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DETECTION AND CLASSIFICATION OF POWER QUALITY DISTURBANCES USING DISCRETE WAVELET TRANSFORM AND RULE BASED DECISION TREE

Nitin Kumar Suyan[1], Mahendra Kumar[2] and Fateh L. Lohar[3]
[1,3]Department of Electronics and Communication Engineering, Government Engineering College Jhalwar, Rajasthan, India
[2]Government Engineering College Baran, Rajasthan, India

Abstract

This paper presents a method for the detection and classification of power quality (PQ) disturbances using discrete wavelet transform (DWT) based decision tree. The power quality disturbances are generated with the help of MATLAB using the mathematical relations as per IEEE Standard-1159. The investigated PQ disturbances include pure sine wave, voltage sag, voltage swell, momentary interruption, harmonics, oscillatory transient, impulsive transient and notch. These power quality signals are decomposed using discrete wavelet transform with db4 as mother wavelet up to third level of decomposition. The detail coefficients and approximation coefficients are used for the detection of PQ disturbances. The features extracted from these coefficients are fed to the rule-based decision tree for classification purpose. The effectiveness of proposed algorithm has been established by testing the 30 data sets of each PQ disturbance obtained by varying the parameters.

Keywords:

Discrete Wavelet Transform, Power Quality, Rule Based Decision Tree

1. INTRODUCTION

The analysis of power quality disturbances has become an important concern for both the industrial and academic fields due to increasing number of disturbing loads in the industry as well as public sectors [1]. The poor power quality is caused due to various disturbances like voltage sag, swell, momentary interruption, flicker, harmonics, oscillatory transient, impulsive transient, spikes, notches etc. [2]. These disturbances cause the problems such as failure of equipment, short life time of the equipment, malfunction of equipment, instability of the system, reduced efficiency of equipment etc. [3].

Power quality disturbances and resulting problems are due to increasing use of the solid-state switching devices, power electronically switched loads, non-linear loads, lighting controls, unbalanced power systems, industrial plant rectifiers and inverters as well as data processing equipment [4]. Therefore, power quality needs to be monitored and improved. Hence, development of automatic tools for detection and classification of power quality disturbances is required which will help the customers and utilities for clear understanding of what is happening in their networks [5].

The mathematical and signal processing techniques have been utilized for the detection and classification of PQ disturbances. Mahela et al. [6], presented a comprehensive review of various signal processing and artificial intelligent techniques utilized for the automatic recognition of PQ disturbances as well as effect of noise on the detection and classification of these events. Commonly used PQ detection techniques include Fourier transform, Kalman filter, wavelet transform, S-transform, Hilbert Huang transform, Gabor transforms etc.

The artificial intelligent tools used for the classification of PQ disturbances are support vector machine, artificial neural network, expert systems, Fuzzy logic, k-nearest neighbour etc. [7]. An approach for the recognition of PQ disturbances in the power system using wavelet transform and radial basis function neural network (RBFNN) has been reported in [8].

Behera et al. [9], presented an approach for detection and classification of power quality events using Stockwell's transform-based Fuzzy expert system. An automatic recognition system for power quality disturbances-based on the S-transform and extreme learning scheme has been reported in [10].

Masoum et al. [11], presented an approach for the detection and classification of PQ disturbances using wavelet transform and wavelet networks and applied on the PQ disturbances generated-based on IEEE-1159 standard. A combinational method-based on ensemble empirical mode decomposition (EEMD) and multilabel learning for classification of complex power quality disturbances has been reported in [12].

Mahela et al. [13], presented an approach-based on the S-transform and rule-based decision tree for the detection and classification of the single stage PQ disturbances. An approach for the recognition of power quality disturbances using S-transform and Fuzzy c-means clustering has been reported in [14]. An image processing-based method for recognition of PQ disturbances has been reported in [15].

Perunicic et al. [16], presented a method-based on wavelet transform and neural network for recognition of PQ disturbances. An approach for detection and classification of PQ disturbances using DWT and self-organizing mapping network (SOMN) is reported in [17].

This paper presents a method-based on discrete wavelet transform and rule-based decision tree for the detection and classification of PQ disturbances. PQ signals are generated using mathematical relations and decomposed using DWT. The features of signals are given to rule-based decision tree for classification. Performance of proposed algorithm has been validated by testing on 30 data sets of each disturbance.

This paper has been organized into seven sections. Section 2 describes the proposed algorithm used for recognition of PQ disturbances. The simulation results and discussion are presented in the section 3. Section 4 details the features utilized for classification of PQ disturbances and classification results-based on rule-based decision tree are illustrated in the section 5. The comparison of performance of proposed algorithm with that reported in literature is described in the section 6. Conclusions of the proposed research work are provided in the section 6.

2. PROPOSED ALGORITHM

The proposed algorithm for recognition of PQ disturbances is shown in Fig.1. The signals of power quality disturbances have been generated in MATLAB using mathematical models as reported in [18].

Investigated PQ disturbances include pure sine wave, voltage sag, voltage swell, momentary interruption, harmonics, oscillatory transient, impulsive transient and notch. These signals are decomposed using discrete wavelet transform with db4 as mother wavelet up to third level of decomposition.

The plots of detail coefficients at all the three levels and approximation coefficient at the third level of decomposition are obtained for all the investigated PQ disturbances. Various features F1, F2, F3 and F4 are obtained from these plots which are given as input to the rule-based decision tree for classification purpose.

The results are tested for 30 data sets of each PQ disturbance. Finally, the performance of proposed algorithm has been compared with the techniques reported in literature to validate the effectiveness of proposed algorithm.

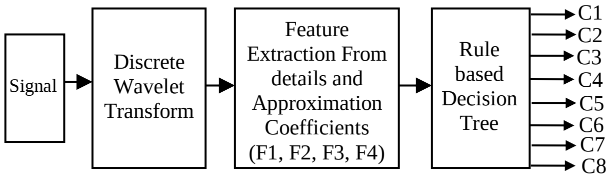

Fig.1. Proposed PQ recognition technique-based on DWT and rule-based decision tree

3. PROPOSED ALGORITH SIMULATION

This section presents the simulation results related to the analysis of PQ events using discrete wavelet transform. The voltage signal with PQ disturbances is decomposed up to third level using discrete wavelet transform with db4 as mother wavelet.

The detail coefficients at levels 1, 2, 3 and approximation coefficient at level 3 are used for the detection of PQ disturbances. In all the DWT-based plots, the x-axis represents the sample numbers whereas the amplitude of coefficients is represented on y-axis. The DWT-based plots related to pure sine waves are utilized as reference curves for the detection of PQ disturbances.

3.1. PURE SINE WAVE

The pure sinusoidal voltage signal is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of pure sine wave, approximation coefficient (cA3), detail coefficient at third level (cD3), detail coefficient at second level (cD2) and detail coefficient at first level (cD1) of decomposition are shown in Fig.2(a)- Fig.2(e) respectively.

It can be observed that significant changes are not detected in the plots related to detail coefficients whereas the fundamental frequency component appears in the approximation coefficient at level 3. These plots can be used as the reference plots for detection of PQ disturbances associated with the voltage signal.

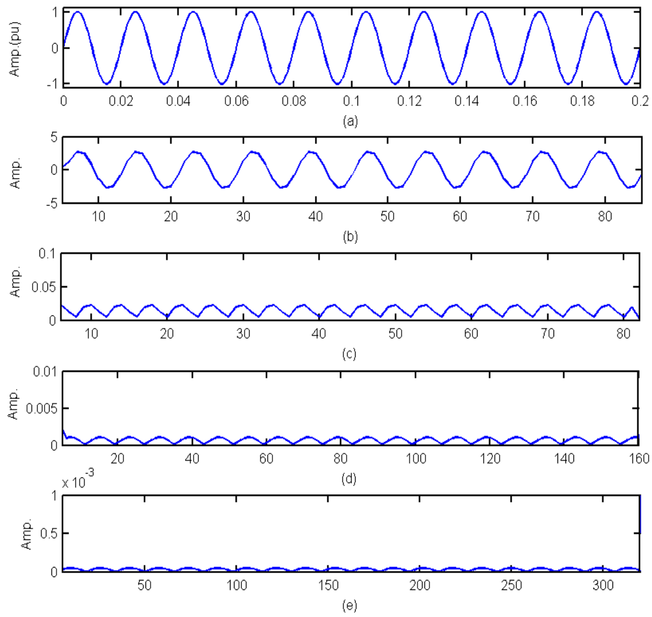

Fig.2. Discrete wavelet transform-based decomposition of pure sine wave (a) pure sine wave signal (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level (cD1)

3.2. VOLTAGE SAG

The voltage signal with sag is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of voltage sag, approximation coefficient at third level (cA3), detail coefficient at third level (cD3), detail coefficient at second level (cD2) and detail coefficient at first level (cD1) of decomposition are shown in Fig.3(a)- Fig.3(e) respectively. High magnitude peaks available at sample numbers 100 and 225 in the detail coefficient cD1 represent the initiation and end of the voltage sag. Similarly, the high magnitude peaks available in the detail coefficient cD2 at sample numbers 50 and 115 can also be utilized for the recognition of start and end of the voltage sag. Decrease in the magnitude of detail coefficient cD3 and approximation coefficient cA3 between the sample numbers 30 to 60 detects the presence of voltage sag in the signal.

3.3. VOLTAGE SWELL

The voltage signal with swell is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of voltage swell, approximation coefficient at third level (cA3), detail coefficient at third level (cD3), detail coefficient at second level (cD2) and detail coefficient at first level (cD1) of decomposition are shown in Fig.4(a)-Fig.4(e) respectively. The high magnitude peaks available at sample numbers 100 and 225 in the detail coefficient cD1 represent the initiation and end of the voltage swell. Similarly, the high magnitude peaks available in detail coefficient cD2 at sample numbers 50 and 115 can also be utilized for the recognition of start and end of the voltage swell. Increase in magnitude of the detail coefficient cD3 and approximation coefficient cA3 between the sample numbers 30 to 60 detects the presence of voltage swell in the signal.

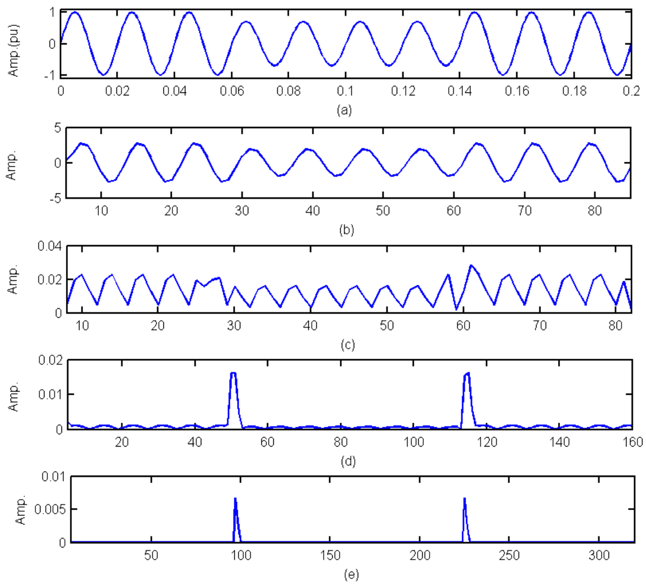

Fig.3. Discrete wavelet transform-based decomposition of voltage sag (a) voltage signal with sag (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level (cD1)

3.4. MOMENTARY INTTERRUPTION

The voltage signal with momentary interruption is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of momentary interruption, approximation coefficient at third level (cA3), detail coefficient at third level (cD3), detail coefficient at second level (cD2) and detail coefficient at first level (cD1) of decomposition are shown in Fig.5(a)-Fig.5(e) respectively.

The high magnitude peaks available at sample numbers 100 and 225 in the detail coefficient cD1 represent the initiation and end of the momentary interruption. Similarly, the high magnitude peaks available in the detail coefficient cD2 at sample numbers 50 and 115 can also be utilized for the recognition of start and end of the voltage swell.

The increase in magnitude of detail coefficient cD3 and approximation coefficient cA3 between the sample numbers 30 to 60 detects the presence of voltage swell in the signal.

3.5. HARMONICS

The voltage signal with harmonics containing 3rd, 5th, and 7th components is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of voltage signal with harmonics, approximation coefficient at third level (cA3), detail coefficient at third level (cD3), detail coefficient at second level (cD2) and detail coefficient at first level (cD1) of decomposition are shown in Fig.6(a)-Fig.6(e) respectively.

The continuous ripples present in the detail coefficient cD3 represent the third harmonic frequency components available in the signal whereas the continuous ripples present in the detail coefficient cD2 indicates the presence of 5th harmonic component frequency. The 7th harmonic frequency component is observed in the detail coefficient cD1. The approximation coefficient indicates the fundamental frequency component of 50 Hz.

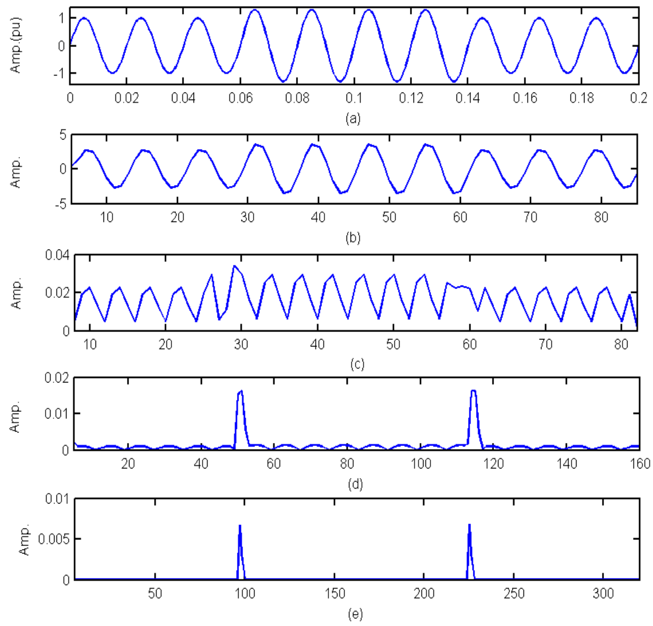

Fig.4. Discrete wavelet transform-based decomposition of voltage swell (a) voltage signal with swell (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level (cD1)

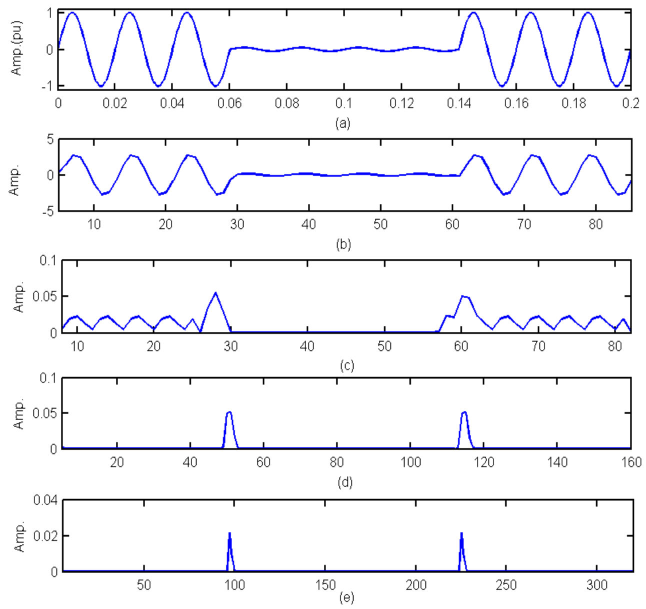

Fig.5. Discrete wavelet transform-based decomposition of voltage signal with momentary interruption (a) voltage signal with interruption (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level (cD1)

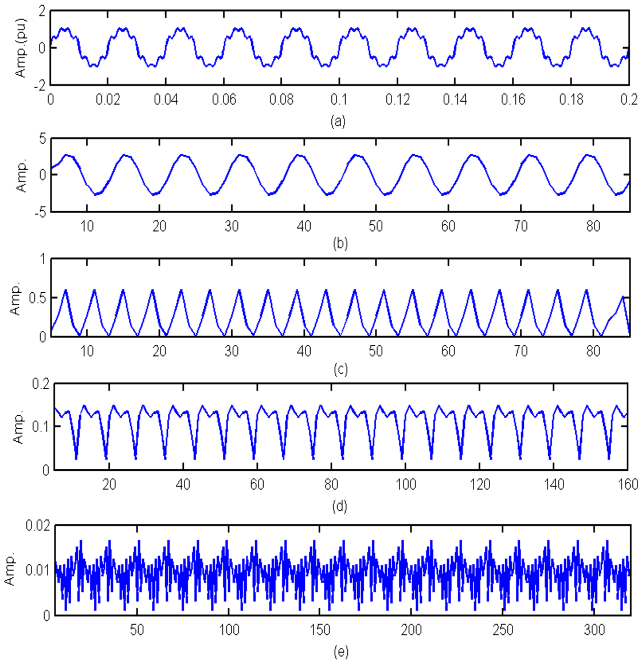

Fig.6. Discrete wavelet transform-based decomposition of voltage signal with harmonics (a) voltage signal with harmonics (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level (cD1)

3.6. OSCILLATORY TRANSIENT

The voltage signal with oscillatory transient is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of oscillatory transient, approximation coefficient at third level (cA3), detail coefficient at third level (cD3), detail coefficient at second level (cD2) and detail coefficient at first level (cD1) of decomposition are shown in Fig.7(a)-Fig.7(e) respectively.

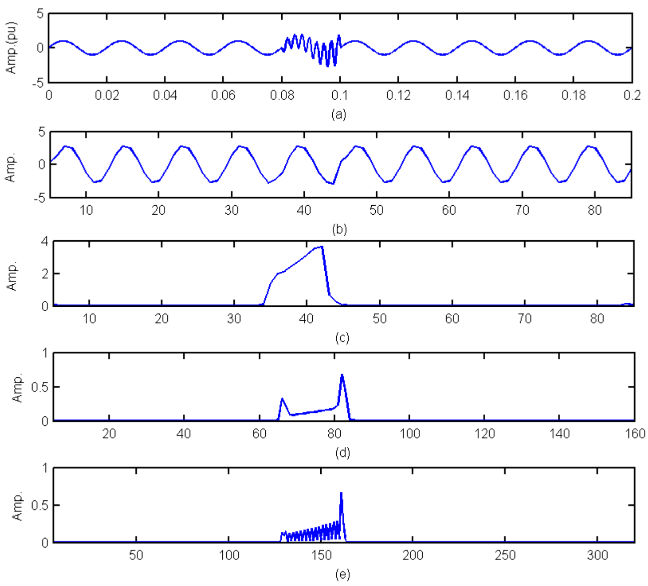

Fig.7. Discrete wavelet transform-based decomposition of voltage signal with oscillatory transient (a) voltage signal with oscillatory transient (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level (cD1)

The presence of high magnitude of amplitude in all the detail coefficients detect the presence of oscillatory transient signal in the voltage signal.

3.7. IMPULSIVE TRANSIENT

The voltage signal with impulsive transient is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of impulsive transient, approximation coefficient at third level (cA3), detail coefficient at third level (cD3), detail coefficient at second level (cD2) and detail coefficient at first level (cD1) of decomposition are shown in Fig.8(a)-Fig.8(e) respectively. The presence of high magnitude peaks for short duration in all the detail coefficients detects the presence of impulsive transient signal in the voltage signal.

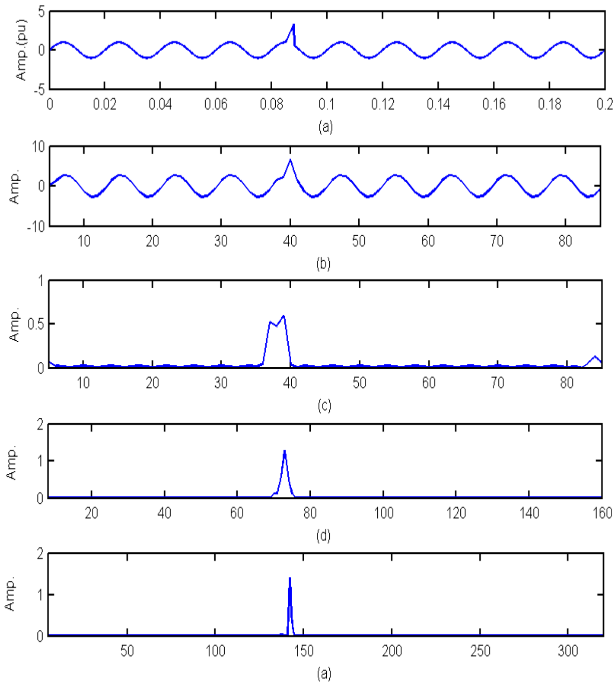

Fig.8. Discrete wavelet transform-based decomposition of voltage signal with impulsive transient (a) voltage signal with impulsive transient (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level (cD1)

3.8. NOTCH

The voltage signal with notches is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of notches, approximation coefficient at third level (cA3), detail coefficient at third level (cD3), detail coefficient at second level (cD2) and detail coefficient at first level (cD1) of decomposition are shown in Fig.9(a)-Fig.9(e) respectively. The presence of continuous train of sharp pointed ripples in the detail coefficients cD1 and cD2 indicate the presence of the notches in voltage signal.

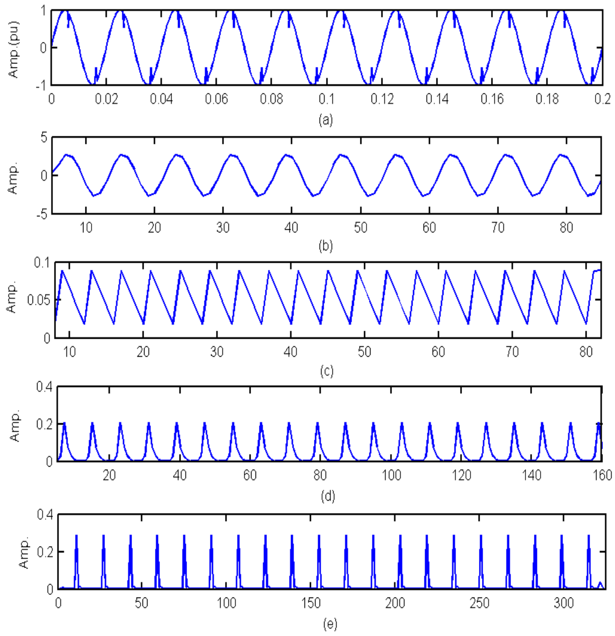

Fig.9. Discrete wavelet transform-based decomposition of voltage signal with notches (a) voltage signal with notches (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level (cD1)

4. FEATURE EXTRACTION

The features F1, F2, F3 and F4 are extracted from the detail coefficients of levels 1 to 3 and approximation coefficient at level 3 and utilized for the classification of PQ disturbances using rule-based decision tree. The definitions of these features are detailed as below:

F1: Kurtosis of detail and approximation coefficient plots as given by the following relation

$$k = \frac{E\left(x-\mu\right)^4}{\sigma^4} \tag{1}$$

where x: array of data of signal, μ: mean of x, σ: standard deviation of x, and E: expected value of the quantity.

F2: Skegness of detail and approximation coefficients plots as given by the following relation.

$$s = \frac{E\left(x-\mu\right)^3}{\sigma^3} \tag{2}$$

F3: Standard deviation of the detail and approximation coefficients plots.

F4: Variance of the detail and approximation coefficients plots.

The numerical values of various features utilized for the classification purpose using rule-based decision tree are provided in the Table.1.

Table.1. Feature used for classification

DWT Plots	F1	F2	F3	F4
Pure Sine Wave				
cD1	155.3195	11.8857	0.0025	6.1128e-06
cD2	38.8278	5.8305	0.0142	2.0100e-04
cD3	42.4149	5.9102	0.0615	0.0038
cA3	1.6010	-0.0488	1.9447	3.7817
Voltage Sag				
cD1	139.3476	11.0440	0.0025	6.4327e-06
cD2	36.8514	5.6101	0.0143	2.0476e-04
cD3	42.0982	5.8850	0.0618	0.0038
cA3	1.7559	-0.0544	1.7360	3.0137
Voltage Swell				
cD1	139.4255	11.0477	0.0025	6.4280e-06
cD2	36.9530	5.6185	0.0143	2.0380e-04
cD3	42.4590	5.9014	0.0612	0.0037
cA3	1.7158	-0.0435	2.1956	4.8207
Momentary Interruption				
cD1	75.0279	8.0413	0.0031	9.5934e-06
cD2	24.2607	4.4393	0.0160	2.5677e-04
cD3	39.7642	5.6386	0.0629	0.0040
cA3	2.6479	-0.0623	1.5098	2.2794
Harmonics				
cD1	83.6006	7.2850	0.0085	7.2119e-05
cD2	7.5449	0.2395	0.0444	0.0020
cD3	2.0456	0.6352	0.2239	0.0502
cA3	1.5208	-0.0774	1.9552	3.8230
Oscillatory Transient				
cD1	53.8566	6.1895	0.0596	0.0035
cD2	37.1084	5.1641	0.0779	0.0061
cD3	11.4450	3.1041	0.7999	0.6398
cA3	1.6049	-0.0701	1.9507	3.8053
Impulsive Transient				
cD1	254.2435	15.4814	0.0828	0.0069
cD2	87.8722	8.7747	0.1171	0.0137
cD3	16.7088	3.8238	0.1112	0.0124
cA3	2.4999	0.2513	2.0540	4.2190
Notch				
cD1	14.1444	3.6162	0.0686	0.0047
cD2	4.6071	1.7103	0.0659	0.0043
cD3	33.6920	4.7384	0.0598	0.0036
cA3	1.5841	-0.0494	1.9003	3.6111

5. CLASSIFICATION OF PQ DISTURBANCES

The flowchart of proposed rule-based classification of PQ disturbances using features extracted from the discrete wavelet transform is shown in Fig.10. Rules used for the classification are also described in this flow chart.

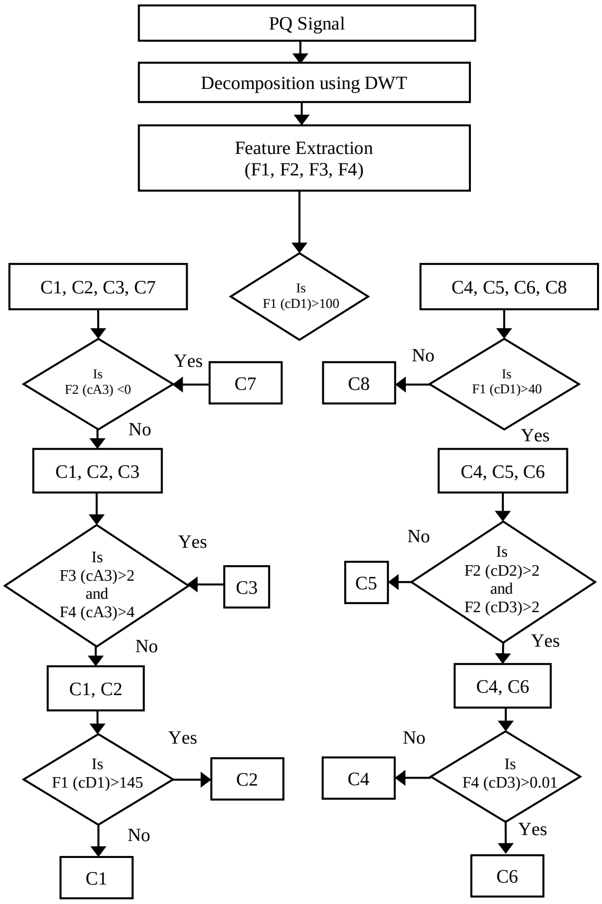

Fig.10. Ruled decision tree-based flow chart for the classification of PQ disturbances

Table.2. Performance Classification

PQ Event	Class symbol	Correctly classified	Misclassified	Efficiency (%)
Pure sine wave	C1	30	0	100
Voltage sag	C2	29	1	96.67
Voltage swell	C3	29	1	96.67
Momentary interruption	C4	30	0	100
Harmonics	C5	27	3	90
Oscillatory transient	C6	29	1	96.67
Impulsive transient	C7	28	2	93.33
Notch	C8	26	4	86.67
Overall efficiency				95.00125

The performance of classification is tested on 30 data sets and provided in Table.2. It is observed that overall efficiency is above 95%.

6. PERFORMANCE COMPARISION

The performance of proposed algorithm has been compared with the techniques reported in [16], and [17] and comparison of performance is provided in Table.3. From the Table.3, it can be observed that the efficiency of proposed algorithm is higher than the algorithms reported in the references [16], and [17].

Table.3. Performance Comparison

Reference	Type of Technique	Overall efficiency (%)
[16]	DWT+ANN	88
[17]	WT+SOMN	92
Proposed	DWT+RBDT	95.00125

7. CONCLUSION

This paper presents a technique for the detection and classification of power quality disturbances. The standard PQ disturbances such as pure sine wave, voltage sag, voltage swell, momentary interruptions, harmonics, oscillatory transient, impulsive transient and notch are generated using the mathematical relations with the help of MATLAB. These generated PQ signals are decomposed using Discrete Wavelet transform and plots of detail and approximation coefficients are obtained. Various features are extracted from these plots and given as input to the rule-based decision tree for the classification of PQ disturbances. The performance of proposed algorithm has been tested on the 30 data sets of each PQ disturbance obtained by varying the parameters. The efficiency of classification has been achieved greater than 95%. The performance of proposed algorithm has been compared with the algorithms already reported in the literature to show the effectiveness of algorithm.

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