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Kalman filter based Neural Network System for classifying Power Quality Disturbances

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Abstract
A new Kalman Filter – Neural network based power quality disturbance classifier is proposed in this paper. This method employs Discrete Wavelet Transform for filtering out the noises and extracts the features using Kalman filer from the distorted voltage waveforms simulated using the parametric equations for various disturbance classes. 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. The performance of the proposed technique has been evaluated by comparing the results against S-transform based and GA-fuzzy based classifiers.

Keywords: Power quality, Power quality disturbances, Discrete Wavelet Transform, Kalman Filter, Neural Network, MLP Based 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 & phase angle of i^{th} harmonic at time 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

A wide variety of power quality detection and classification tools were developed over the past few decades and are being constantly improved with a view of making them more flexible so as to analyze stationary and non stationary signals and a wide range of comparatively newer classes of disturbances such as notches and flickers, in both time and frequency domain. The data processing burden of the classification algorithm has been considerably reduced by compressing the signals through wavelet transform methods as illustrated in [1]. An adaptive neural network based power quality analyzer for the estimation of electric power quality has been applied and the disturbances were classified in [2]. Classification of power quality events using a combination of SVM and RBF networks has been presented in [3]. 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 [4].

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 [5] and a fuzzy logic based pattern recognition system along with multi resolution S-transform for power quality event classification has been discussed in [6]. Wavelet based neural network classifier based on learning vector quantization network and a decision making scheme has been presented in [7]. An S-transform based modular neural network has been presented in [8] and this combines the frequency resolution characteristics of S transform with the pattern recognizing ability of a neural network.

Wavelet transform neural network based power quality disturbance classifier is presented in [9] where the analysis takes into account the different noise conditions also. A combination of multi wavelet and neural network has been implemented for power quality disturbance recognition in[10]. As multi wavelets have two or more scaling functions and wavelet functions, multi resolution decomposition has been made possible. Selecting an optimal feature set for power quality event classification has been discussed in [11] and classification of disturbances of short duration using S-transform has been demonstrated 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]. A set of power quality indices applicable for stationary sinusoidal and non sinusoidal disturbances were developed using wavelet packet transform in [14]. As Hilbert transform shows greater immunity towards noise, it has been used for the detection and classification of power quality events along with ANN in [15]. A representative quality power vector has been derived for power quality analysis through an adaptive neuro fuzzy interface system in [16].
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 [17]. Probabilistic neural network method based on optimal feature selection for power quality event classification has been illustrated in [18]. A real time classification method for the power quality disturbances based on RMS values of the waveforms and DWT has been discussed in [19]. A combination of linear Kalman filter and fuzzy expert system has been used for the analysis of power quality events in [20] wherein the signal noise is estimated using a block of DWT. Classification of both the single and combined nature of power quality disturbances using signal spare decomposition (SSD) has been illustrated in [23]. 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 classification technique proposed has two stages namely a feature extraction stage and a classification stage. In the feature extraction stage the DWT block is used to eliminate the noises and Kalman Filter is used for extracting features such as amplitude and slope. The classification stage consists of a MLP based neural network with four hidden layers. Disturbance waveforms were generated using a set of parametric equations.

2.1 Feature Extraction Stage

2.1.1 Wavelet Transform

Wavelet transform is highly useful tool in signal analysis. The continuous wavelet transform of a signal x (t) is defined as

$$X_{a,b}=\frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty}x(t)\,\Psi\left(\frac{t-b}{a}\right)dt \tag{1}$$

$$\Psi_{a,b}(t)=\frac{1}{\sqrt{|a|}}\Psi\left(\frac{t-b}{a}\right) \tag{2}$$

The Discrete Wavelet Transform (DWT) calculations are usually carried out for a chosen subset of scales and positions. This is usually done by using filters for computing approximations and details. The approximations are the high-scale, low frequency components of the signal and details are the low-scale, high-frequency components. The DWT coefficients are computed using the equation:

$$X_{a,b}=X_{j,k}=\sum_{n\in z}x[n]g_{j,k}[n] \tag{3}$$

Where $a = 2j$, $b = k2j$, $j\varepsilon N$, $k\varepsilon N$.

The wavelet filter g acts as mother wavelet ψ and the covariance of the details is considered as an initial input to the Kalman filter.

1.1.2 Kalman Filter

As Kalman filter has been identified as an optimal estimator with minimum error covariance it has been used here for the purpose of 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.

$$X_{k+1}=\varphi_k x_k+w_k \tag{4}$$

$$z_k=H_k x_k+v_k \tag{5}$$

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 time t_k be the sum of y_k and v_k, which represents M sinusoids and the additive noise for sampling points. Then

$$z_k=y_k+v_k \tag{6}$$

$$z_k=\sum_{i=1}^{n}A_{k,i}\sin\left((i\omega k)\Delta T+\theta_{k,i}\right)+v_k \tag{7}$$

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 1_{st} harmonics: $x_1 = A_1\cos(\theta_1)\ x_1 = A_1\sin(\theta_1)$
For 2_{nd} harmonics: $x_2 = A_2\cos(\theta_2)\ x_2 = A_1\sin(\theta_2)$ (8)
For n_{th} harmonic: $x_{2n-1} = A_n\cos(\theta_n) x_{2n-1} = A_n\sin(\theta_n)$
The above set of equations can be written in matrix form as,

$$X_{k+1}=\begin{pmatrix}X_1\\X_2\\.\\.\\.\\X_{2n}\end{pmatrix}_{k+1}=\begin{pmatrix}1\ 0\ ....\ 0\\0\ 1\ ....\ 0\\0\ 0\ 1....0\\.\\.\\.\\0\ 0\ 0\ ....1\end{pmatrix}\begin{pmatrix}X_1\\X_2\\.\\.\\.\\X_{2n}\end{pmatrix}_k+w_k \tag{9}$$

The measurement equation can be similarly expressed in matrix form as

$$z_k = H_k x_k + v_k = \begin{pmatrix} \sin(\omega k\Delta T) \\ \cos(\omega k\Delta T) \\ . \\ . \\ . \\ \sin(n\omega k\Delta T) \\ \cos(n\omega k\Delta T) \end{pmatrix}^T \begin{pmatrix} X_1 \\ X_2 \\ . \\ . \\ . \\ X_{2n-1} \\ X_{2n} \end{pmatrix}_k + v_k \quad (10)$$

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

$$P_{k+1}^- = \Phi_k P_k \Phi_k^T + v_k \quad (11)$$

Measurement update
1) Compute the Kalman gain
$K_K = P_K^- H_K^T (H_K P_K^- H_K^T + R_K)^{-1}$
2) Update estimate with measurement (12)
$x_k = x_K^- + K_K(z_K - H_K)x_K^-$
3) Update the error covariance
$P_k = (I - K_K H_K)P_K^-$

Time and measurement update equation (11) & (12) 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

$$A_{i,k} = \sqrt{X_{1,K}^2 + X_{2,K}^2} \quad (13)$$

$$A_{i,k} = \sqrt{X_{2i-1,K}^2 + X_{2,Ki}^2} \quad i = 1,2,\dots\dots\dots\dots n \quad (14)$$

Slope of the signals,

$$Slope_{,k} = (A_{i,k} - A_{i,k} - 1)/\Delta T \quad (15)$$

3. Classification Stage

In this stage, features extracted through the Kalman filter are applied as inputs 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 which cannot be defined mathematically. Further, MLP networks have redundant networking and are very robust, providing a mathematical flexibility. The training parameters and the structure of the MLP used in this work are shown in Table 1.

Table 1 MLP architecture and training parameters

Architecture	
The number of layers	3
The number of neuron: 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

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 PQ disturbances and
- Block-3 Identification of the disturbances

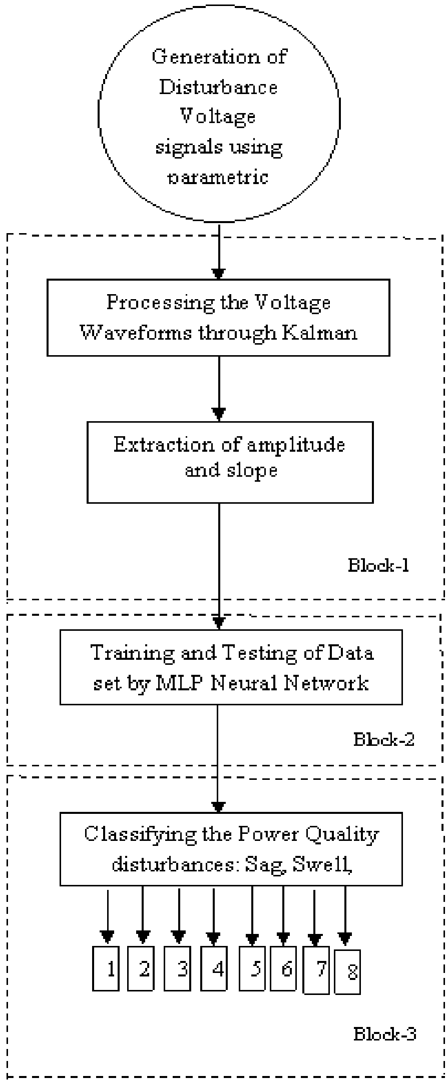

Figure 1. Flowchart for the Classification of PQ disturbances

4. Simulation and Test Results

Training and Test data were generated using a set of parametric equations 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 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. Nine classes (S1–S9) of different PQ disturbances, namely pure sine (normal), sag, swell, outage, harmonics, sag with harmonic, swell with harmonic, notch and flicker were considered. Table 2 gives the signal generation models and their control parameters. 200 cases of each class with different parameters were generated for training and another 200 cases were generated for testing. Both the training and testing signals were sampled at 256 points/cycle at the normal frequency of 50 Hz and feature extraction of these signals has been done through Kalman filter.

Table2 Power Quality Disturbance Model

SN	PQ events	Symbols	Model	Parameters
1	Pure Sine	S1	f (t)=sin (ωt)	
2	Sag	S2	f (t)=A (1-α (u (t-t_1) -u (t-t_2)))sin (ωt)	0. 1≤α≤0. 9;T≤t_2-t_1≤9T
3	Swell	S3	f (t)=A (1+α (u (t-t_1) -u (t-t_2)))sin (ωt), t_1<t_2, u (t)=$\sum_{0,t\leq 0}^{1,t\geq 0}$	0. 1≤α≤0. 8;T≤t_2-t_1≤9T
4	Outage	S4	f (t)=A (1-α (u (t-t_1) -u (t-t_2)))sin (ωt)	0. 9≤α≤1;T≤t_2-t_1≤9T
5	Harmonics	S5	f (t)=A ($\alpha_1$sin (ωt)+ $\alpha_3$sin (3ωt)+ $\alpha_5$sin (5ωt)+ $\alpha_7$sin (7ωt)	0. 05≤α_3≤0. 15;0. 05≤α_5≤0. 15;0. 05≤α_7≤0. 15;$\sum\alpha_i^2$=1
6	Sag and Harmonics	S6	f (t)=A (1-α (u (t-t_1) -u (t-t_2))) ($\alpha_1$sin (ωt)+ $\alpha_3$sin (3ωt)+ α_5 sin (5ωt))	0. 1≤α≤0. 9;T≤t_2-t_1≤9T; 0. 05≤α_3≤0. 15;0. 05≤α_5≤0. 15; $\sum\alpha_i^2$=1
7	Swell and Harmonics	S7	f (t)=A (1+α (u (t-t_1) -u (t-t_2))) ($\alpha_1$sin (ωt)+ $\alpha_3$sin (3ωt)+ $\alpha_5$sin (5ωt))	0. 1≤α≤0. 8;T≤t_2-t_1≤9T; 0. 05≤α_3≤0. 15;0. 05≤α_5≤0. 15; $\sum\alpha_i^2$=1
8	Notch	S8	y (t)= (sin (ω_dt)+sign (sin (ω_dt))*[$\sum_{n=1}^{i} k$*[u (t- (t_1+0. 002n))-u (t- (t_1+0. 002n))]	0. 1≤k≤0. 4;0. 01T≤t_2-t_1≤0. 05T; 0≤t_2, t_1≤0. 5
9	Flicker	S9	y (t)=[1+αsin (2πβt)]sin (ω_dt)	0. 1≤α≤0. 2;5H_z≤β≤20H_z

Total size of the training data set is 2*1800, where 2 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. These input signals, when applied to the MLP layer gives the result in the form of the matrix display which shows the correctly classified disturbances as the diagonal elements of the matrix. The of PQ disturbance signals generated using the Matlab based parametric equations and the training performance of neural network with 200 epochs are shown in figures 2 (a) to 10 (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 1 V at 50 Hz and its waveform is as shown in the figure 2 (a). The amplitude and the slope outputs of signal are shown in the fig 2 (b) & 2 (c).

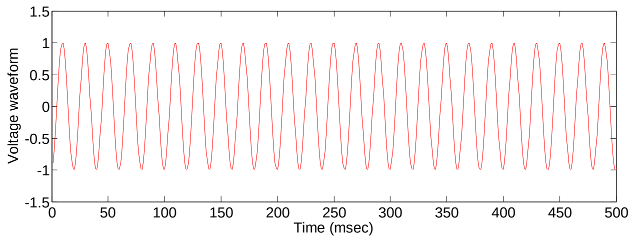

Figure 2 (a)

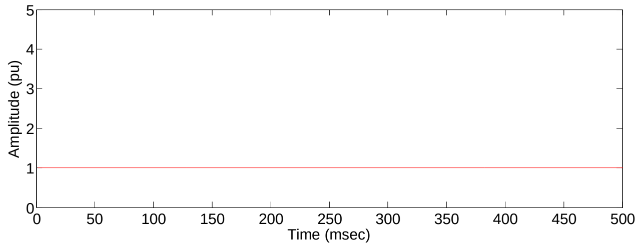

Figure 2 (b)

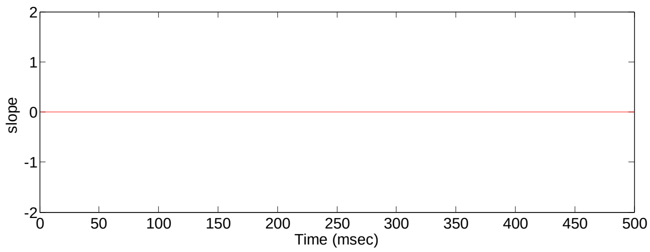

Figure 2 (c)

Voltage sag

The voltage sag (or) voltage dips cause the decrease of system voltage. The duration of the sag disturbance is 0. 2 to 0. 4 cycles in 1 min. The voltage dip waveform is shown in the figure 3 (a). The amplitude and slope outputs of the sag disturbance signal are shown in the figures 3 (b) and 3 (c).

International Journal of Applied Engineering Research ISSN 0973-4562 Volume 10, Number 21 (2015) pp 42445-42453

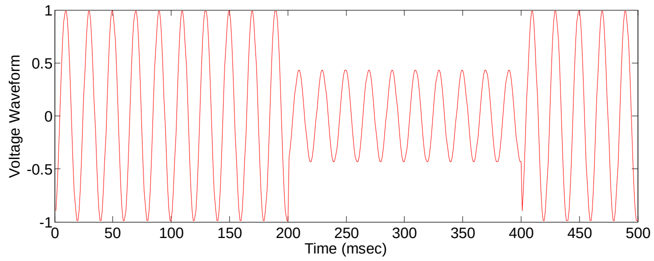

Figure 3 (a)

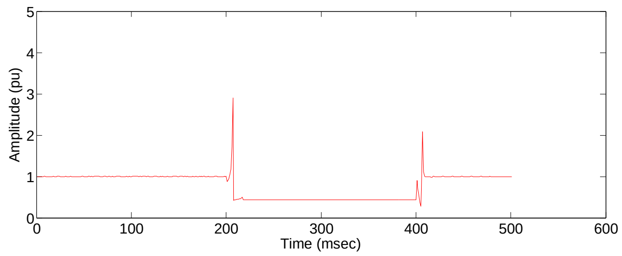

Figure 3 (b)

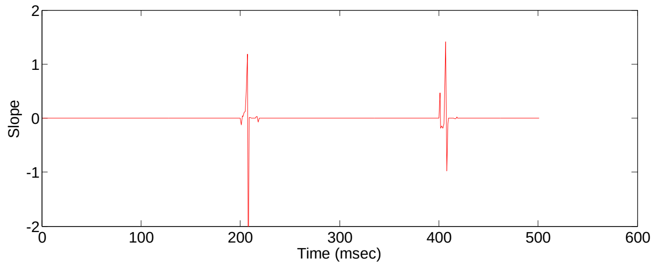

Figure 3 (c)

Voltage swell

Voltage swell causes the rise of system voltage. 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 4 (a). The amplitude and slope outputs of the sag disturbance signal are shown in the fig 4 (b) & 4 (c).

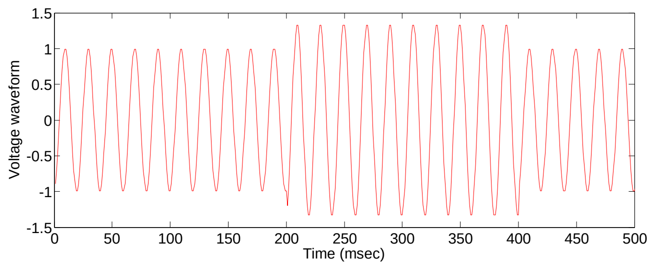

Figure 4 (a)

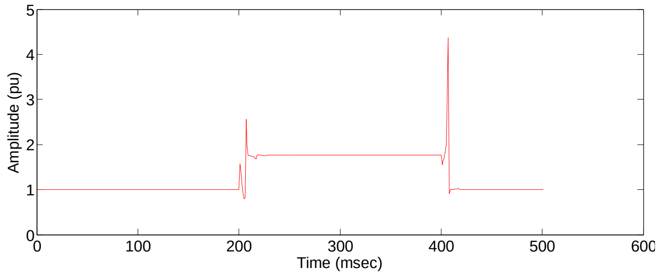

Figure 4 (b)

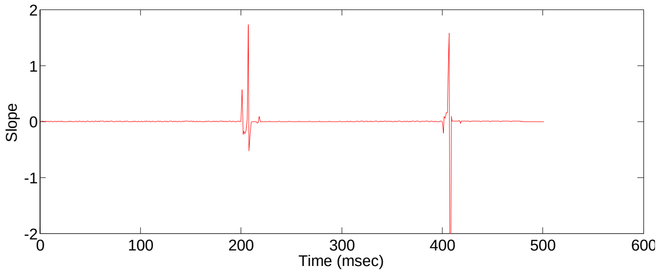

Figure 4 (c)

Outages

The Outages may be seen as a loss of voltage on the system for the duration of 0. 5 cycles to 1min. The voltage outage waveform is shown in the figure 5 (a). The amplitude and slope outputs of the voltage outage disturbance signal are shown in the figures 5 (b) and 5 (c).

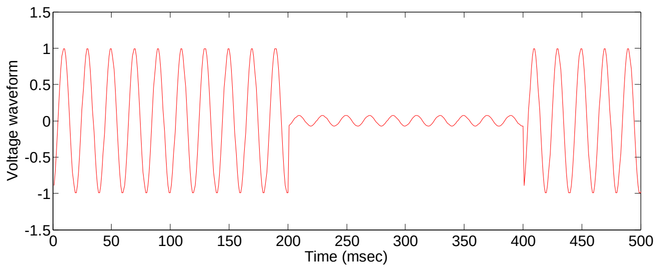

Figure 5 (a)

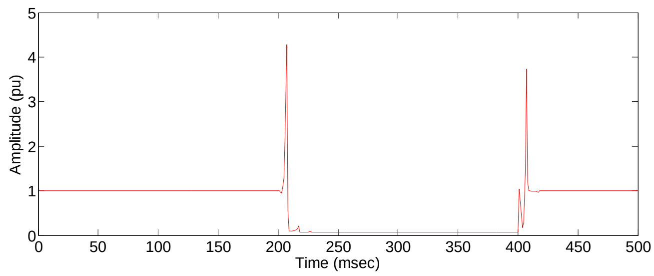

Figure 5 (b)

International Journal of Applied Engineering Research ISSN 0973-4562 Volume 10, Number 21 (2015) pp 42445-42453

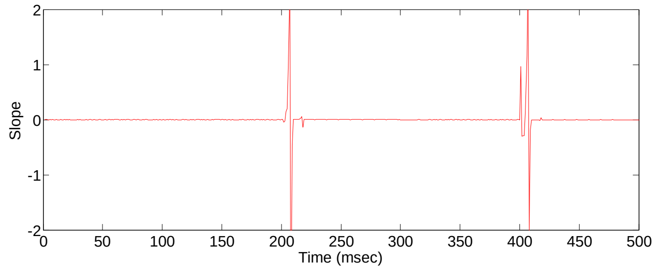

Figure 5 (c)

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 6 (a). The amplitude and slope outputs of the original distortion waveforms are shown in the figures 6 (b) and 6 (c).

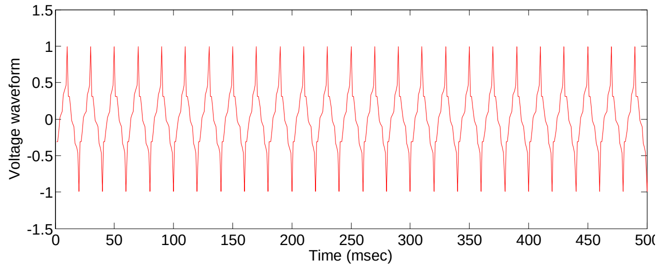

Figure 6 (a)

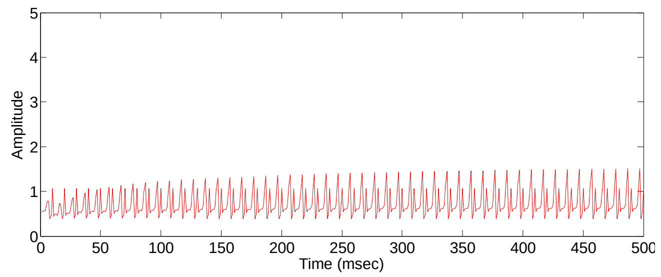

Figure 6 (b)

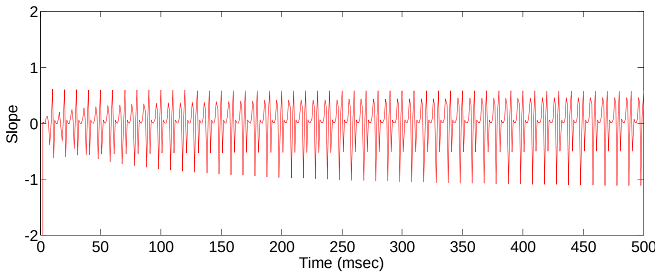

Figure 6 (c)

Sag with harmonics

This disturbance type is caused by the presence of a nonlinear load and a voltage dip in the system for a duration of 0. 2 to 0. 4 cycles. The waveform contain harmonic distortion with sag event as shown in the figure 7 (a). The amplitude and slope outputs sag with harmonics signal are shown in the figures 7 (b) and 7 (c).

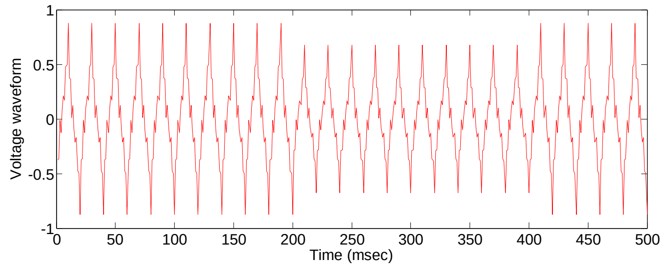

Figure 7 (a)

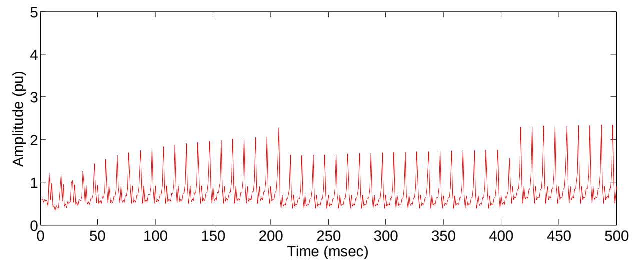

Figure 7 (b)

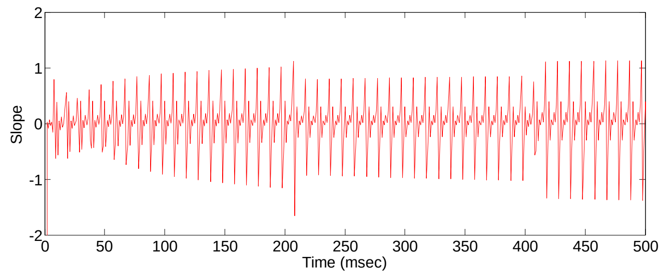

Figure 7 (c)

Swell with harmonics

This disturbance is caused by the presence of nonlinear load and a voltage swell in the system for a duration of 0. 2 to 0. 4 cycles. The waveform contains harmonic distortion with swell event as shown in the figure 8 (a). The amplitude and slope outputs swell with harmonics signal are shown in the figure 8 (b) and 8 (c).

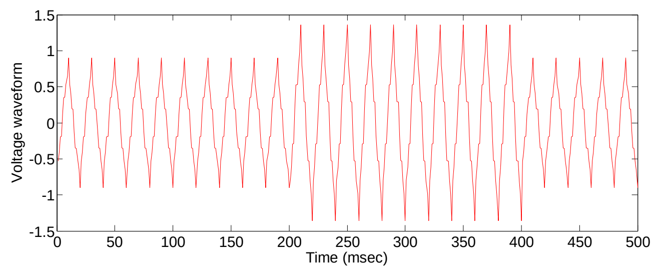

Figure 8 (a)

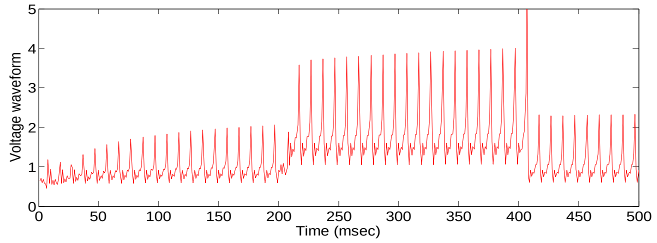

Figure 8 (b)

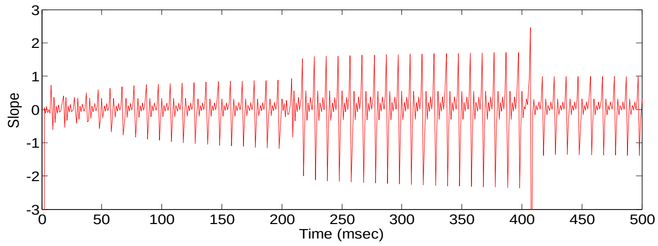

Figure 8 (c)

Flicker

This type of disturbance type is caused by the continuous and rapid variation of the system load. The waveform of the flicker is shown in the figure 9 (a). The amplitude and slope outputs flicker signal are shown in the figure 9 (b) and 9 (c).

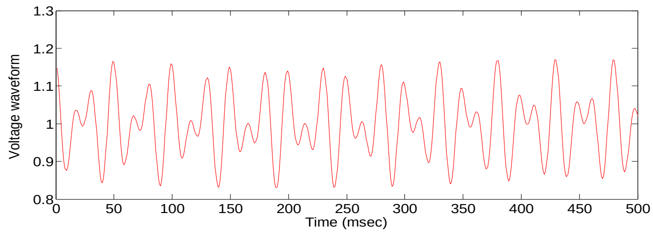

Figure 9 (a)

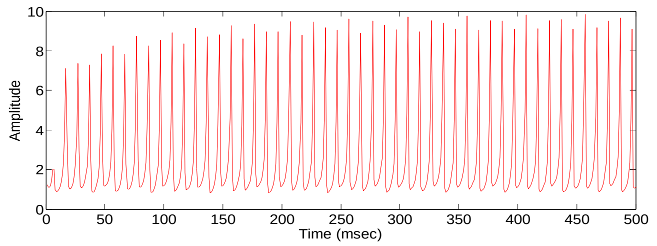

Figure 9 (b)

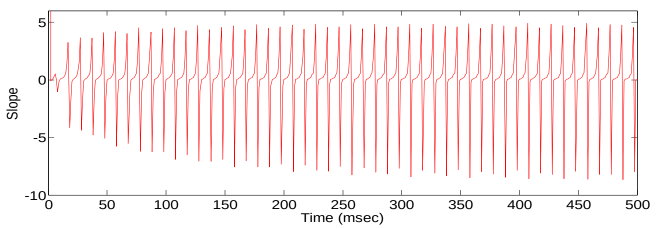

Figure 9 (c)

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. The voltage notch waveform is shown in the figure 10 (a). The amplitude and slope outputs signal are shown in the figure 10 (b) and 10 (c).

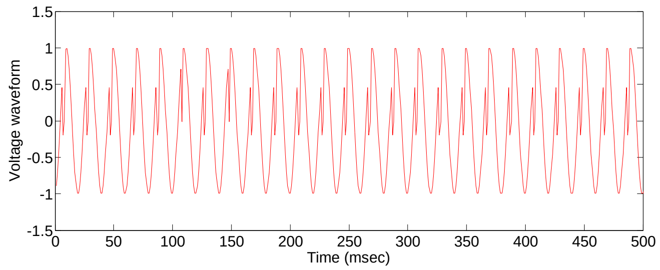

Figure 10 (a)

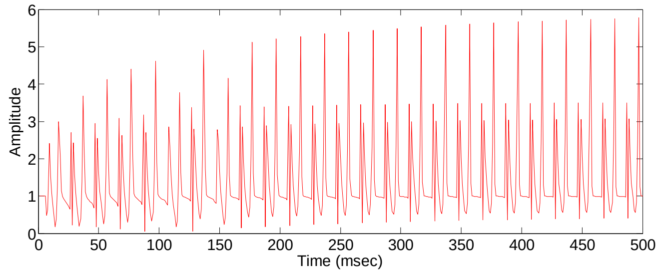

Figure 10 (b)

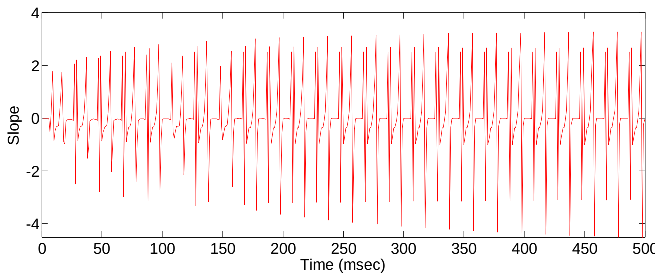

Figure 10 (c)

MLP based ANN model has been developed using MATLAB coding and it has been applied to classify the disturbances from the features extracted features. Kalman Filter and DWT blocks were also developed using MATLAB coding. Figure 11 (a) shows the graphical representation of the training, testing and validation data based on mean squared error.

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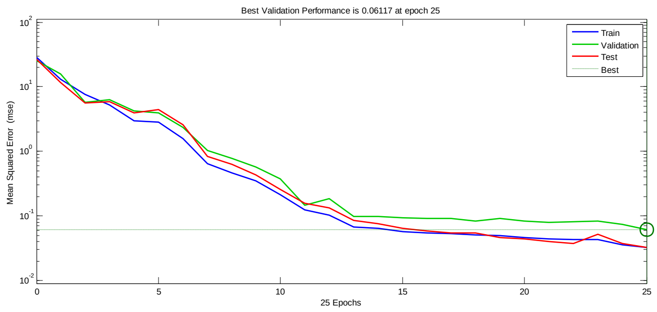
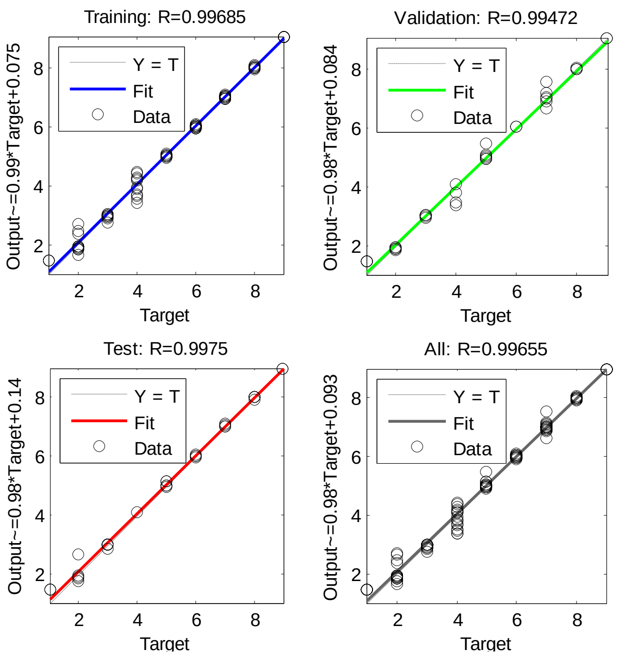


Figure 11 (a)

Figure 11 (b) shows the regression wave form for the training, testing and validation data of individual and the combined form. The classification accuracy for various types of disturbances is presented in tabular form in table3 and in the form of a bar chart in Figure 12. In order to validate the performance, the results obtained by the proposed method are compared with the already existing S-transform and GA-fuzzy based techniques presented in [21] and [22].



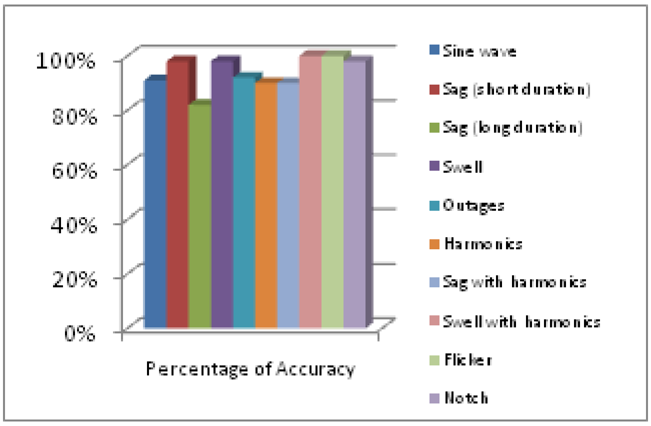


Table 3. Classification accuracy

Sno	PQ disturbance	Percentage of Accuracy			
		Input Feature	MLP based NN	S-Transform	GA-Fuzzy
1	Voltage Sag	100	98	-	-
2	Voltage Swell	100	98	-	99
3	Outages	100	92	99	-
4	Harmonics	100	90	88	98
5	Sag with Harmonics	100	90	91. 37	90
6	Swell with Harmonics	100	100	87. 18	99
7	Flicker	100	100	90	96
8	Notch	100	98	96	91
Overall accuracy			95. 75	91. 925	95. 5

5. Conclusion

A new Kalman filter-Neural Network based technique has been proposed for identifying and classifying the power quality disturbances. The disturbance waveforms were generated through parametric equations and the disturbances are inclusive of notch and flicker also. Features such as amplitude and slope were extracted through Kalman filter and an MLP based neural network has been applied for classifying the disturbances. The classification accuracy has been validated by comparing the results obtained by the proposed technique against S transform based and GA fuzzy based classifiers and it has been concluded that the proposed method performs better than those two techniques. It has also been found that all the nine disturbances were classified accurately by the proposed method and it is well suitable for real world applications were the classifier is applied over the data captured in field. Neural Network is a versatile classifier that can be trained for any input combination and its application makes the suggested technique particularly suitable for classification of disturbances of varying nature.

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