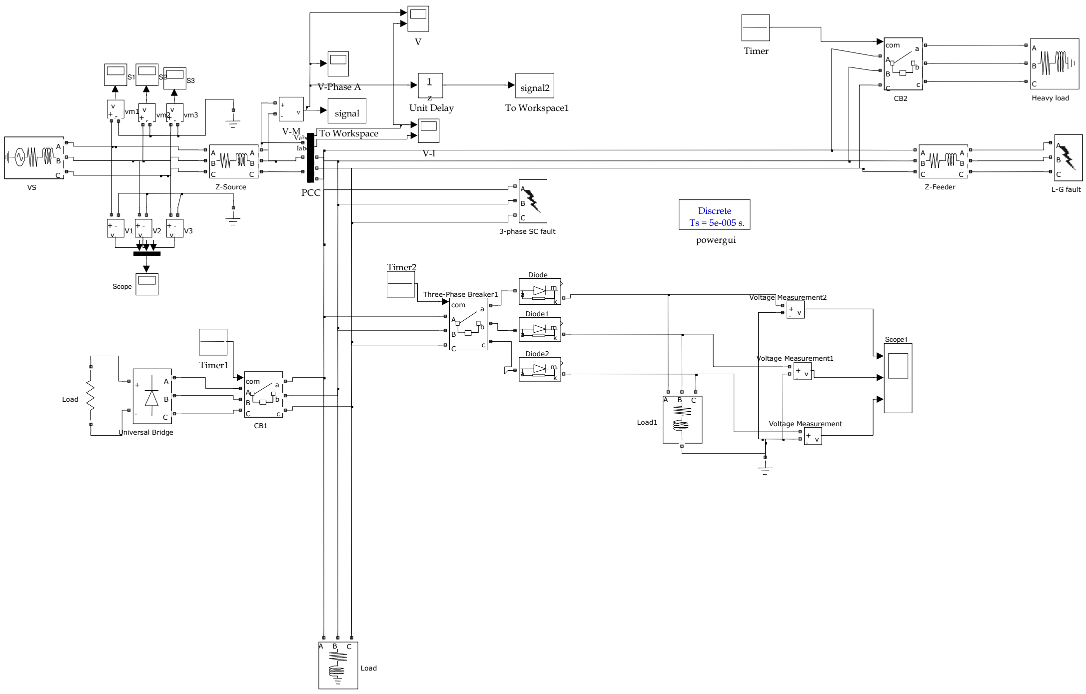

Figure-4. Matlab simulation block diagram for the test system model.

Nine classes of different PQ disturbances, namely pure sine (normal), sag, swell, outage, harmonics, sag with harmonic, swell with harmonic, notch and flicker were considered. Total size of the training data set is 3*900, where 3 represents the number of features extracted for each type of disturbance and 900 represents the total number of samples at the rate of 100 samples for each one of the 9 disturbances. The PQ disturbance signals generated using the Matlab simulink and the training performance of neural network with 100 epochs are shown in figures 5(a) to 14(c) for various classes of disturbance.

The following case studies are presented to highlight the suitability of the application of the proposed method.

- **Pure sine wave**

It is a voltage signal of amplitude at the frequency 50 Hzand its waveform is as shown in the Figure-5(a). The mean, peak value and the standard deviation outputs of the signal are shown in the Figures 5(b) and 5(e).

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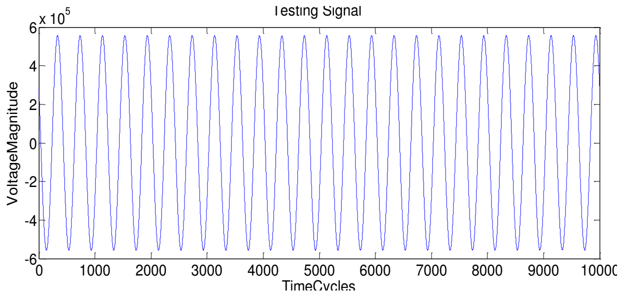

Figure-5(a).

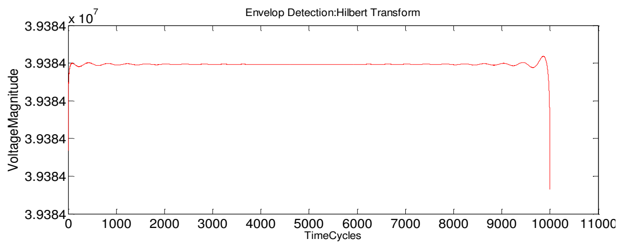

Figure-5(b).

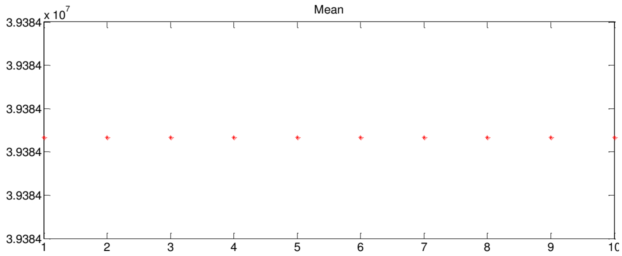

Figure-5(c).

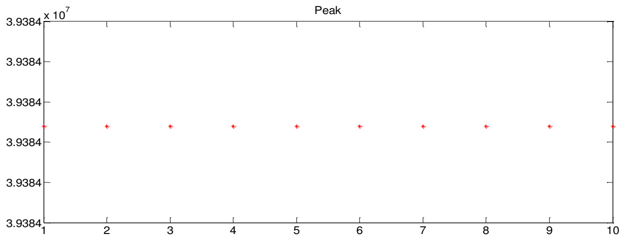

Figure-5(d).

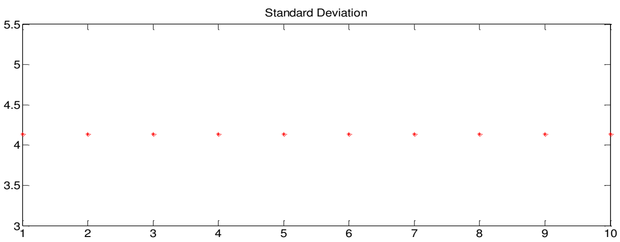

Figure-5(e).

Figure-5. Pure voltage signal.

a, Waveform, b) Envelop detection using Hilbert Transform, c) Mean, d) Peak value, e) Standard deviation

- **Voltage sag**

The voltage sag (or) voltage dips cause the decrease of system voltage. The duration of the sag disturbance is 0.4 to 0.8 cycles in 1 min. The voltage dip is generated by the occurrence of a single line to ground fault and its waveform is shown in the Figure-6(a). The mean, peak value and standard deviation outputs are shown in the Figures 6(b) to 6(e).

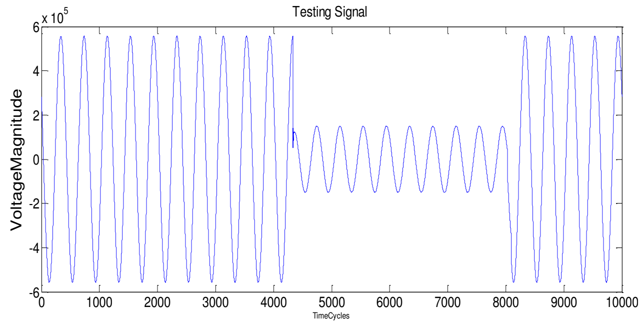

Figure-6(a).

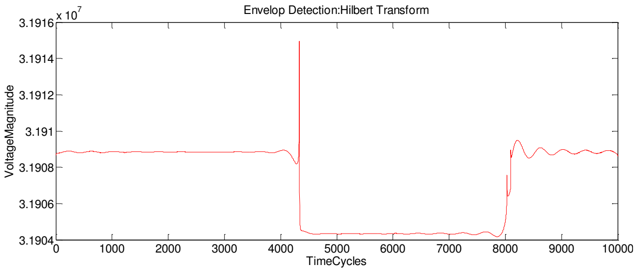

Figure-6(b).

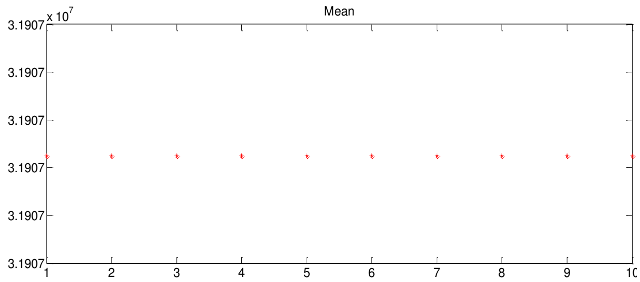

Figure-6(c).

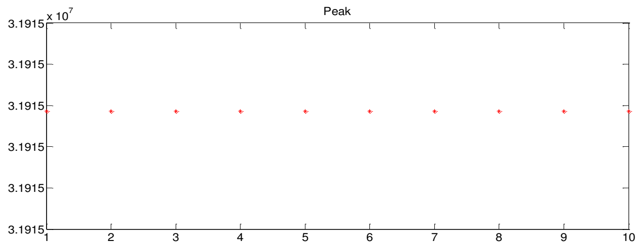

Figure-6(d).

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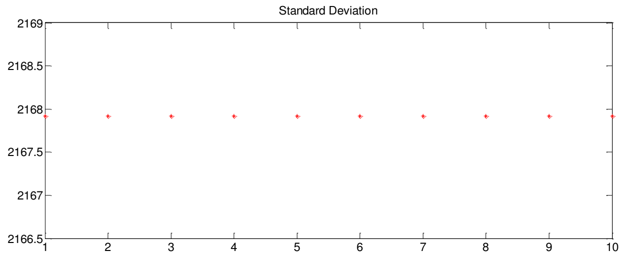

Figure-6(e)

Figure-6. Voltage sag.

a, Waveform, b) Envelop detection using Hilbert Transform, c) Mean, d) Peak value, e) Standard deviation

- **Voltage swell**

Voltage swell causes the rise of system voltage. The duration of the swell disturbance is 0.4 to 0.2 cycles in 1 min. The voltage swell is generated by disconnecting the heavy load for 10 cycles and its waveform is shown in the Figure-7(a). The mean, peak value and standard deviation outputs of the Hilbert transform are shown in the Figures 7(b) to 7(e).

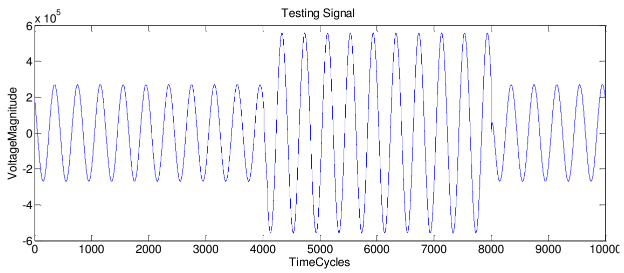

Figure-7(a).

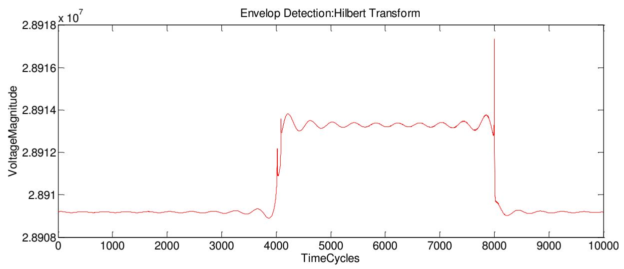

Figure-7(b).

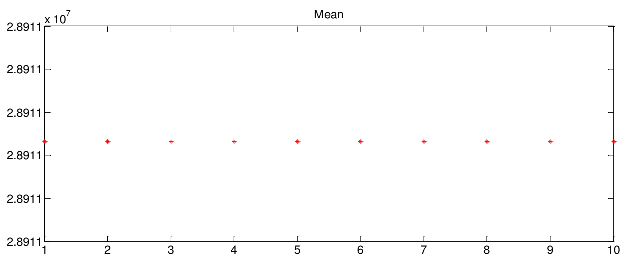

Figure-7(c).

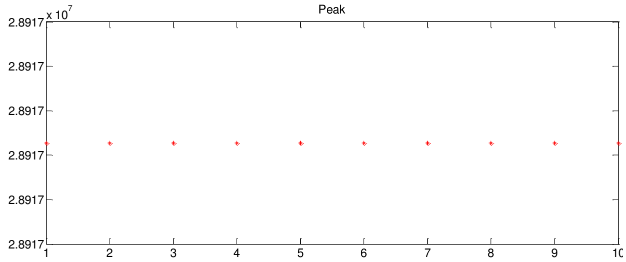

Figure-7(d).

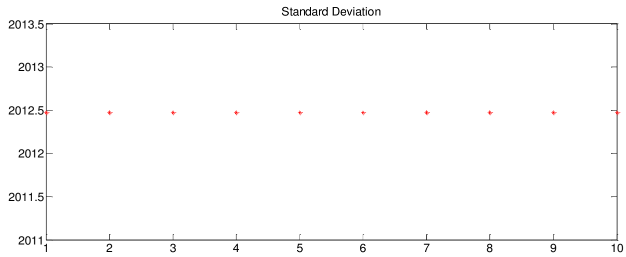

Figure-7(e).

Figure-7. Voltage swell.

a, Waveform, b) Envelop detection using Hilbert Transform, c) Mean, d) Peak value, e) Standard deviation

- **Voltage surge**

The voltage surge causes the sudden rise of the voltage in the short duration of time. The duration of the surge disturbance is 0.2 to 0.22 cycles in 1 min. The voltage surge is generated by disconnecting the heavy load for one quarter cycle and its waveform is shown in the Figure-8(a). Figures 8(b) to 8(e) represents the feature extraction outputs of Hilbert transform.

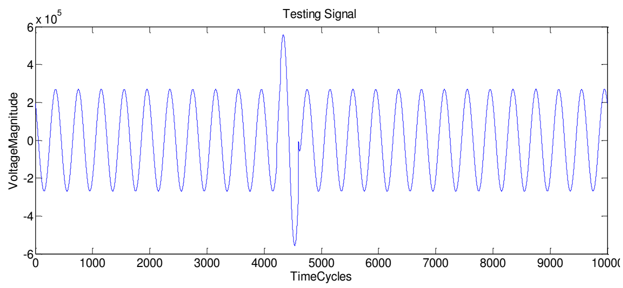

Figure-8(a).

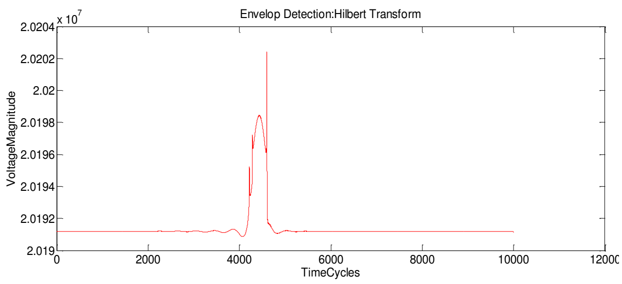

Figure-8(b).

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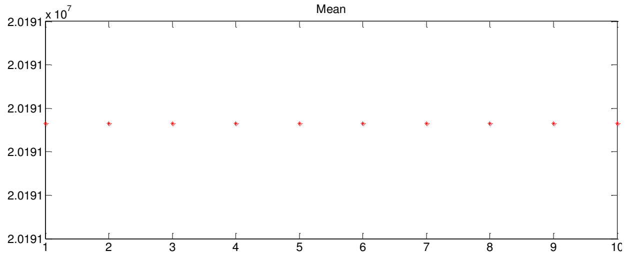

Figure-8(c).

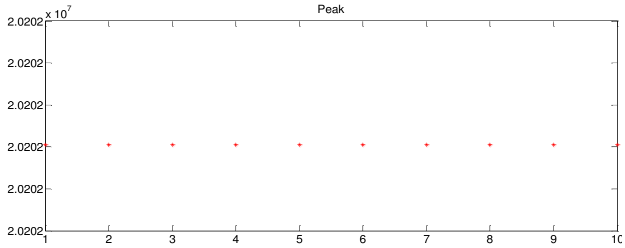

Figure-8(d).

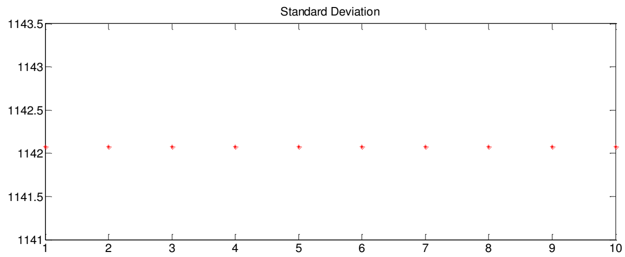

Figure-8(e).

Figure-8. Voltage surge.

a. Waveform, b) Envelop detection using Hilbert Transform, c) Mean, d) Peak value, e) Standard deviation

- **Voltage interruption**

The Voltage interruption causes the loss of the voltage on the system. The duration of the voltage interruption is 0.4 to 0.8 cycles. The voltage surge is generated by three phase short circuit fault and its waveform is shown in the Figure-9(a). The mean, peak value and standard deviation outputs of the Hilbert transform are shown in the Figures 9(b) and 9(e).

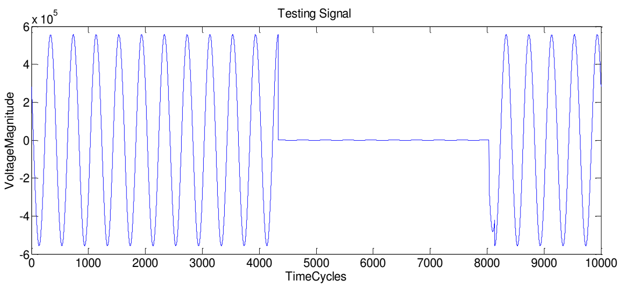

Figure-9(a).

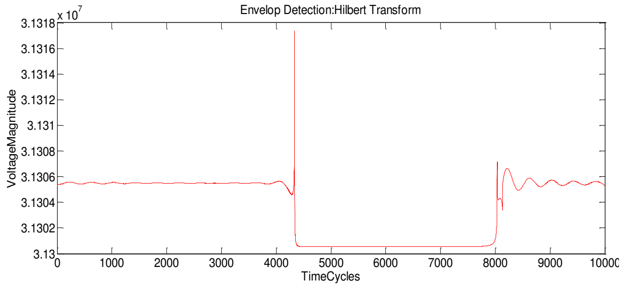

Figure-9(b).

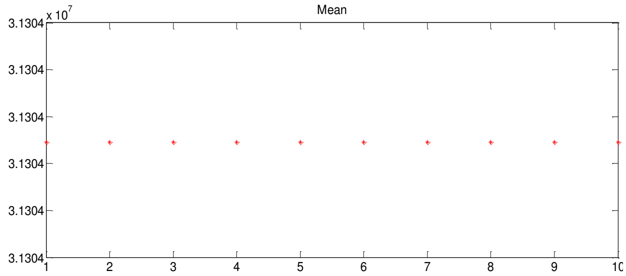

Figure-9(c).

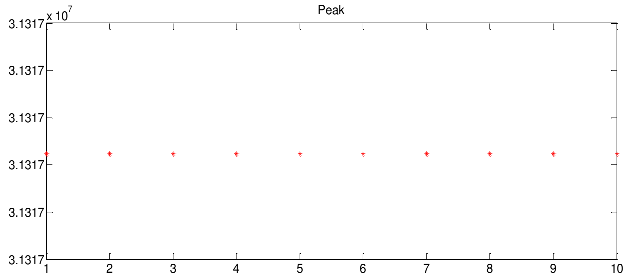

Figure-9(d).

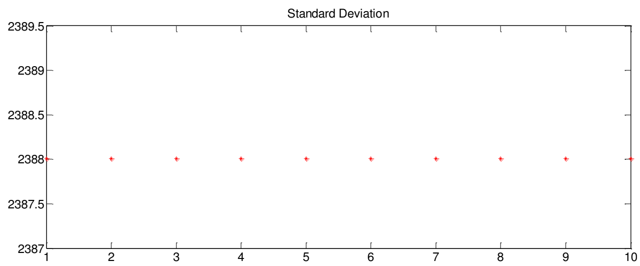

Figure-9(e).

Figure-9. Voltage surge.

a. Waveform, b) Envelop detection using Hilbert Transform, c) Mean, d) Peak value, e) Standard deviation

- **Harmonics**

Harmonics are generated by the connection of non linear load to the system. The distortion of the voltage waveform is shown in the Figure-10(a). Hilbert transform extract the three types of features. They are shown in the Figures 10 (b) to 10(e).

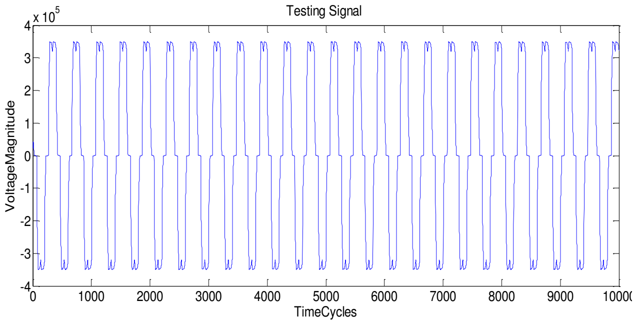

Figure-10(a).

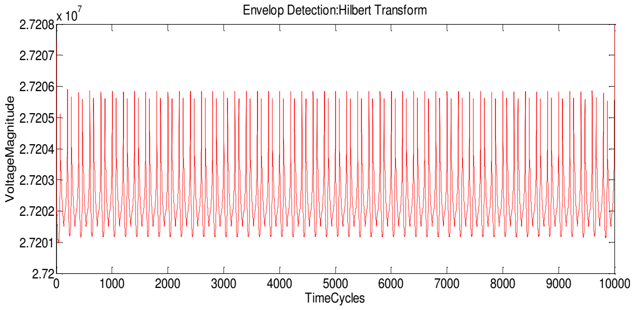

Figure-10(b).

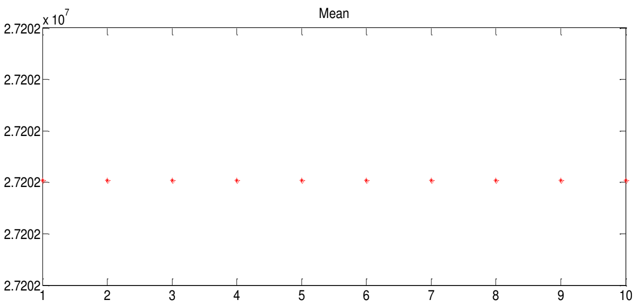

Figure-10(c).

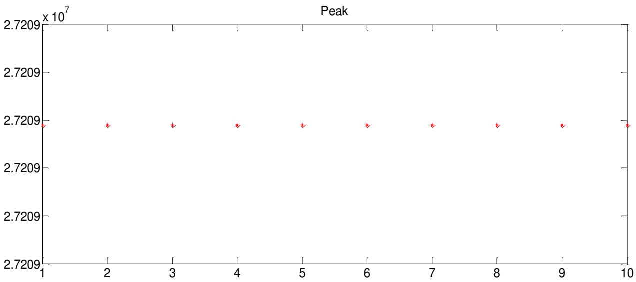

Figure-10(d).

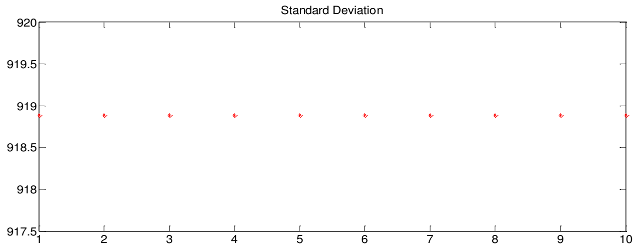

Figure-10(e).

Figure-10. Harmonics.

a, Waveform, b) Envelop detection using Hilbert Transform, c) Mean, d) Peak value, e) Standard deviation

- **Sag with harmonics**

This type of disturbance is caused by the presence of a nonlinear load and a voltage dip in the system for duration of 0.5 to 0.8 cycles. The waveform contains harmonic distortion with sag event as shown in the Figure-11(a). The mean, peak value and standard deviation outputs are shown in the Figures 11(b) to 11(e).

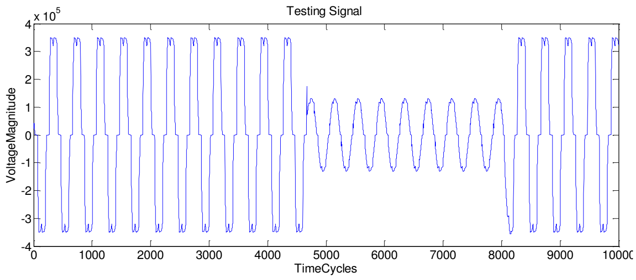

Figure-11(a).

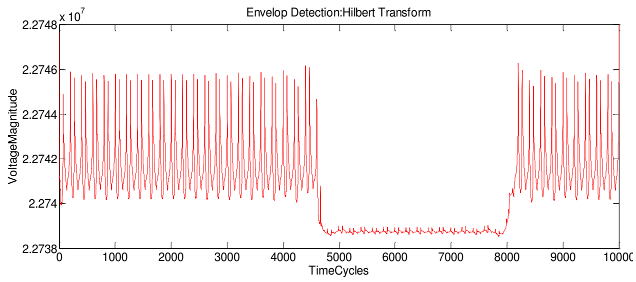

Figure-11(b).

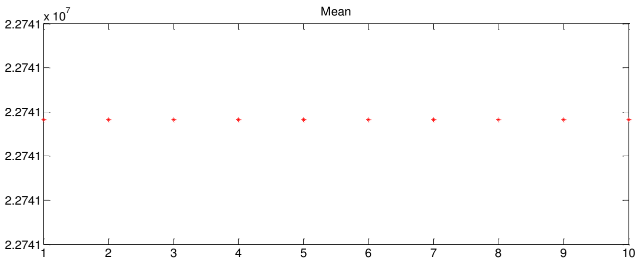

Figure-11(c).

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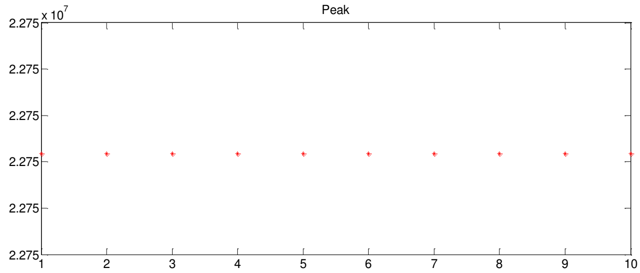

Figure-11(d).

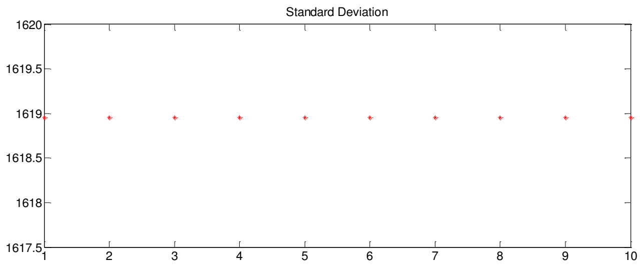

Figure-11(e).

Figure-11. Sag with harmonics.

a, Waveform, b) Envelop detection using Hilbert Transform, c) Mean, d) Peak value, e) Standard deviation

- **Swell with harmonics**

This type of disturbance is caused by the presence of nonlinear load and a voltage swell in the system for the duration of 0.4 to 0.8 cycles. The waveform contains harmonic distortion with swell event as shown in the Figure-12(a). Figures 12(b) to 12(e) represents the feature extraction outputs of Hilbert transform.

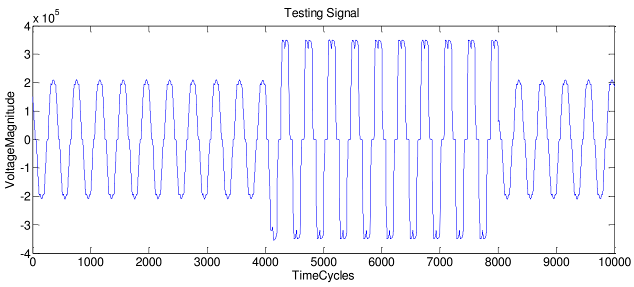

Figure-12(a).

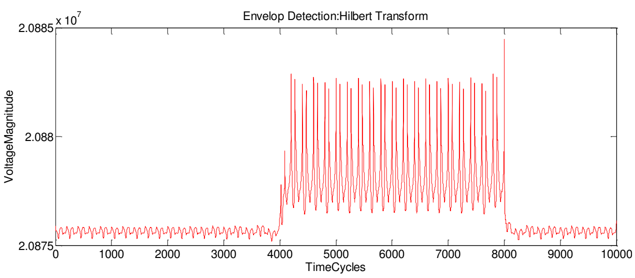

Figure-12(b).

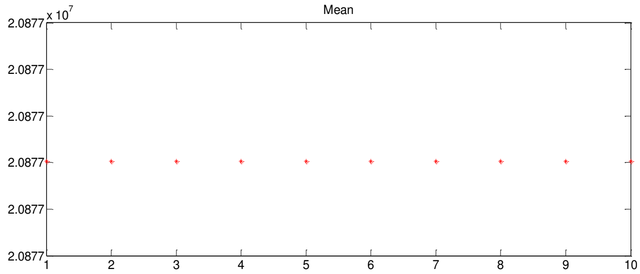

Figure-12(c).

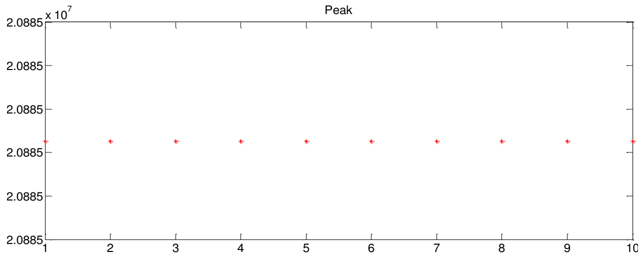

Figure-12(d).

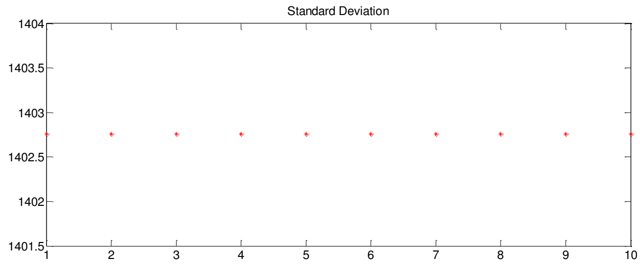

Figure-12(e).

Figure-12. Swell with harmonics.

a, Waveform, b) Envelop detection using Hilbert Transform, c) Mean, d) Peak value, e) Standard deviation

- **Flicker**

This type of disturbance type is caused by the continuous and rapid variation of the system load. Theflicker disturbance is generated by disconnecting the heavy load in the continuous nature at regular interval and the waveform of the flicker is shown in the Figure-13(a). The mean, peak value and standard deviation outputs of the Hilbert transform are shown in the Figures 13(b) and 13(e).

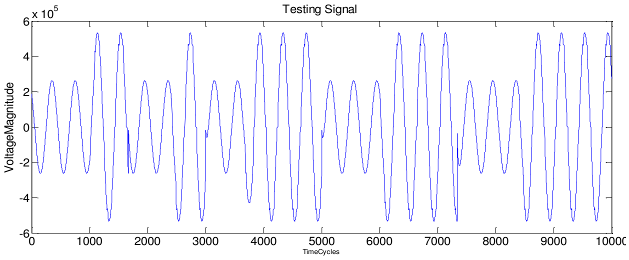

Figure-13(a).

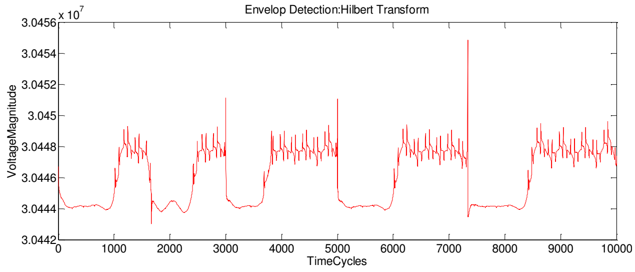

Figure-13(b).

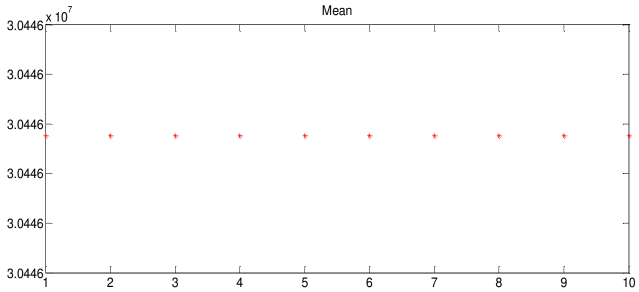

Figure-13(c).

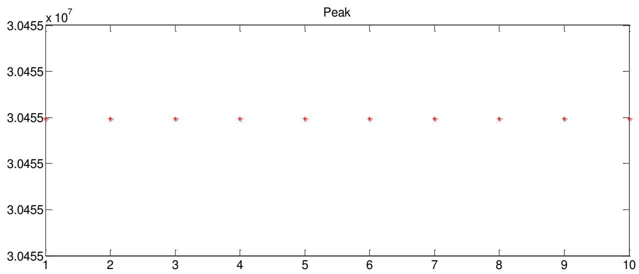

Figure-13(d).

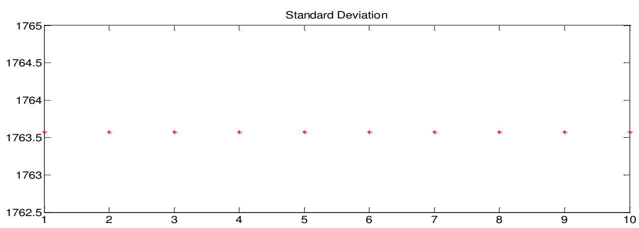

Figure-13(e)

Figure-13. Flicker.

a, Waveform, b) Envelop detection using Hilbert Transform, c) Mean, d) Peak value, e) Standard deviation

- **Notch**

This is a disturbance of the nominal power voltage waveform lasting for less than half a cycle. The disturbance is initially of opposite polarity and hence it is to be subtracted from the waveform as shown in the Figure-14(a). Figures 14(b) to 14(e) represents the feature extraction outputs of Hilbert transform.

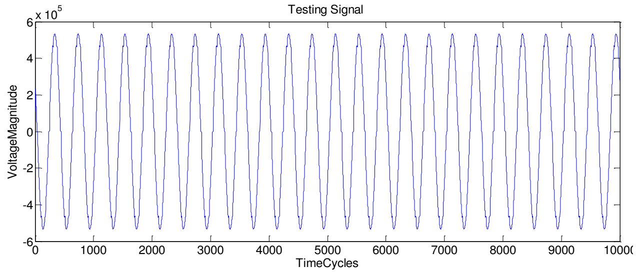

Figure 14(a).

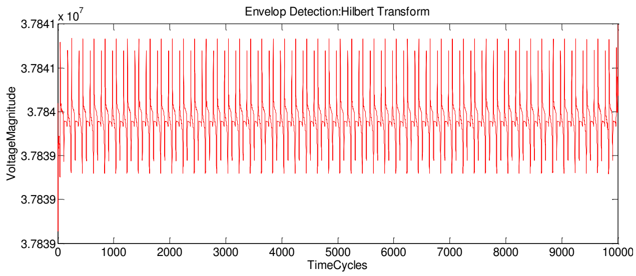

Figure-14(b).

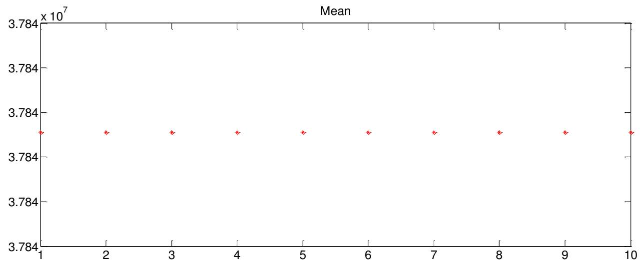

Figure-14(c).

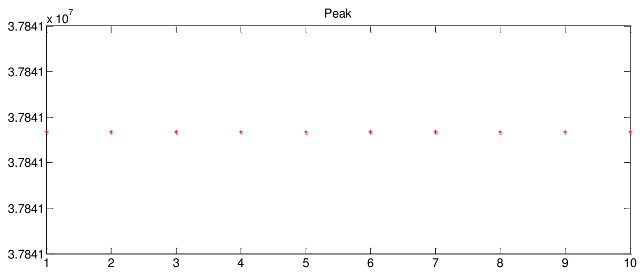

Figure-14(d).

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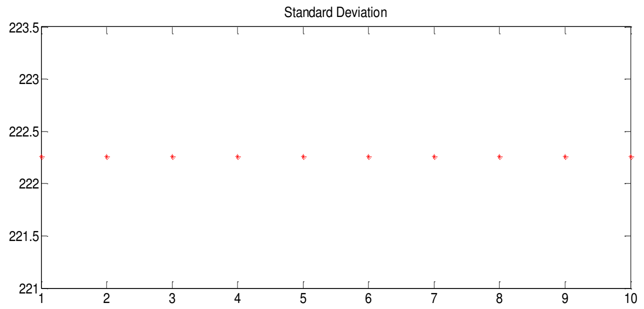

Figure-14(e).

Figure-14. Voltage notch.

a. Waveform, b) Envelop detection using Hilbert Transform, c) Mean, d) Peak value, e) Standard deviation

Table-3. Classification accuracy.

S. No.	Power quality disturbances	Input Features	Percentage of accuracy
1	Voltage Sag	100	100
2	Voltage Swell	100	100
3	Voltage interruption	100	99
4	Voltage surge	100	98
5	Harmonics	100	99
6	Sag with Harmonics	100	100
7	Swell with Harmonics	100	100
8	Flicker	100	98
9	Notch	100	99
Overall accuracy			99.22

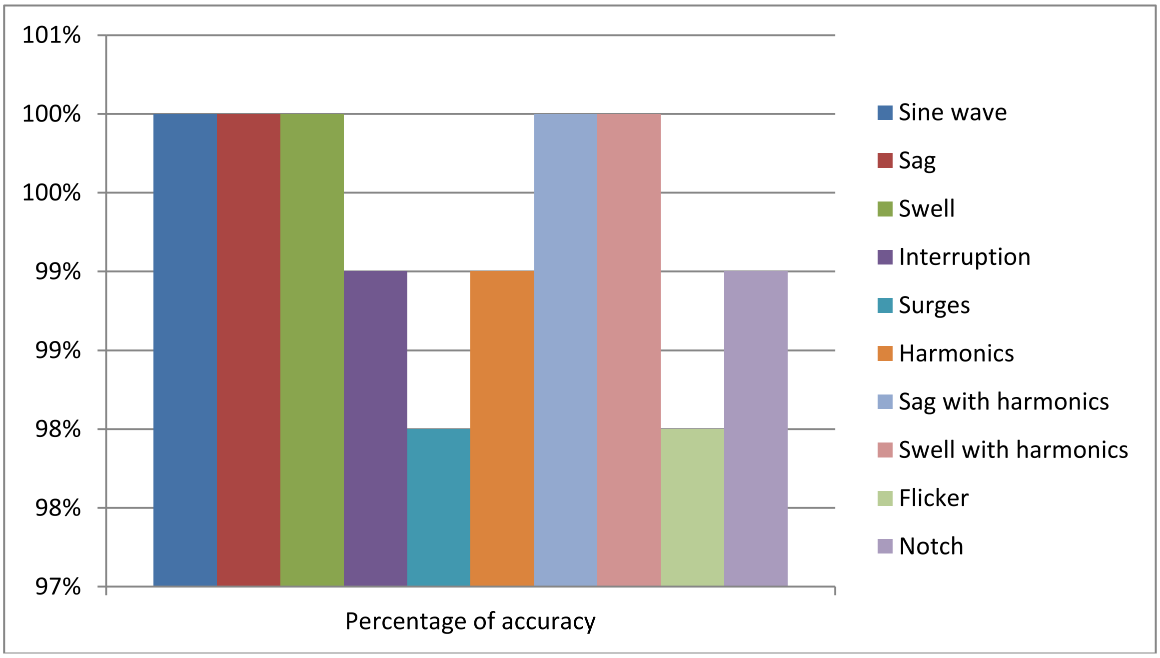

Figure-15. Bar diagram for the percentage of accuracy of the proposed method.

4. CONCLUSIONS

The paper has presented a new method for detection and classification of power quality disturbances in the electric power systems. The method combines the Hilbert transform and MLP based neural network. The disturbance waveforms were generated through Matlab simlink and features such as mean, peak value and standard deviation were extracted through Hilbert transform and an MLP based neural network has been applied for classifying the disturbances. The method enables the accurate classification of all nine types of PQ disturbances and it is well suitable for real world applications were the classifier is applied over the data captured in field. MLP neural network has the wide range of skills that it can be trained for any input combination and its application is particularly suitable for classification of disturbances of varying nature.

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