Automatic Recognition of Power Quality Disturbances using Kalman Filter and Fuzzy Expert System

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ABSTRACT
An efficient method for power quality disturbances recognition and classification is presented in this paper. The method used is based on the Kalman filter and fuzzy expert system. Various classes of disturbances are generated using Matlab parametric equations. Kalman filter is used for extracting the input features of various power disturbances. The extracted features such as amplitude and slope are applied as inputs to the fuzzy expert system that uses some rules on these inputs to classify the PQ disturbances. Fuzzy classifier has been implemented and tested for various types of power quality disturbances. The results clearly indicate that the proposed method has the ability to detect and classify PQ disturbances accurately. The performance of the proposed method has been evaluated by comparing the results against Kalman filter based neural classifier.

Keywords
Power quality, Power quality events, Kalman Filter, Fuzzy logic, Fuzzy-expert system.

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 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
In the recent years, power quality related problems have become an important issue for both utilities and customers. Reasons for the poor quality of electric power are power line disturbances such as sag, swell, interruption, harmonics, etc. In order to improve the electric power quality, the sources and occurrences of such disturbances must be detected and the events are to be classified. The various types of power quality disturbances were detected and localized based on wavelet transform analysis as illustrated in [1] Time and frequency of multi resolution wavelets have been presented in [2] to analyze and classify the electromagnetic power system transients.

Another approach based on wavelets to identify the various power system transient signals such as capacitor switching, lighting impulse, etc has been discussed in [3]. The data processing burden of the classification algorithm has been considerably reduced by compressing the signals through wavelet transform methods as illustrated in [4]. An adaptive neural network based power quality analyzer for the estimation of electric power quality has been applied and the disturbances were classified in [5].

Classification of power quality events using a combination of SVM and RBF networks has been presented in [6]. The short time Fourier transforms (STFT) based power frequency harmonic analyzer has been discussed in [7] for the non stationary signals. The Fourier and wavelet transform based fuzzy expert system for the detection and classification of PQ disturbances has been demonstrated in [8].

Wavelet multi-resolution technique along with neuro-fuzzy classifier for PQ disturbance detection has been explained [9]. 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 [10] and a fuzzy logic based pattern recognition system along with multi resolution S-transform for power quality event classification has been discussed in [11].

The classification of the power quality disturbances in both single and multiple natures using S-transform and Pattern recognition techniques has been implemented in [12]. A combination of wavelet transform along with both ANN and fuzzy logic classifier has been implemented for the PQ events classification in [13].Artificial neural network (ANN) based real time electric power quality disturbance classification has been illustrated in [14]. Support vector machine (SVM) based electrical voltage disturbance classification has been illustrated in [15]. A hybrid method for the real time frequency estimation based on Taylor series and discrete Fourier algorithm has been illustrated in [16].

Classification of power quality disturbances using the combined form of Hilbert huang transform (HHT) and Relevance vector machine (RVM) has been presented in [17]. Dual neural network namely ADALINE and FFNN have been implemented for the classification of single and combined form power quality disturbance in [18].Classification of both the single and combined nature of power quality disturbances using signal spare decomposition (SSD) has been illustrated in [19].A Kalman filter and fuzzy expert system based power quality analyzer in which features are extracted using Kalman Filter and disturbances are classified using an fuzzy expert system is presented in this paper.

2. PROPOSED METHOD

The proposed method has two stages namely

i. Feature extraction stage and

ii. Classification stage.

In the feature extraction stage, Kalman Filter is used for extracting features such as standard deviation and variances. The classification stage consists of the Fuzzy expert system. Disturbance waveforms were generated using Matlab 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

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

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

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:

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

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.

2.1.2 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.

$$X_{k+1}=\varphi_k x_k+w_k \quad (4)$$

$$z_k = H_k x_k+v_k \quad (5)$$

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

$$z_k= y_k+v_k \quad (6)$$

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

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: $x_1 = A_1\cos(\theta_1)$ $\quad x_1 = A_1\sin(\theta_1)$

For 2_{nd} harmonics: $x_2 = A_2\cos(\theta_2)$ $\quad x_2 = A_1\sin(\theta_2)$ (8)

For n_{th} 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,

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

The measurement equation can be similarly expressed in matrix form as

$$z_k = H_k x_k+v_k=\begin{pmatrix}\sin(\omega k\Delta T)\\\cos(\omega k\Delta T)\\.\\.\\.\\\sin(n\omega k\Delta T)\\\cos(n\omega k\Delta T)\end{pmatrix}^T\begin{pmatrix}X_1\\X_2\\.\\.\\.\\X_{2n-1}\\X_{2n}\end{pmatrix}_k+v_k \quad (3)$$

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

$$X_{k+1}^{-}=\Phi_k x_k \quad (11)$$

2) Project the error covariance ahead

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

Measurement update

1) Compute the Kalman gain

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

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

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

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

Slope of the signals, $Slope_{,k} = (A_{i,k} - A_{i,k} - 1)/\Delta T$ (15)

2.1.3 Fuzzy Expert System

Fuzzy system provides a simple way to get definite conclusion based upon ambiguous. The accuracy of the fuzzy logic system depends on the knowledge of human experts. The mamdani type of fuzzy inference system used to perform the classification of the PQ events. It has two inputs, one output with 25 rules.

The first input to the system is the value of standard deviation. The input is divided into five trapezoidal membership functions namely VSA (very small amplitude), SA (small amplitude), NA (normal amplitude), LA (large amplitude), and VLA (very large amplitude). The second input to the system is the value of slope. It is broken into five triangular membership functions namely VSS (very small slope), SS (small slope), NS (normal slope), LS (large slope), and VLS (very large slope). The fuzzy expert system is shown in figure 1.

The brief rule sets of fuzzy expert system are given below:

1) If (Amplitude is VA) and (Slope is VSS) then (output is INTERRUPTION).
2) If (Amplitude is VA) and (Slope is SS) then (output is INTERRUPTION).
3) If (Amplitude is VA) and (Slope is NS) then (output is INTERRUPTION).
4) If (Amplitude is VA) and (Slope is LS) then (output is SWELL).
5) If (Amplitude is VA) and (Slope is VSS) then (output is NORMAL).
6) If (Amplitude is SA) and (Slope is VSS) then (output is INTERRUPTION).
7) If (Amplitude is SA) and (Slope is SS) then (output is INTERRUPTION).
8) If (Amplitude is SA) and (Slope is NS) then (output is SAG).
9) If (Amplitude is SA) and (Slope is LS) then (output is NORMAL).
10) If (Amplitude is SA) and (Slope is VLS) then (output is SWELL).
11) If (Amplitude is NA) and (Slope is VS) then (output is INTERRUPTION).
12) If (Amplitude is NA) and Slope is SS) then (output is SAG).
13) If (Amplitude is NA) and (Slope is NS) then (output is NORMAL).
14) If (Amplitude is NA) and (Slope is LS) then (output is SWELL).
15) If (Amplitude is NA) and (Slope is VSS) then (output is HARMONICS).
16) If (Amplitude is LA) and (Slope is VSS) then (output is SAG).
17) If (Amplitude is LA) and (Slope is SS) then (output is NORMAL).
18) If (Amplitude is LA) and (Slope is NS) then (output is SWELL).
19) If (Amplitude is LA) and (Slope is VSS) then (output is SAG WITH HARMONICS).
20) If (Amplitude is LA) and (Slope is VSS) then (output is SWELL WITH HARMONICS).
21) If (Amplitude is VLA) and (Slope is VSS) then (output is NORMAL).
22) If (Amplitude is VLA) and (Slope is SS) then (output is SWELL).
23) If (Amplitude is VLA) and (Slope is NS) then (output is HARMONICS).
24) If (Amplitude is VLA) and (Slope is VLS) then (output is FLICKER).
25) If (Amplitude is VLA) and (Slope is VLS) then (output is NOTCH).

3. CLASSIFICATION STAGE

In this stage, features extracted through the Kalman filter are applied as inputs to the fuzzy expert system in order to classify the various power quality disturbances. Fuzzy logic with the rule based expert system has emerged the classification tool for PQ events. The rules of this technique are based on modeling human experience and expertise.

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) – Extraction of features
- Block-(b) – Detection and classification of the disturbances

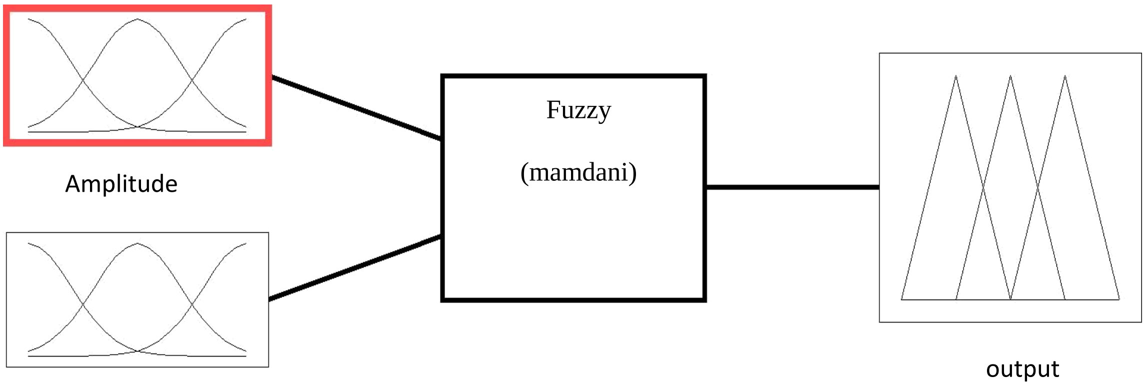


Figure 1.Fuzzy expert system

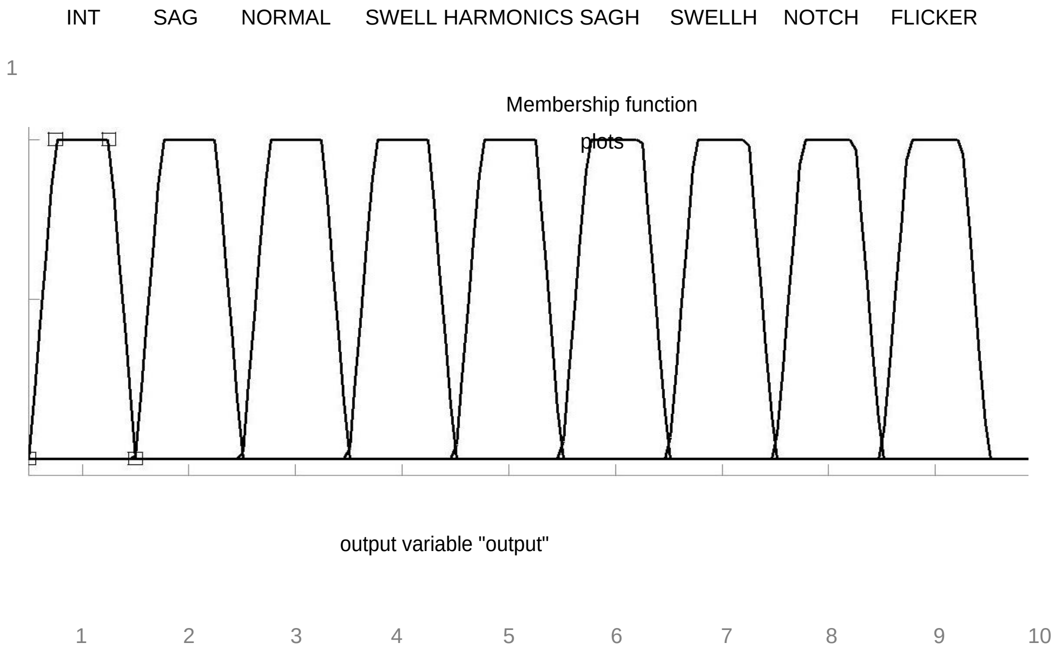


Figure 2.Output membership function

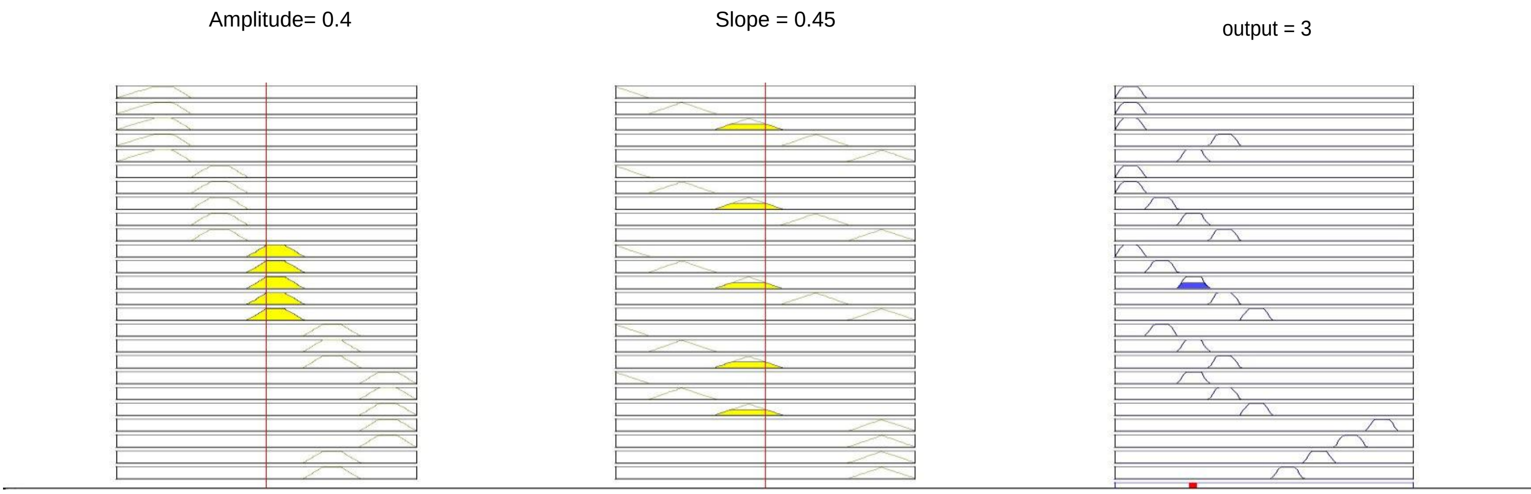
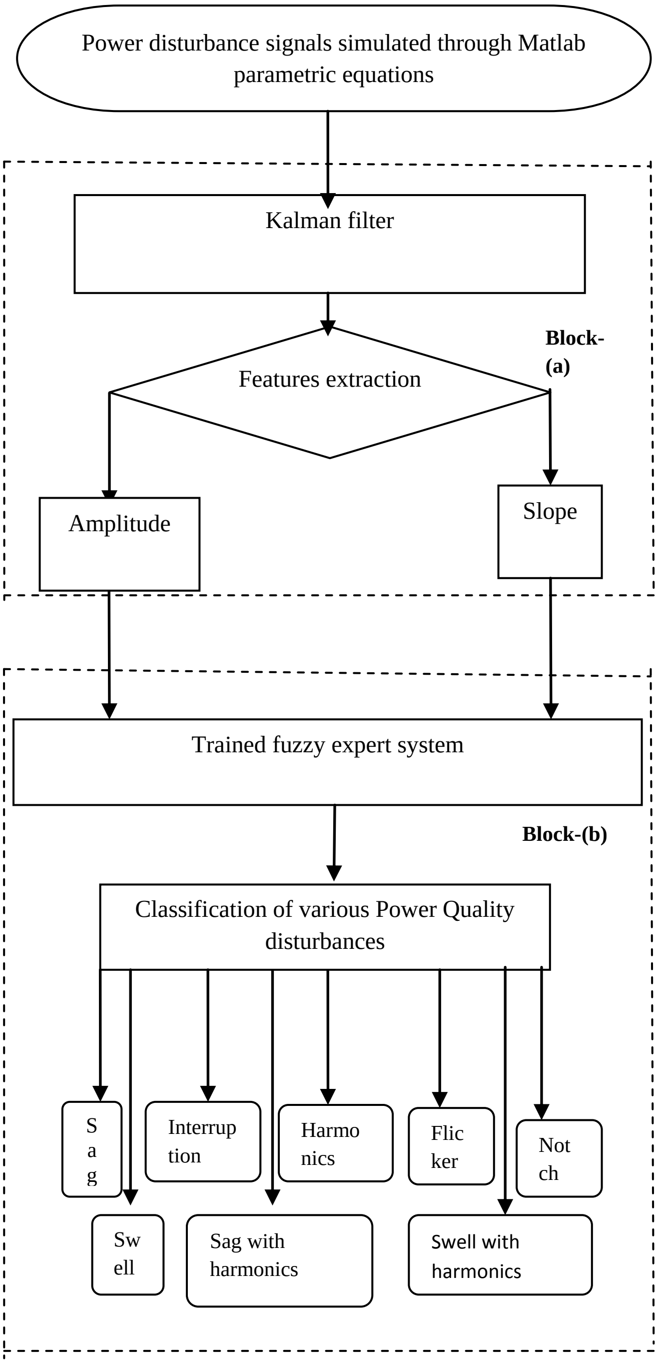


Figure 3.Rule viewer of fuzzy expert system



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 fuzzy 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

Table1 Power Quality Disturbance Model

Sl. No	PQ disturbances	Class Symbol	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)=$\sum\cdot_{0,t\le0}^{1,t\ge0}$	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;5 H_Z≤β≤20H_Z

These input signals are applied to the fuzzy expert system to get accurate classification of disturbances. The PQ disturbance signals generated using the Matlab based parametric equations. The following case studies are presented to highlight the suitability of the application of the proposed method. The following case studies are presented to highlight the suitability of the application of the proposed method.

1) Pure sine wave

It is a voltage signal of amplitude 1 V at 50 Hz and its waveform is as shown in the figure 5(a).The amplitude and the slope outputs of the signal are shown in the figures 5(b) and 5(c).

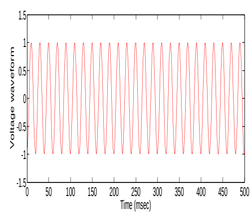


Figure 5(a)

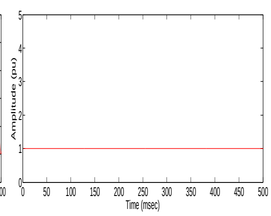


Figure 5(b)

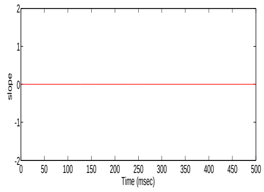


Figure 5(c)

Figure5 voltage signal

(a) Waveform
(b) Amplitude and
(c) Slope

2) 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 6(a). The amplitude and slope outputs of the sag disturbance signal are shown in the figures 6(b) and 6(c).

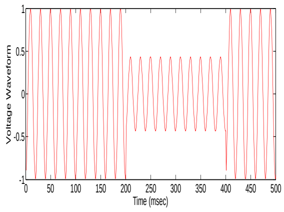


Figure 6(a)

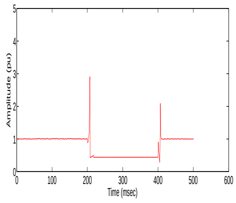


Figure 6(b)

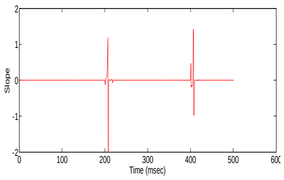


Figure6 voltage sag

(a) Waveform
(b) Amplitude and
(c) Slope

Figure 6(c)

3) 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 7(a). The amplitude and slope outputs of the sag disturbance signal are shown in the fig 7(b) & 7(c).

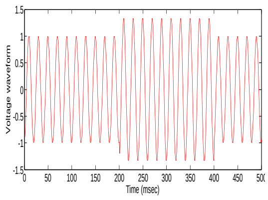


Figure 7(a)

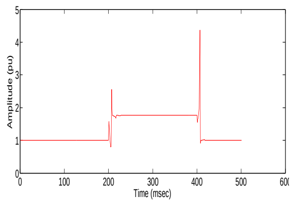


Figure 7(b)

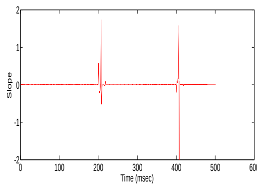


Figure7 voltage swell

(a) Waveform
(b) Amplitude and
(c) Slope

Figure 7(c)

4) Voltage 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 8(a). The amplitude and slope outputs of the voltage outage disturbance signal are shown in the figures 8(b) and 8(c).

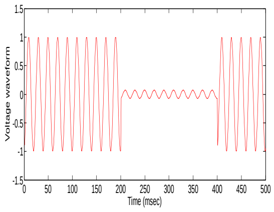


Figure 8(a)

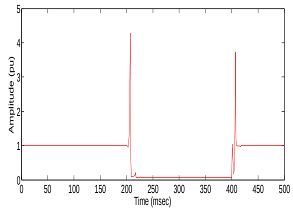


Figure 8(b)

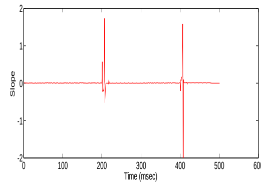


Figure8 voltage Outages

(a) Waveform
(b) Amplitude and
(c) Slope

Figure 8(c)

5) 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 9(a). The amplitude and slope outputs of the original distortion waveforms are shown in the figures 9(b) and 9(c).

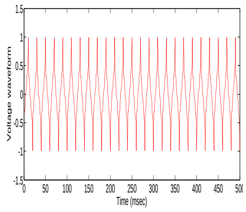


Figure 9(a)

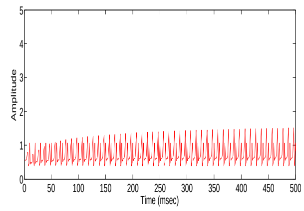


Figure 9(b)

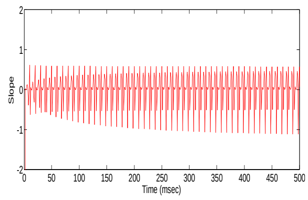


Figure9 Harmonics

(a) Waveform
(b) Amplitude and
(c) Slope

Figure 9(c)

6) 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 10(a). The amplitude and slope outputs sag with harmonics signal are shown in the figures 10(b) and 10(c).

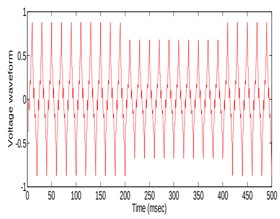


Figure 10(a)

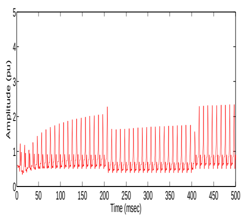


Figure 10(b)

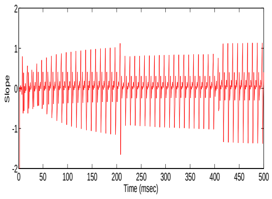


Figure10.Sag with harmonics

(a) Waveform
(b) Amplitude and
(c) Slope

Figure10(c)

7) 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 11(a). The amplitude and slope outputs swell with harmonics signal are shown in the figure 11(b) and 11(c).

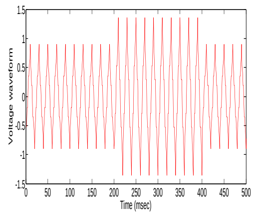


Figure 11(a)

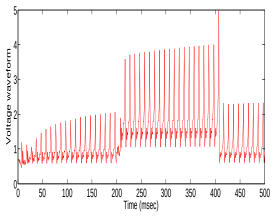


Figure 11(b)

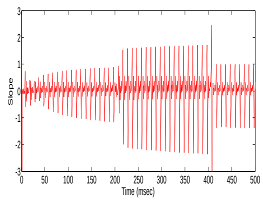


Figure11.Swell with harmonics

(a) Waveform
(b) Amplitude and
(c) Slope

Figure11(c)

8) 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 12(a). The amplitude and slope outputs flicker signal are shown in the figure 12(b) and 12(c).

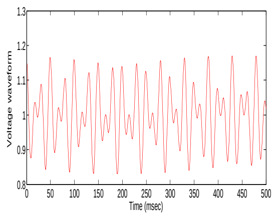


Figure 12(a)

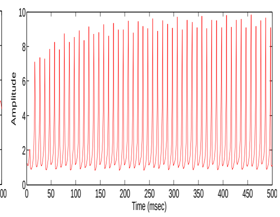


Figure 12(b)

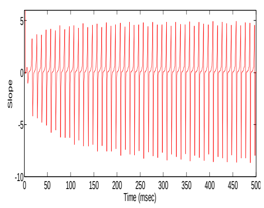


Figure12.Flicker

(a) Waveform
(b) Amplitude and
(c) Slope

Figure12(c)

9) 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 13(a). The amplitude and slope outputs signal are shown in the figure 13(b) and 13(c).

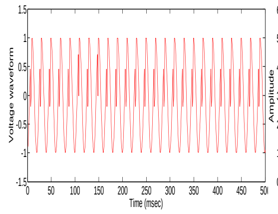


Figure 13(a)

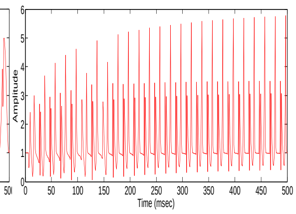


Figure 13(b)

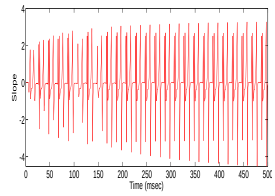


Figure13.Voltage notch

(a) Waveform
(b) Amplitude and
(c) Slope

Figure13(c)

The classification performance of the method has been demonstrated through Table 3 and Fig 14.

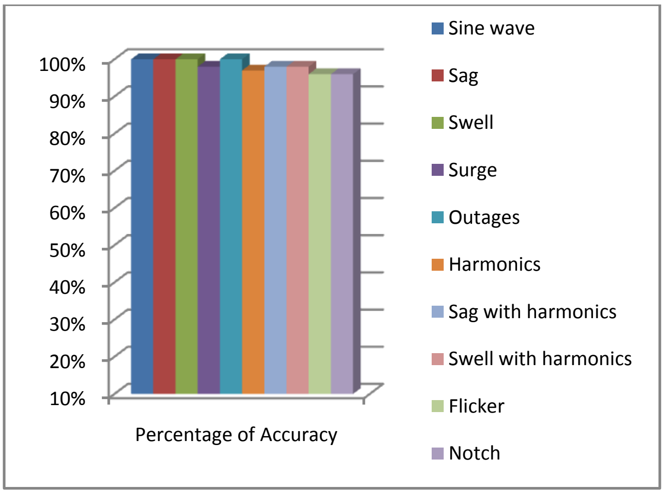


Figure 14.Bar diagram for the percentage of accuracy of the proposed method

Table 2.Classification accuracy

Sno	PQ disturbances	Percentage of Accuracy		
		Input Features	Kalman filter based neural network	Kalman filter based fuzzy system
1	Pure Sine wave	100	100	100
2	Voltage Sag	100	98	98
3	Voltage Swell	100	98	96
4	Outages	100	92	95

5	Harmonics	100	90	96
6	Sag with Harmonics	100	90	96
7	Swell with Harmonics	100	100	97
8	Flicker	100	100	96
9	Notch	100	98	96
Overall accuracy			96.22	96.67

5. CONCLUSION

This paper introduces a new method for the recognition and classification of various power quality disturbances using kalman filter technique. The disturbance waveforms were generated through the Matlab parametric equations and the input features such as amplitude and slope were extracted through Kalman filter. Fuzzy expert system has been applied for classifying the various power quality disturbances. The method enables the accurate classification of all nine types of PQ disturbances. The classification accuracy has been validated by comparing the results obtained by the proposed technique against Kalman filter based neural classifier and it has been concluded that the proposed method performs better than those technique. The result shows that the proposed system performs very well in classification of PQ disturbances.

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