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ANALYSIS OF POWER QUALITY DISTURBANCES BASED ON KALMAN FILTER AND MLP NEURAL NETWORK

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ABSTRACT

This paper aims to develop a new technique for the classification of various power quality disturbances using Kalman filter and Multi-layer perceptron (MLP) neural network. Kalman filter is adopted to extract the three types of input features (standard deviation, peak value and variances) from the power quality disturbance waveforms simulated on a Matlab test system. The extracted features are given as inputs to the neural network.MLP based neural network has been used for disturbance classification and the neural network has been trained using 1800 number of test data at the rate of 200 samples for each class of disturbance. The algorithm has been tested with 1800 number of test data and the outcomes are recorded.

Keywords: power quality, power quality disturbances, kalmanfilter, neural network, MLPbased neural network.

Nomenclature

$X_{a,b}$- Continuous wavelet transform
a & b - Dilation and translation parameter
Ψ(t) - Mother wavelet
x_k - State vector
y_k – Voltage sinusoid
z_k - Measurement at the time instant t_k
Φ_k - State transition matrix
H_k - Measurement matrix
w_k&v_k - Model and measurement errors
ω - Fundamental angular frequency
$A_{i,k}$&θ_k- Amplitude and phase angle of the i^{th} harmonic attime t_k
Δt - Sampling interval
R_k - Covariance matrix of v_k
K_k- Kalman gain
P_K^-- Prior process covariance
Q_k- Covariance matrix of w_k
P_k- Error covariance

1. INTRODUCTION

Over the past few years, a wide range of power quality detection and classification tools were developed. Normally electric power quality disturbances are classified as sag, swell, interruption, harmonics, sag with harmonics, swell with harmonics, notches and flickers and these are created by power line disturbances and such other factors. Hence it is necessary to detect and localize these disturbances and further identify the types of disturbances. Various types of power quality disturbances were detected and classified using wavelet transform analysis as illustrated in [1]. Analysis of electromagnetic power system transient waveform using wavelet transform has been illustrated in [2].The data processing burden of the classification algorithm has been considerably reduced by compressing the signals through wavelet transform methods as illustrated in [3].

Classification of power quality events using a combination of SVM and RBF networks has been presented in [4]. The windowed FFT which is the time windowed version of discrete Fourier transform has been applied for power quality analysis to classify a variety of disturbances in [5]. A combination of Fourier and wavelet transform along with fuzzy expert system has been presented in [6] for the automatic monitoring and analysis of power quality disturbances. Wavelet multi resolution analysis based neural network classifier is presented in [7] for the detection and extraction of power quality disturbances. Automated online power quality disturbances classification using wavelet based pattern recognition technique has been illustrated in [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]. S-transform based neural network classifier is presented in [10] where the analysis of the non stationary signals in the power system has been carried out. A fuzzy logic based pattern recognition system along with multi resolution S-transform for power quality event classification has been discussed in [11]. A combination of wavelet transform

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along with both ANN and fuzzy logic classifier has been implemented for the PQ events classification in [12].

The binary feature matrix of the system has been designed using Fourier and S-transform and a rule base has been formulated to classify the power quality events in [13].Probabilistic neural network method based on optimal feature selection for power quality event classification has been illustrated in [14].A representative quality power vector has been derived for power quality analysis through an adaptive neuro fuzzy interface system in [15].A rule based system in which power quality event generation and signal capturing were implemented in the hardware and classification has been implemented through an expert system has been presented in [16]. A real time classification method for the power quality disturbances based on RMS values of the waveforms and DWT has been discussed in [17].

A combination of linear Kalman filter and fuzzy expert system has been used for the analysis of power quality events in [18] wherein the signal noise is estimated using a block of DWT. Classification of power quality disturbances using a combination of Hilbert huang transform (HHT) and Relevance vector machine (RVM) has been presented in [19].The detection and classification of single and combined power quality disturbances are based on signal spare decomposition (SSD) on overcomplete hybrid dictionary (OHD) matrix in [20].A Kalman filter-neural network based power quality analyzer in which features are extracted using Kalman Filter and disturbances are classified using an MLP based neural network is presented in this paper.

2. PROPOSED METHOD

The proposed method has two main stages namely feature extraction stage and classification stage. In the feature extraction stage, Kalman Filter is used for extracting the input features such as standard deviation, peak value and variances. The classification stage consists of a MLP based neural network with four hidden layers. Disturbance waveforms were generated using Matlab simulation of the test system.

2.1 Feature extraction stage using Kalman filter

Kalman filter has been used for the purpose of the input feature extraction. Kalman filter is characterized by a set of dynamic state equations and measurement equations, given a set of observed data, as illustrated below.

$$X_{k+1}= \varphi_k x_k+w_k \tag{1}$$

$$z_k = H_k x_k+v_k \tag{2}$$

In order to obtain a satisfactory performance of Kalman filter, it is necessary to know both the dynamic process and the measurement model. In the power system, the measured signal can be expressed by a sum of sinusoidal waveforms and the noise. Let an observed signal z_k at timet_k be the sum ofy_k andv_k, which represents M sinusoids and the additive noise for sampling points. Then

$$z_k= y_k+v_k \tag{3}$$

$$z_k=\sum_{i=1}^{n} A_{k,i}\sin((i\omega k)\Delta T + \theta_{k,i}) + v_k \tag{4}$$

where$k$= 1,2,3……N .

Each frequency component requires two state variables and hence the total number of state variables is 2n. At any time k, these state variables are defined as

For 1st harmonics: $x_1 = A_1\cos(\theta_1) x_1 = A_1\sin(\theta_1)$
For 2nd harmonics: $x_2 = A_2\cos(\theta_2) x_2 = A_1\sin(\theta_2)$ (5)
. . . .
For nth harmonics: $x_{2n-1} = A_n\cos(\theta_n) x_{2n-1} = A_n\sin(\theta_n)$

The above set of equations can be written in matrix form as,

$$X_{k+1}= \begin{pmatrix} X_1 \\ X_2 \\ . \\ . \\ . \\ X_{2n} \end{pmatrix}_{k+1} = \begin{pmatrix} 1\ 0 \dots.\ 0 \\ 0\,1 \dots.\ 0 \\ 0\,0\,1 \dots.0 \\ . \\ . \\ . \\ 0\ 0\ 0 \dots.\ 1 \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \\ . \\ . \\ . \\ X_{2n} \end{pmatrix}_{k} + w_k \tag{6}$$

The measurement equation can be similarly expressed in matrix form as

$$z_k = H_k x_k+v_k= \begin{pmatrix} \sin(\omega k\Delta T) \\ \cos(\omega k\Delta T) \\ . \\ . \\ \sin(n\omega k\Delta T) \\ \cos(n\omega k\Delta T) \end{pmatrix}^T \begin{pmatrix} X_1 \\ X_2 \\ . \\ . \\ X_{2n-1} \\ X_{2n} \end{pmatrix}_k + v_k \tag{7}$$

The system covariance matrices for w_k and $v_k$can be written as
E[$w_k w_k^T$] = [R_k] and E[$v_k v_k^T$] = [Q_k]

The Kalman Filter execution procedure is a recursive one, with steps for time and measurement updates as listed as below.

Time update

1) Project the state ahead

$$X_{k+1}^{-}=\Phi_k x_k$$

2) Project the error covariance ahead (8)

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$P_{k+1}^{-}=\Phi_k P_k \Phi_k^T + v_k$

Measurement update

1) Compute the Kalman gain

$$K_K = P_K^- H_K^T (H_K P_K^- H_K^T + R_K)^{-1}$$

Update estimate with measurement

$$x_k = x_K^- + K_K(z_K - H_K)x_K^- \quad (9)$$

2) Update the error covariance

$$P_k = (I - K_K H_K)P_K^-$$

Time and measurement update equations (8) and (9) are alternatively solved. After each time and measurement update pair, the process is repeated using the previous posterior estimates to project the new a prior estimates. At any given instant k, the amplitudes of the fundamental and harmonic frequencies are computed from estimated variables as

$$A_{i,k} = \sqrt{X_{1.K}^2 + X_{2,K}^2} \quad (10)$$

$$A_{i,k} = \sqrt{X_{2i-1.K}^2 + X_{2,Ki}^2} i = 1,2,\ldots\ldots\ldots\ldots n \quad (11)$$

Slope of the signals, $Slope_{,k} = (A_{i,k} - A_{i,k-1})/\Delta T$ (12)

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.

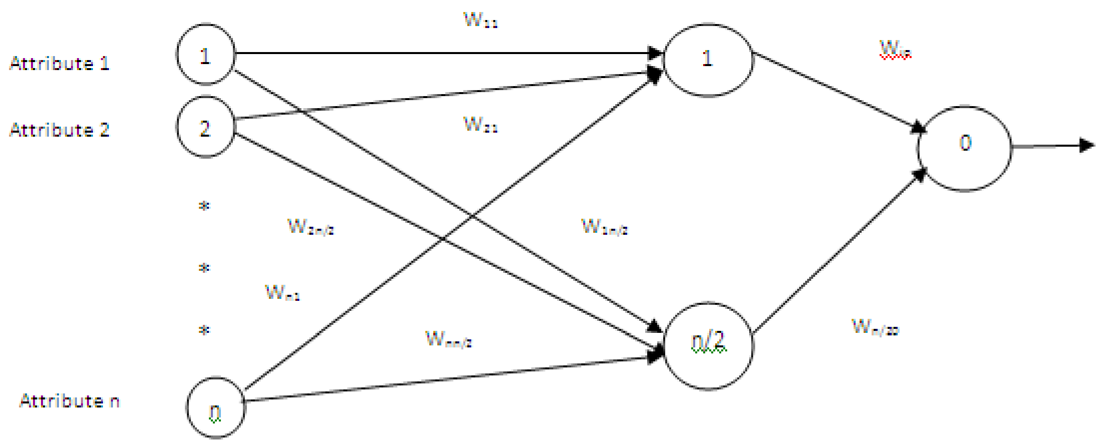

Figure-1. Architecture of MLP neural network.

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

Back propagation learning algorithm

BP has two phases:

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- **Forward pass phase:** Calculates the 'functional signal' and propagates input pattern signals through network in the forward direction.

- **Backward pass phase:** Calculates 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 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 order to classify the power quality disturbances, the extracted features through Kalman filter namely standard deviation, peak value and the variances are applied as inputs to the multi-layer perception based neural network.MLP networks are very useful for the classification of those input signals which cannot be defined mathematically.

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-1 - Extraction of the features

- Block-2 Classification of the power quality disturbances and

- Block-3 Identification of the disturbances

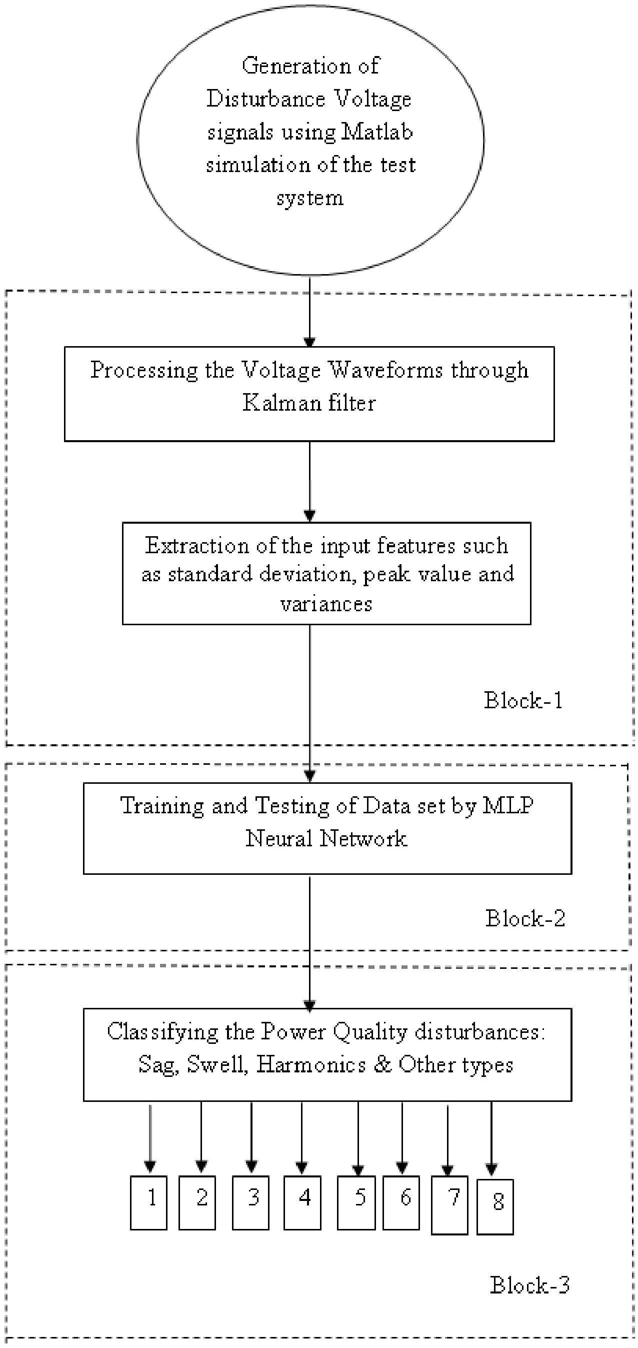

Figure-2. Flowchart for the classification of power quality disturbances.

4. SIMULATION AND TEST RESULTS

Training and Test data were generated using Matlab Simulink on the test system for various classes of disturbances and this method of data generation offers the advantages such as a wide range of parameters can be generated in a controlled manner, signals closer to real situation can be simulated. The single line diagram for the test system and the Matlab simulation block diagram are shown in Figure-3 and Figure-4.

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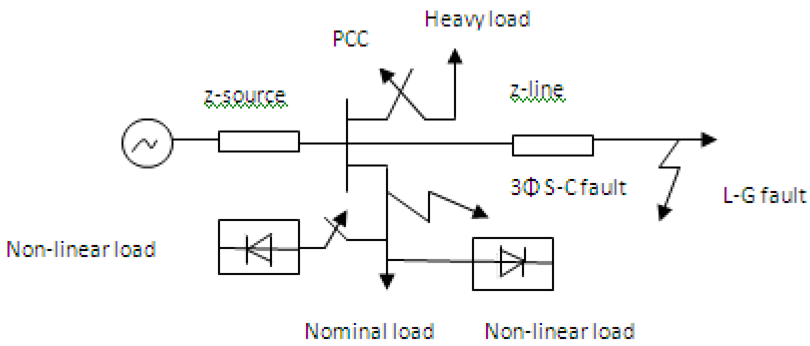

Figure-3. Single line diagram of test system model.

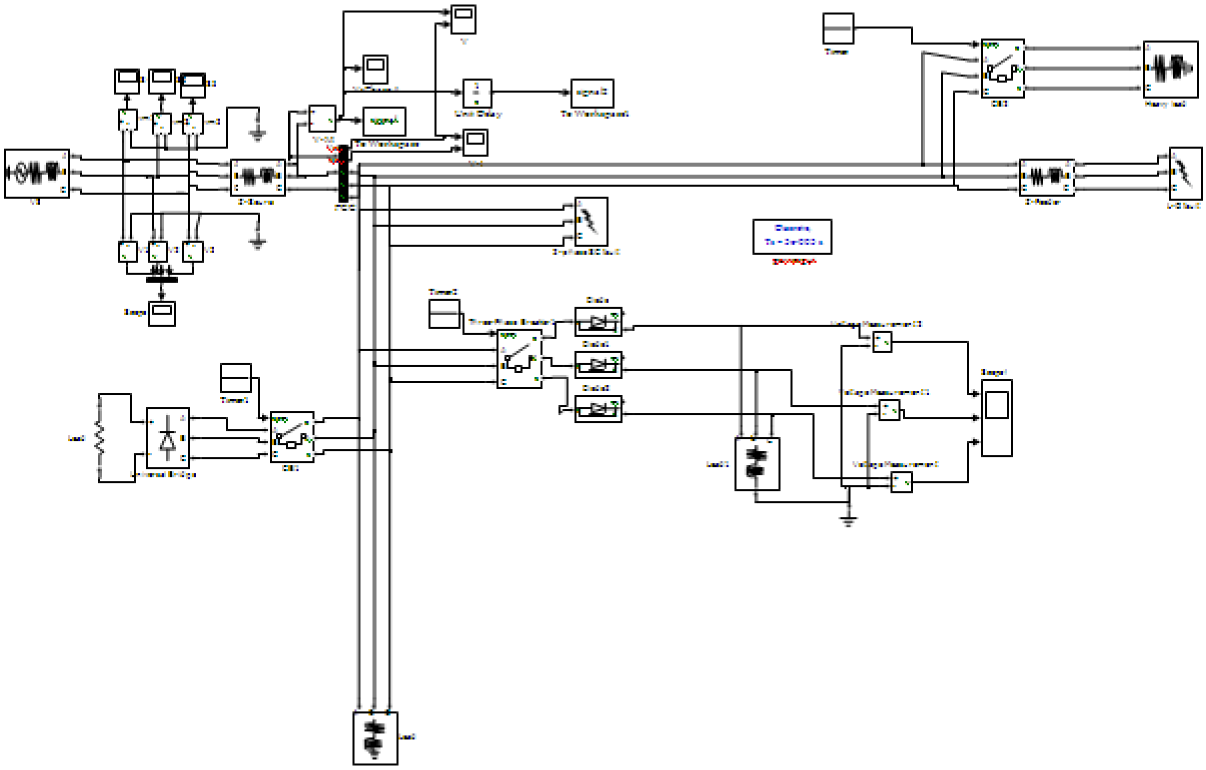

Figure-4. Matlab simulation block diagram for the test system model.

Nine classes of different PQ disturbances, namely pure sine (normal), sag, swell, surge, outage, harmonics, sag with harmonic, swell with harmonic, notch and flicker were considered. Total size of the training data set is 3*1800, where 3 represents the number of features extracted for each type of disturbance and 1800 represents the total number of samples at the rate of 200 samples for each one of the 9 disturbances.

In the following case studies, the analysis and classifications of power quality disturbances are presented.

Pure sine wave is a normal voltage signal of amplitude 1 V at the frequency 50 Hzand its waveform is as shown in the Figure-5(a).The standard deviation, peak value and variance outputs of the kalman filter are shown in the Figures 5(b), 5(c) and 5(d).

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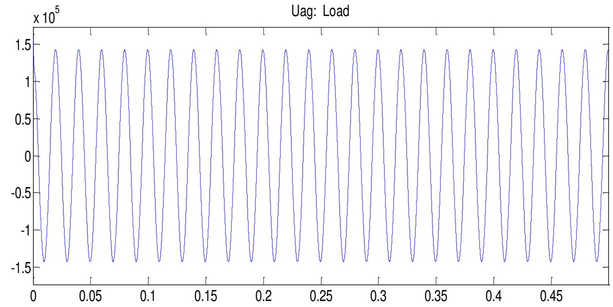

Figure-5(a).

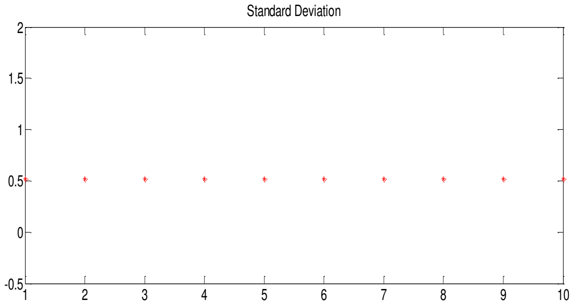

Figure-5(b).

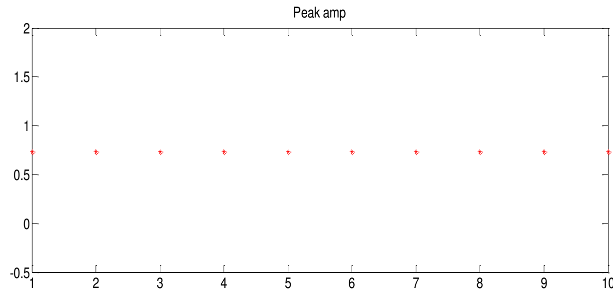

Figure-5(c).

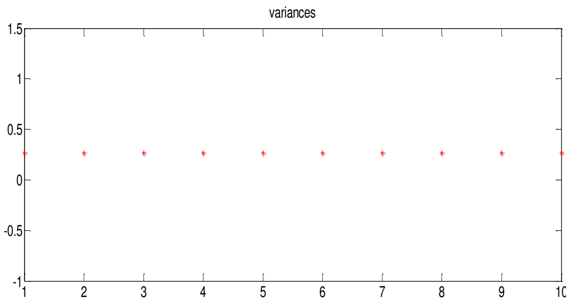

Figure-5(d).

Voltage sag (or) **voltage dips** cause a decrease of 10-90% in system voltage. The duration of the sag disturbance is 0.2 to 0.4 cycles in 1 min. It is generated by the occurrence of a single line to ground fault for 10 cycles. The voltage dip waveform is shown in the figure 6(a). The three input features extracted using kalman filter from the disturbance signal are shown in the figures 6(b), 6(c) and 6(d).

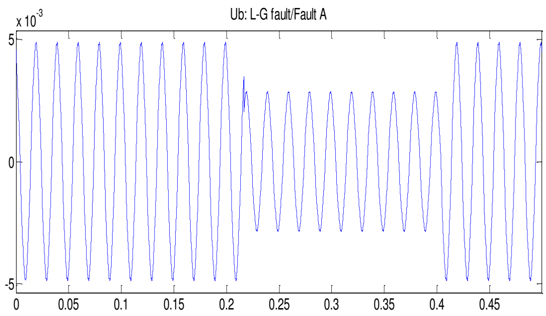

Figure-6(a).

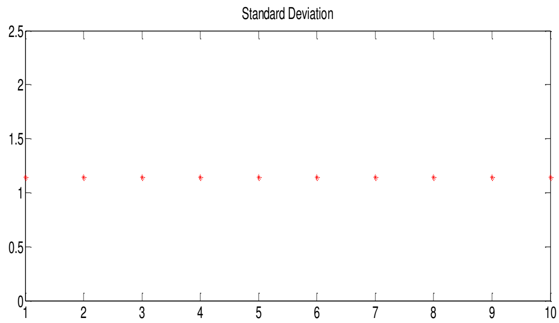

Figure-6(b).

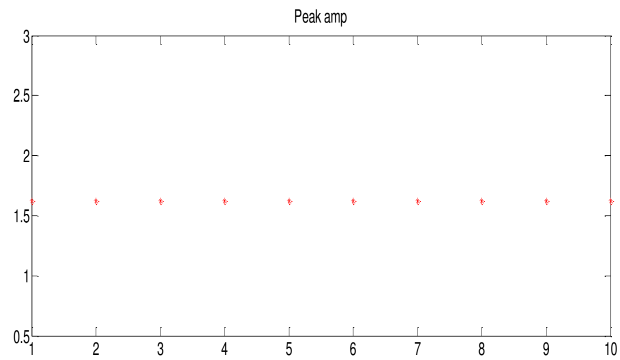

Figure-6(c).

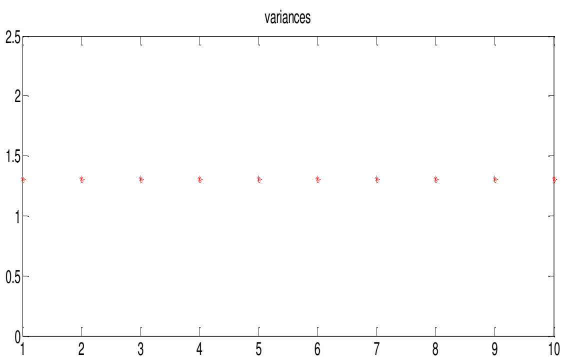

Figure-6(d).

Voltage swell causes the rise of 10-90% of the system voltage. It is generated by disconnecting the heavy load for 10 cycles. The duration of the swell disturbance is 0.2 to 0.4 cycles in 1 min. The voltage swell waveform is shown in the Figure-7(a) and their corresponding features extracted from the kalman disturbance signal are shown in the Figures 7(b), 7(c) and 7(d).

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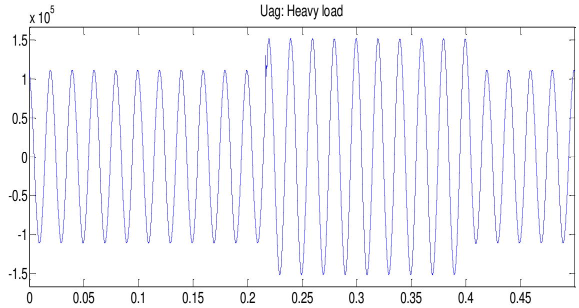

Figure-7(a).

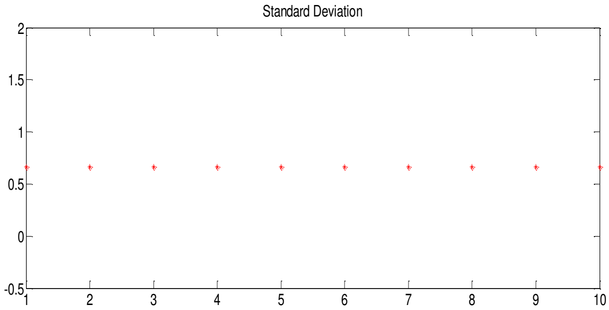

Figure-7(b).

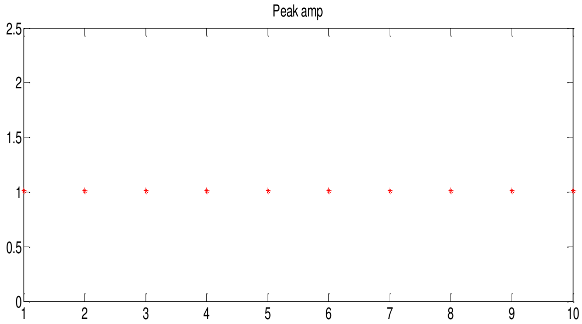

Figure-7(c).

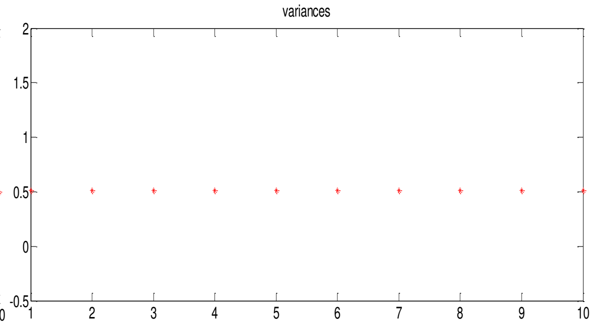

Figure-7(d).

Voltage surge causes a sudden increase of the system voltage for a short duration of 0.28 to 0.32 cycles in less than 1 minute. It occurs while disconnecting a heavy load for one quarter cycle as shown in the Figure-8(a) and the corresponding features are shown in Figure 8(b), 8(c) and 8(d).

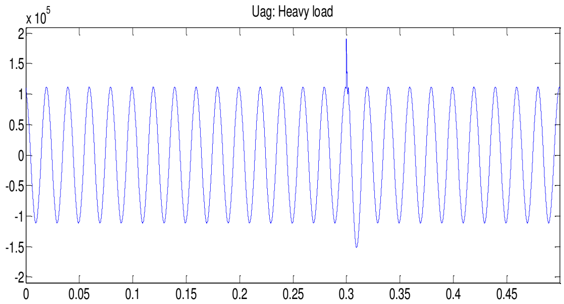

Figure-8(a).

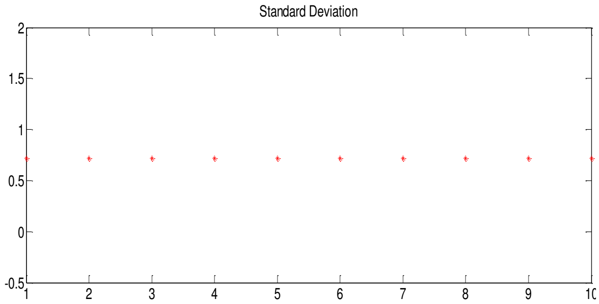

Figure-8(b).

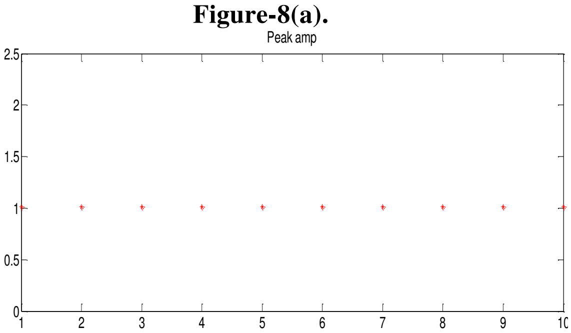

Figure-8(c).

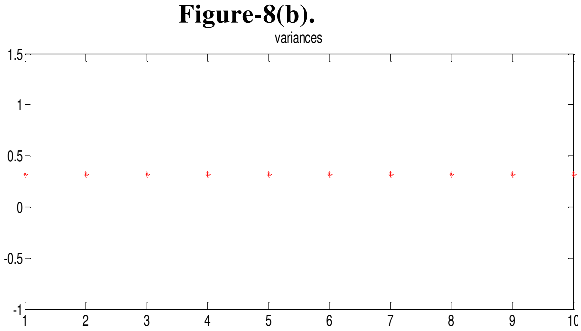

Figure-8(d).

Outages may be seen as a loss of voltage on the system for the duration of 0.5 cycles to 1min. An outages is generated by simulating a 3-phase dead short circuit to ground. The voltage waveform for an outage event shown in the Figure-9(a) and the corresponding features are shown in the Figure 9(b), 9(c) and 9(d).

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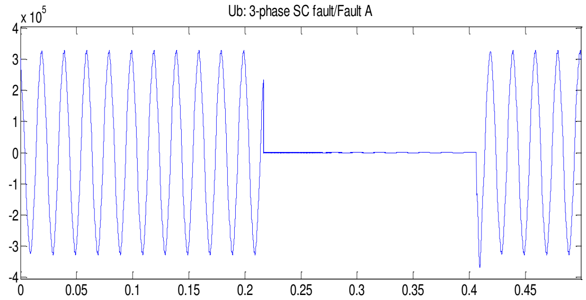

Figure-9(a).

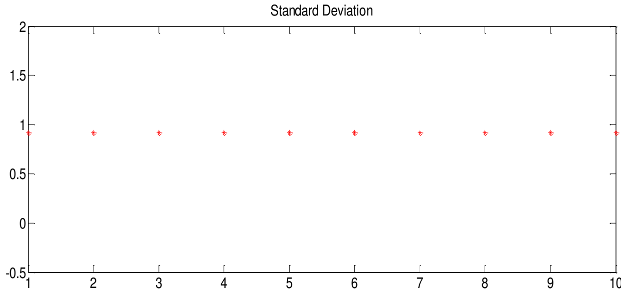

Figure-9(b).

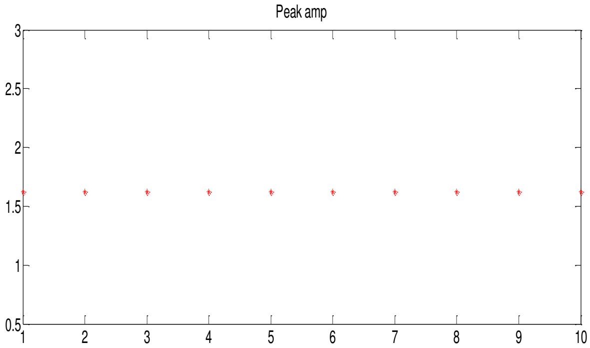

Figure-9(c).

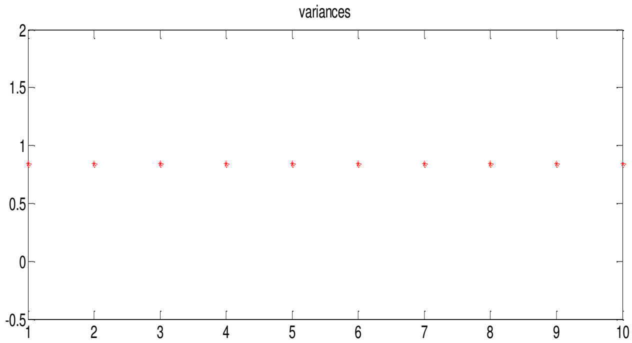

Figure-9(d).

Harmonics are generated by connecting a non linear load to the system for 10 cycles. Figure-10(a) shows the distortion of voltage waveform and their corresponding kalman filter outputs are given in the Figures 10(b), 10(c) and 10(d).

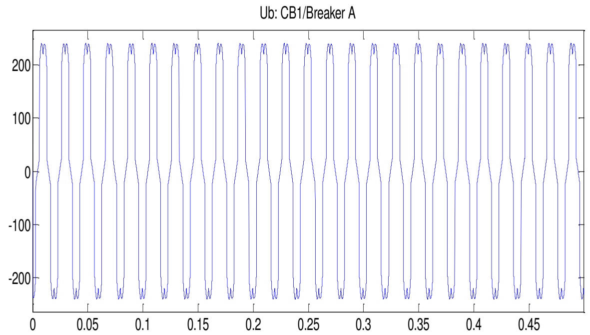

Figure-10(a).

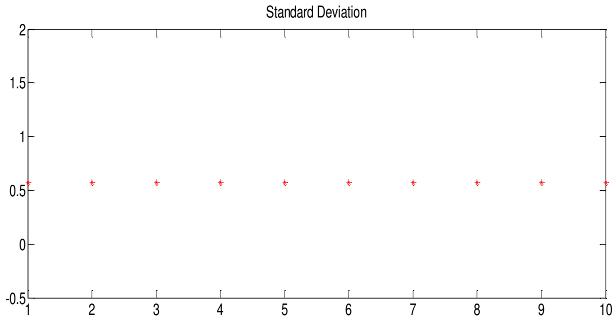

Figure-10(b).

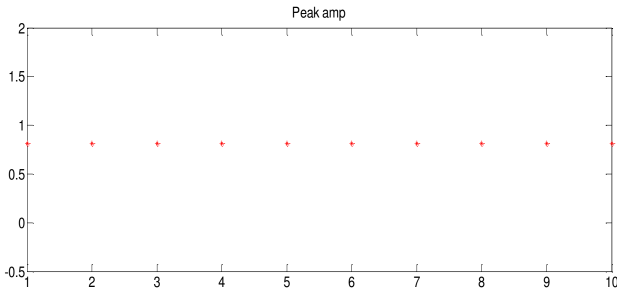

Figure-10(c).

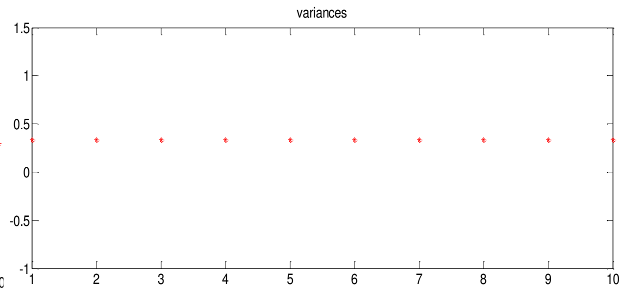

Figure-10(d).

Sag with harmonics are caused by the presence of a nonlinear load and occurrence of single line to ground fault for duration of 0.2 to 0.4 cycles .The waveform which contains harmonic distortion with sag event is shown in the Figure-11(a). The standard deviation, peak value and variances outputs of the kalman filter for this type of disturbances are shown in the Figures 11(b), 11(c) and 11(d).

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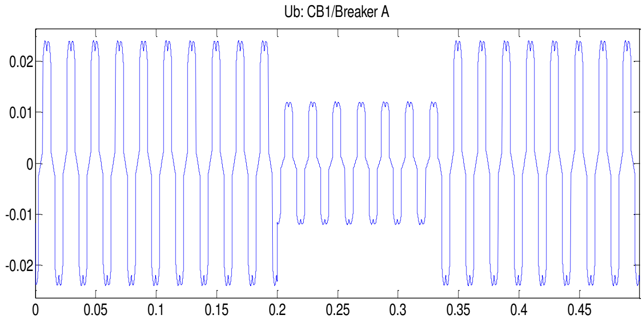

Figure-11(a).

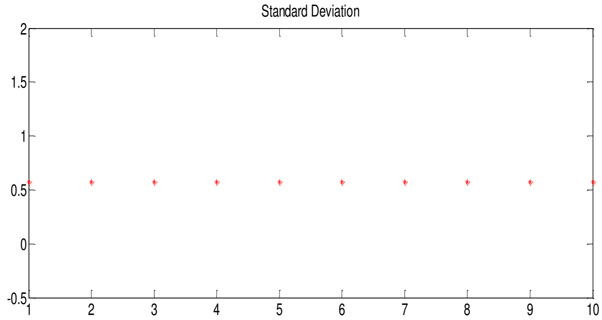

Figure-11(b).

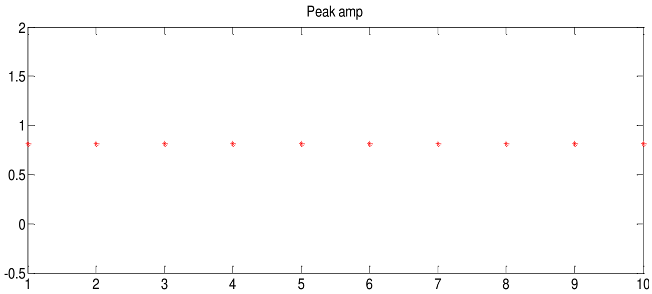

Figure-11(c).

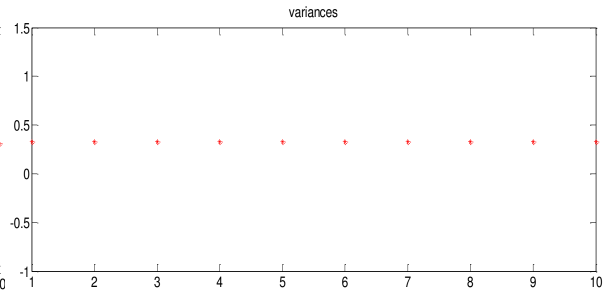

Figure-11(d).

Swell with harmonics is caused by the presence of nonlinear load and disconnecting the heavy load for 5 cycles in the duration of 0.2 to 0.4 cycles. The waveform for harmonic distortion with swell is shown in the Figure-12(a) and the corresponding kalman filter outputs are given in the Figures 12(b), 12(c) and 12(d).

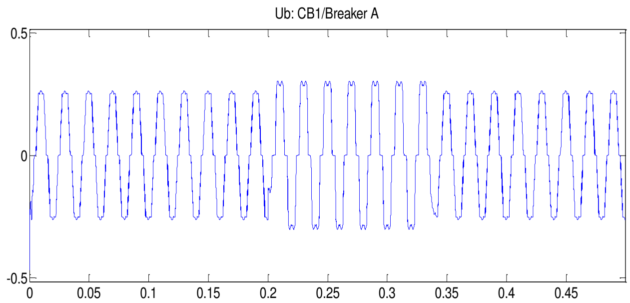

Figure-12(a).

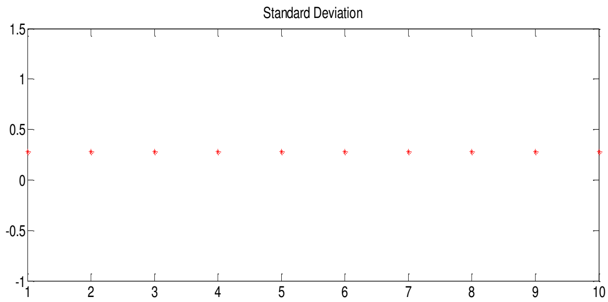

Figure-12(b).

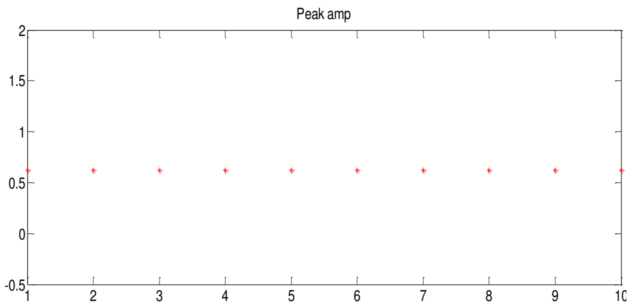

Figure-12(c).

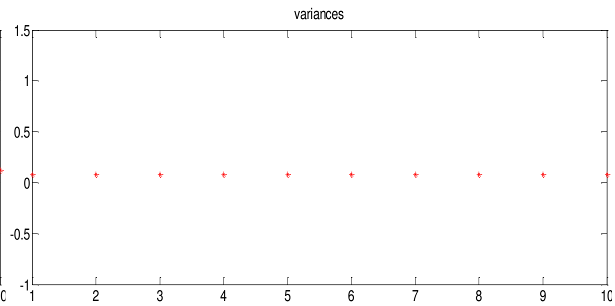

Figure-12(d).

Flicker disturbance is caused by a continuous and rapid variation of the system load. It is simulated by the continuous connection and disconnection of the heavy load. The waveform of the flicker is shown in the Figure-13(a). The standard deviation, peak value and variance outputs of the kalman filter of the flicker waveform are shown in the Figures 13(b), 13(c) and 13(d).

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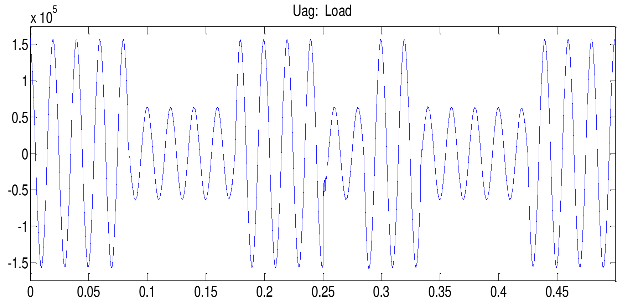

Figure-13(a)

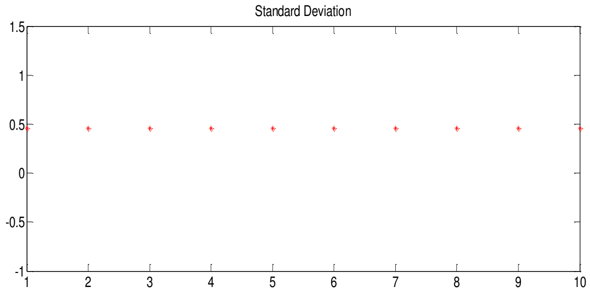

Figure-13(b).

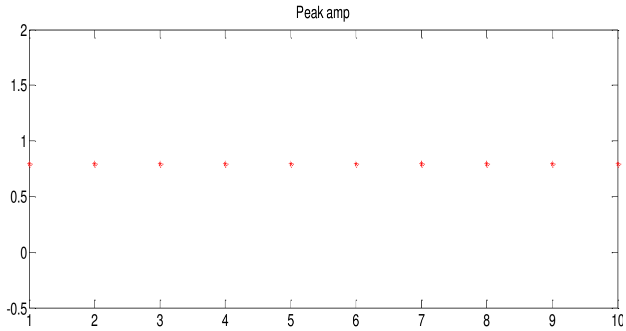

Figure-13(c).

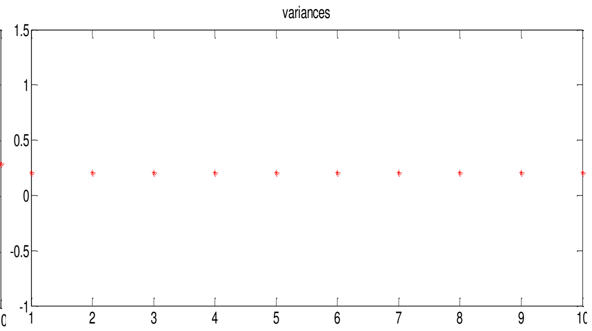

Figure-13(d).

Notch 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. It is generated by the connection of the 3 phase non-linear load. The voltage notch waveform is shown in the Figure-14(a) and its corresponding features are given in the Figures 14(b), 14(c) and 14(d).

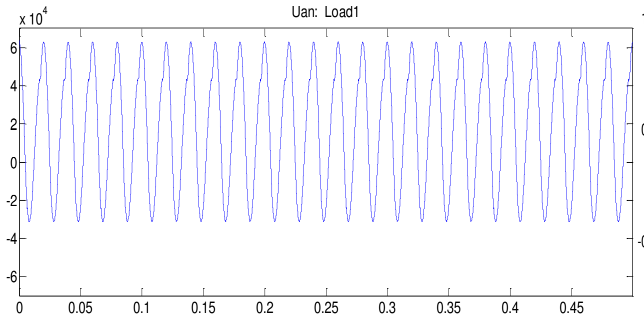

Figure-14(a).

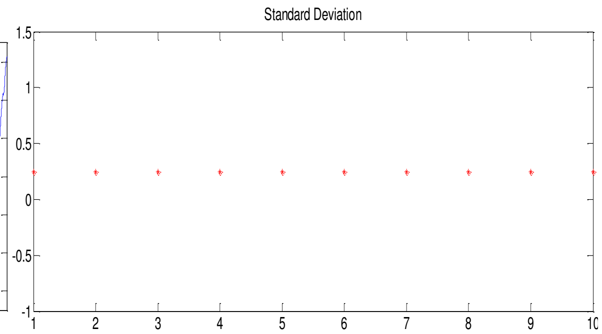

Figure-14(b).

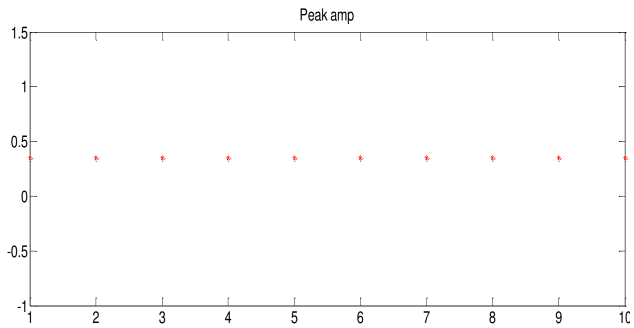

Figure-14(c).

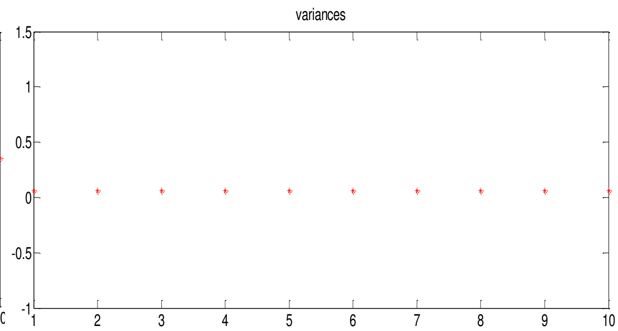

Figure-14(d).

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The classification performance of the proposed method has been demonstrated through Table-3 and Figure-15.

Table-3. Classification accuracy.

S. No.	Power quality disturbances	Percentage of accuracy	
		Input features	Kalman filter based MLP Neural network
1	Pure Sine wave	100	100
2	Voltage Sag	100	100
3	Voltage Swell	100	95
4	Voltage Surge	100	100
5	Outages	100	96
6	Harmonics	100	100
7	Sag with Harmonics	100	96
8	Swell with Harmonics	100	96
9	Flicker	100	97
10	Notch	100	98
Overall accuracy			97.8

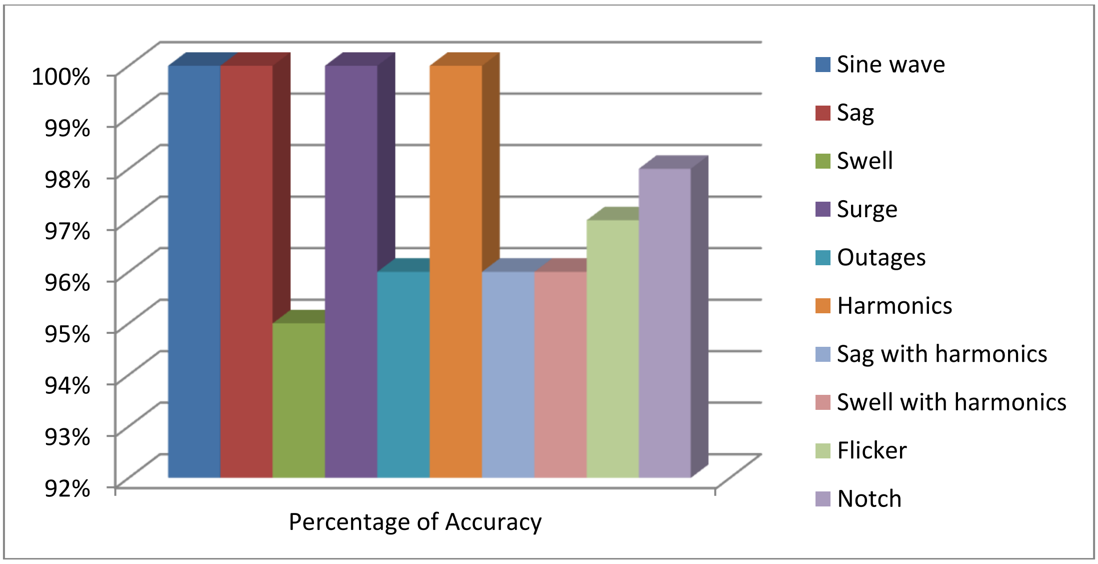

Figure-15. Bar diagram for the percentage of accuracy of the proposed method.

5. CONCLUSIONS

This paper presents a new method based on Kalman filter and Neural Network for the analysis and classification of the various power quality disturbances. The disturbance waveforms were generated through Matlab Simulink on the test system and the disturbances are inclusive of notch and flicker also. The PQ features such as standard deviation, peak value and variances were extracted through Kalman filter and a MLP based neural network has been applied for classifying the disturbances. It has been found that all the nine disturbances were classified accurately by the proposed method. MLP neural network can be trained for any input combination and its application is particularly suitable for classification of disturbances of varying nature.

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