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

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Abstract

This paper presents a method for the detection and classification of complex power quality (PQ) disturbances using discrete wavelet transform (DWT) based ruled 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 various combinations of voltage sag, voltage swell, momentary interruption, harmonics, oscillatory transient and impulsive transient. These power quality signals are decomposed using discrete wavelet transform with db4 as mother wavelet up to level 4 of decomposition. The detail coefficients and approximation coefficients are used for recognition of complex PQ disturbances. The features extracted from plots of these coefficients are given as input to the rule-based decision tree for classification of complex PQ disturbances. The effectiveness of proposed algorithm has been established by testing 30 data sets of each complex PQ disturbance obtained by varying the parameters.

Keywords:

Complex Power Quality Disturbance, Discrete Wavelet Transform, Power Quality, Rule-Based Decision Tree

1. INTRODUCTION

Power quality has become an important concern amongst the power customers, academics and power utilities over the past few years. The utilities are more concerned about harmonics in the power system network and voltage distortion [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]. A power quality problem is defined as any deviation in the voltage, current and frequency from the standard values which may lead to equipment failure or malfunction of the equipment’s [3]. This is due to increase in the use of power electronic devices, switching of loads and capacitors, fault clearing, lightning, use of non-linear loads, commercial and domestic applications [4]. These disturbances cause problems such as overheating, equipment failures, inaccurate metering and malfunctioning of protective equipment’s [5]. The effective and efficient detection of these disturbances is required to design appropriate mitigation techniques.

The mathematical and signal processing techniques are used for the detection and classification of PQ disturbances. Mahela et al. [6], presented a comprehensive review of the various signal processing and artificial intelligent techniques used 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 neighbor etc. [7]. Behera et al. [8], presented an approach for detection and classification of power quality events using Stock well’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 [9]. Mahela et al. [10] presented an approach based on the S-transform and rule-based decision tree for the detection and classification of 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 [11]. Punicic et al. [12], 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 [13]. Mahela et al. [14], proposed a method based on the S- transform and Fuzzy C-means clustering for the recognition of PQ disturbances associated with the grid integrated solar PV system. A method based on the Hilbert-Huang transform (HHT) for time-frequency analysis of multi-disturbance complex power quality signal has been reported in [15].

This paper presents a method based on discrete wavelet transform and rule-based decision tree for the detection and classification of complex PQ disturbances. Complex PQ signals are generated using various combinations of the mathematical relations of single stage PQ disturbances and decomposed using DWT. The statistical features are extracted from the plots related to detail and approximation coefficients using kurtosis, skewness, standard deviations and variance. These features are given to rule based decision tree for classification of the complex PQ disturbances. Performance of proposed algorithm has been validated by testing on 30 datasets of each complex PQ disturbance.

This paper is organized into 7 sections. Section 2 describes the proposed algorithm used for recognition of complex PQ disturbances. The simulation results and discussion is presented in the section 3. Section 4 details the feature extraction. The classification results based on rule-based decision tree are illustrated in the Section 5. The comparison of performance of the proposed algorithm with that reported in the literature is described in the Section 6. Conclusions of the proposed research work are elaborated in the Section 7.

2. PROPOSED ALGORITHM

The proposed algorithm for recognition of complex PQ disturbances is shown in the Fig.1. The signals of complex PQ disturbances are generated in MATLAB with the help of various combinations of mathematical models of single stage PQ disturbances as reported in [16].

Investigated complex PQ disturbances include various combinations of voltage sag, voltage swell, momentary interruption, harmonics, oscillatory transient, and impulsive transient. 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 complex PQ disturbances. Various features F_1, F_2, F_3 and F_4 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 the proposed algorithm has been compared with the techniques reported in literature to validate the effectiveness of the proposed algorithm.

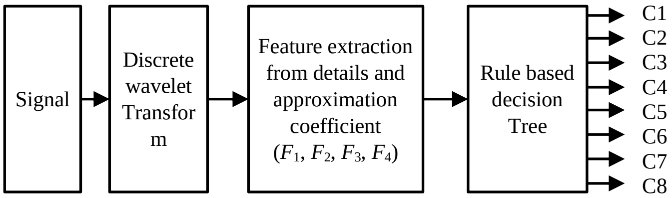

Fig.1. Proposed complex PQ recognition technique based on DWT and rule-based decision tree

3. SIMULATION RESULTS ANDDISCUSSION

The results related to analysis of complex PQ disturbances using discrete wavelet transform are presented in this section. The voltage signal with complex PQ disturbances is decomposed using discrete wavelet transform with db4 as mother wavelet up to third level of decomposition. The detail coefficients at all the levels and approximation coefficient at third level are used for recognition of complex PQ disturbances. The numbers of PQ disturbances available simultaneously in the voltage signal indicate the degree of complexity. The DWT based plots related to pure sine wave are used as reference curves for the detection of complex PQ disturbances.

3.1 VOLTAGE SAG WITH HARMONICS

The voltage signal with voltage sag and harmonics has the degree two complexities. This signal is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of voltage signal, 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 Figs. 2 (a), (b), (c), (d) and (e) respectively. The high magnitude peaks at sample numbers 100 and 230 indicate the initiation and end of voltage sag. The decrease in magnitude of all the plots related to the detail and approximation coefficients indicate the presence of voltage sag. Presence of continuous ripples in the detail coefficients cD2 and cD3 detects the harmonic components present in the voltage signal.

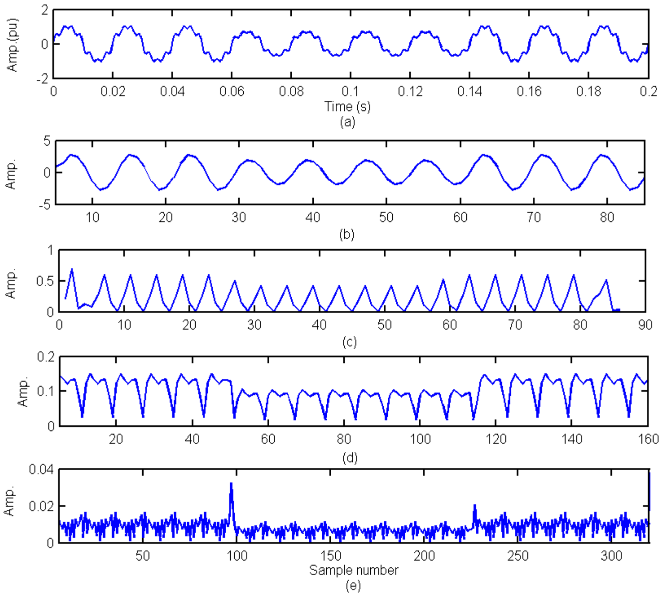

Fig.2. Discrete wavelet transforms-based decomposition of voltage signal with voltage sag and harmonics (a)voltage signal (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level (cD1)

3.2 VOLTAGE SWELL WITH HARMONICS

The voltage signal with voltage swells and harmonics is a degree two complex PQ disturbance. This signal is decomposed using DWT with db4 as mother wavelet up to third level of decomposition. The plots of voltage signal, 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. The high magnitude peaks at sample numbers 100 and 230 indicate the initiation and end of voltage swell. Increase in the magnitude of all plots related to the detail and approximation coefficients indicate the presence of voltage swell. Presence of continuous ripples in the detail coefficients cD2 and cD3 detects the harmonic components present in the voltage signal.

3.3 MOMENTARY INTERRUPTION WITH HARMONICS

The voltage signal with momentary interruption and harmonics is known as degree two complex PQ disturbance. The voltage with this PQ disturbance is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of voltage signal, 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.4(a)-Fig.4(e) respectively. The high magnitude peaks at sample numbers 100 and 230 indicate the initiation and end of momentary interruption. Reduction in magnitude of all the plots related to the detail and approximation coefficients nearly zero indicate the presence of momentary interruption in the voltage signal. The presence of continuous ripples in the detail coefficients cD2 and cD3 detects the harmonic components present in the voltage signal.

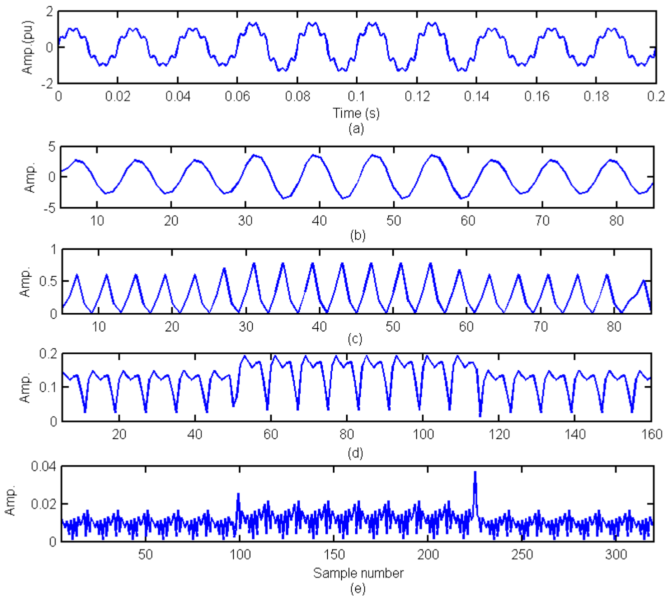

Fig.3. Discrete wavelet transforms-based decomposition of voltage signal with voltage swells and harmonics (a) voltage signal (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level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

3.4 OCILLATORY TRANSIENT WITH VOLTAGE SAG

The voltage signal with oscillatory transient and voltage sag is also a degree two complex PQ disturbance. This voltage signal is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of voltage signal, 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.5(a)-Fig.5(e) respectively. The high magnitude values in all the plots related to detail and approximation coefficients indicate the presence of oscillatory transient in the voltage signal. Decrease in the magnitude of plot related to the approximation coefficient between the sample numbers 45 to 70 indicate the presence of voltage sag in the voltage signal.

3.5 IMPULSIVE TRANSIENT WITH VOLTAGES AG

The voltages signal with impulsive transient (IT) and voltage sag is a PQ disturbance of degree two complexities. This signal is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of voltage signal, 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.6(a)-Fig.6(e) respectively. The high magnitude peaks available in all the plots related to detail and approximation coefficients indicate detects the impulsive transient available in the voltage signal. Decrease in magnitude of plot related to the approximation coefficient between the sample numbers 45 to 70 indicate the presence of voltage sag in the voltage signal

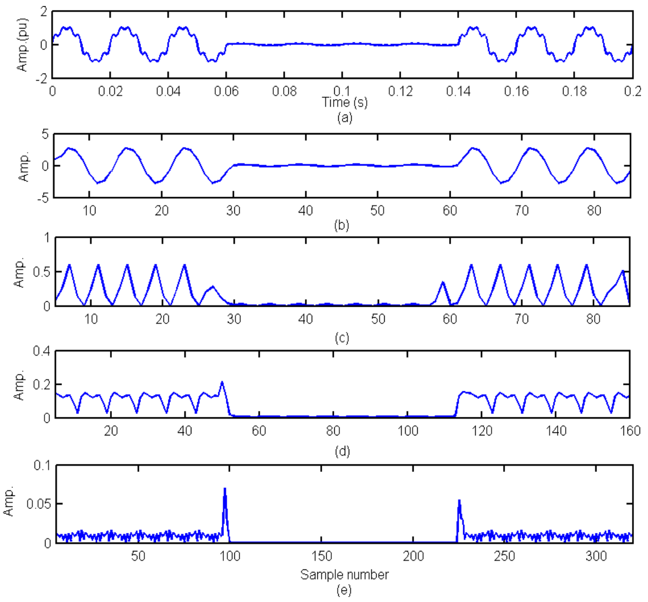

Fig.4. Discrete wavelet transforms-based decomposition of voltage signal with momentary interruption and harmonics (a) voltage signal (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first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

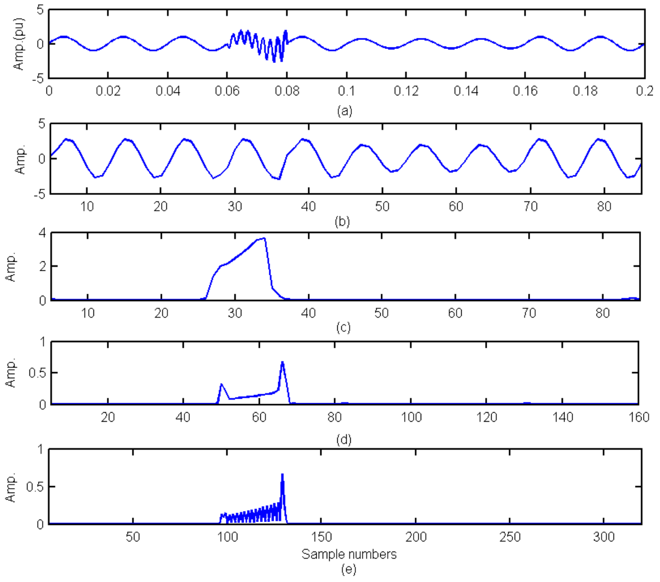

Fig.5. Discrete wavelet transforms-based decomposition of voltage signal with oscillatory transient and voltage sag (a) voltage signal (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level (cD1)

3.6 SIMULTANEOUS OCCURRENCE OF VOLTAGE SWELL, OSCILLATORY TRANSIENT ANDHARMONICS

The voltage signal with simultaneous occurrence of voltage swell, oscillatory transient (OT) and harmonics is PQ disturbance of degree three complexity. This signal is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of voltage signal, 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. High magnitudes available in the plots related to the detail coefficients cD1 and cD3 indicate the presence of oscillatory transient. The two high magnitude peaks in the plot of detail coefficient cD2 are due to the initiation and end of the OT. Hence, this also help in the detection of OT. Presence of continuous ripples in the detail coefficients cD2 and cD3 detects the harmonics in voltage signal. Increase in magnitude of plot related to the approximation coefficient between the sample numbers 45 to 70 indicate the presence of voltage swell in the voltage signal.

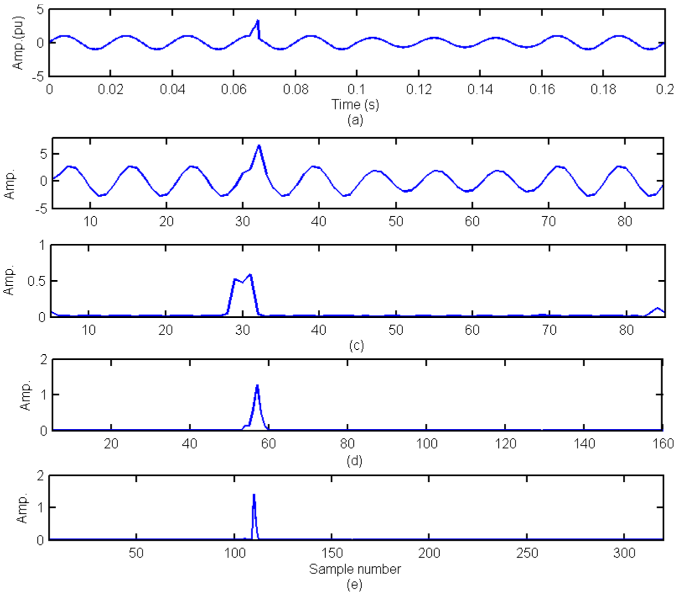

Fig.6. Discrete wavelet transforms-based decomposition of voltage signal with impulsive transient and voltage sag (a) voltage signal (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first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

3.7 SIMULTANEOUS OCCURRENCE OF VOLTAGE SAG, OSCILLATORY TRANSIENT ANDHARMONICS

The voltage signals with simultaneous occurrence of voltage sag, oscillatory transient (OT) and harmonics is PQ disturbance of degree three complexities. This signal is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of voltage signal, 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. High magnitudes available in the plots related to detail coefficients cD1 and cD3 indicate the presence of oscillatory transient. The two high magnitude peaks in the plot of detail coefficient cD2 are due to the initiation and end of the OT. Hence, this also helps in the detection of OT. The presence of continuous ripples in the detail coefficients cD2 and cD3 detects the harmonics in the voltage signal. Decrease in magnitude of plot related to the approximation coefficient between the sample numbers 45 to 70 indicate the presence of voltage sag in the voltage signal.

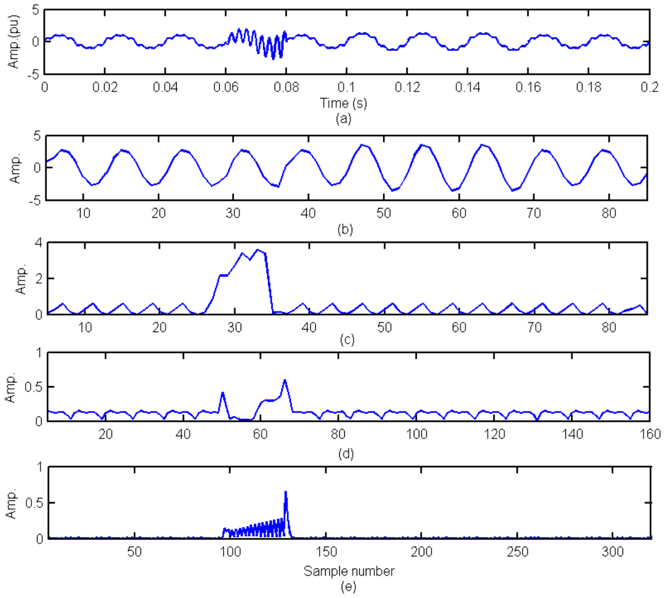

Fig.7. Discrete wavelet transforms-based decomposition of voltage signal with oscillatory transient, voltage swell and harmonics (a) voltage signal (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient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

3.8 SIMULTANEOU OCCURRENCE OF OSCILLATORY TRANSIENT, IMPULSIVE TRANSIENT, VOLTAGE SAG AND HARMONICS

The voltage signals with simultaneous occurrence of voltage sag, oscillatory transient (OT), impulsive transient and harmonics are PQ disturbance of degree four complexities. This signal is decomposed up to level 3 using DWT with db4 as mother wavelet. The plots of voltage signal, 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. High magnitudes available in the plots related to the detail coefficients cD1 and cD3 indicate presence of the oscillatory transient. The two high magnitude peaks at sample number 50 and 70 in the plot of detail coefficient cD2 are due to the initiation and end of the OT. Hence, this also helps in the detection of OT. The first high magnitude sharp peak in the plots related to all the detail coefficients detects the presence of IT in the voltage signal. The presence of continuous ripples in the plots of detail coefficients cD2 and cD3 detects the harmonics in the voltage signal. Decrease in magnitude of plot related to the approximation coefficient between the sample numbers 45 to 70 indicate the presence of voltage sag in the voltage signal.

4. FEATURE EXTRACTION

The features are extracted from detail and approximation coefficients. These features are used for classification of complex PQ disturbances using rule-based decision tree. The features are detailed below:

- F_1: Kurtosis of detail and approximation coefficient plots

- F_2: Skewness of detail and approximation coefficients plots F_3: Standard deviation of the detail and approximation coefficients plots.
- F_4: Variance of the detail and approximation coefficients plots.

The numerical values of the features for all the plots used for the classification of complex PQ disturbances using rule-based decision tree are illustrated in the Table.1.

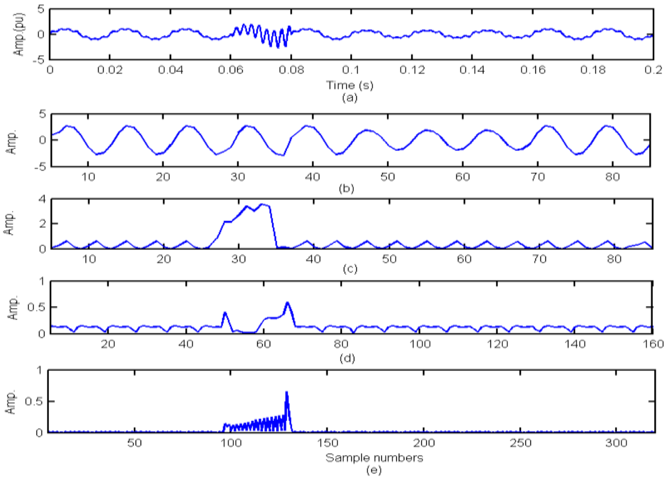

Fig.8. Discrete wavelet transforms-based decomposition of voltage signal with oscillatory transient, voltage sag and harmonics (a) voltage signal (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient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

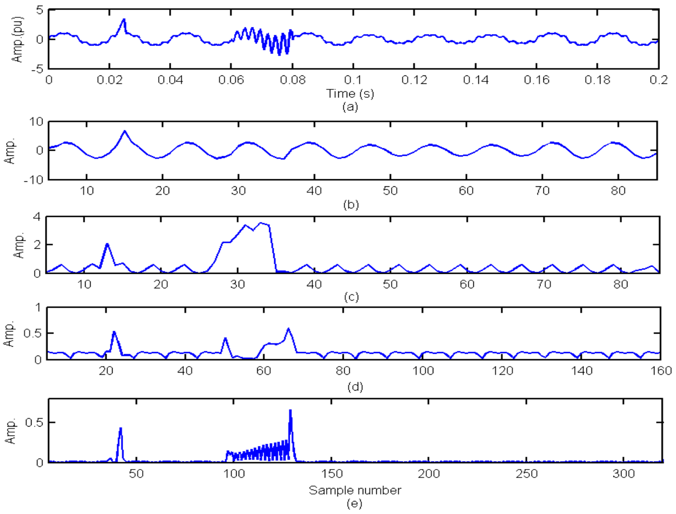

Fig.9. Discrete wavelet transforms-based decomposition of voltage signal with oscillatory transient, impulsive transient, sag and harmonics (a) voltage signal (b) approximation coefficient at third level (cA3) (c) detail coefficient at third level (cD3) (d) detail coefficient at second level (cD2) (e) detail coefficient at first level (cD1)

Table.1. Features used for Classification Purpose

DWT Plots	F_1	F_2	F_3	F_4
Voltage Sag with Harmonics				
cD1	85.1274	7.5114	0.0085	7.3005e-05
cD2	7.4677	0.8133	0.0460	0.0021
cD3	2.4496	0.7820	0.2034	0.0414
cA3	1.6587	-0.0837	1.7481	3.0558
Voltage Swell with Harmonics				
cD1	65.2367	6.0826	0.0089	7.9963e-05
cD2	4.8053	-0.1762	0.0500	0.0025
cD3	2.3214	0.7309	0.2537	0.0644
cA3	1.6356	-0.0703	2.2048	4.8612
Momentary Interruption with harmonics				
cD1	44.7646	5.2674	0.0106	1.1188e-04
cD2	2.8452	0.4258	0.0686	0.0047
cD3	3.4594	1.3010	0.2051	0.0420
cA3	2.4711	-0.0899	1.5242	2.3231
Oscillatory Transient with Voltage Sag				
cD1	53.8794	6.1906	0.0596	0.0035
cD2	37.1662	5.1667	0.0779	0.0061
cD3	11.4413	3.1035	0.8002	0.6403
cA3	1.7286	-0.0780	1.7970	3.2293
Impulsive Transient with Voltage Sag				
cD1	254.2347	15.4809	0.0828	0.0069
cD2	87.8748	8.7738	0.1171	0.0137
cD3	16.6706	3.8180	0.1114	0.0124
cA3	2.9587	0.3342	1.9087	3.6430
Voltage Swell + Oscillatory Transient + Harmonics				
cD1	52.1869	6.0697	0.0579	0.0034
cD2	13.4084	2.4009	0.0765	0.0058
cD3	10.4031	2.8548	0.7800	0.6083
cA3	1.6394	-0.0893	2.1501	4.6231
Voltage Sag + Oscillatory Transient + Harmonics				
cD1	52.1863	6.0697	0.0579	0.0034
cD2	13.4034	2.4002	0.0765	0.0059
cD3	10.4136	2.8578	0.7803	0.6088
cA3	1.6371	-0.1066	1.8081	3.2691
Oscillatory Transient + Impulsive Transient + Voltage sag + Harmonics				
cD1	40.6033	5.4403	0.0639	0.0041
cD2	12.1148	2.4397	0.0845	0.0071
cD3	9.3155	2.6618	0.7975	0.6360
cA3	2.8734	0.2948	1.9325	3.7345

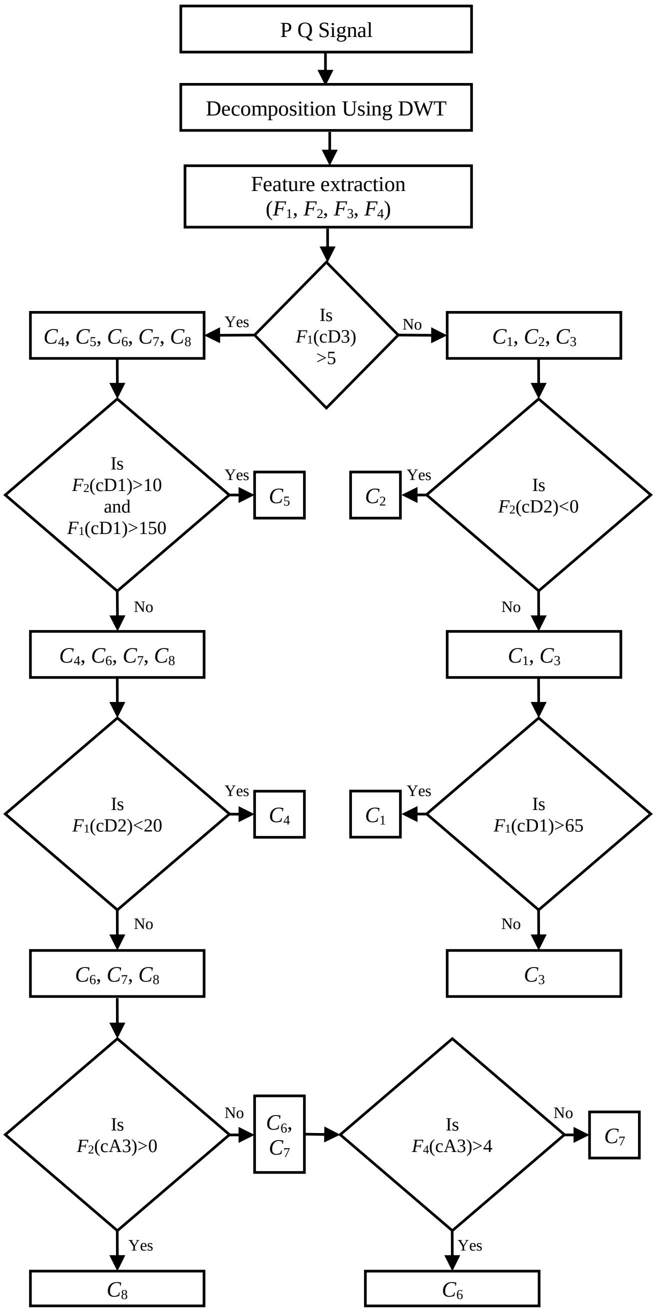

Fig.10. Ruled decision tree-based flow chart for classification of complex PQ disturbances

Table.2. Performance of Classification

PQ Event	**Class symbol**	**Correctly classified**	**Mis-classified**	**Efficiency (%)**
Voltage Sag + Harmonics	C_1	28	2	93.33
Voltage Swell + Harmonics	C_2	28	2	93.33
Interruption + harmonics	C_3	29	1	96.67
OT + Voltage Sag	C_4	29	1	96.67
IT+Voltage Sag	C_5	29	1	96.67
Voltage Swell + OT + Harmonics	C_6	27	3	90.00
Voltage Sag+ OT + Harmonics	C_7	27	3	90.00
OT + IT + Voltage sag + Harmonics	C_8	26	4	86.67
Overall Efficiency				92.92

4.1 CLASSIFICATION OF PQ DISTURBANCES

The features extracted from DWT based plots are used for ruled decision tree to classify various complex PQ disturbances. Flowchart of classification with decision rules is shown in the Fig.10.

5. PERFORMANCECOMPARISON

The performance of proposed algorithm has been compared with the techniques reported in [12], and [15] 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 [12], and [15].

Table.3. Performance comparison

Type of Technique	**Overall efficiency (%)**
DWT+ANN [12]	89.00
WT+SOMN [15]	91.00
Proposed DWT+RBDT	92.92

6. CONCLUSION

This paper presents a technique for the detection and classification of complex PQ disturbances. Complex PQ disturbances are generated by various combinations of single stage PQ disturbances such voltage sag, voltage swell, momentary interruptions, harmonics, oscillatory transient, and impulsive transient using the mathematical relations with the help of MATLAB. These generated complex 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 in put to the rule-based decision tree for the classification of these complex PQ disturbances. The performance of proposed algorithm has been tested on the 30 datasets of each PQ disturbance obtained by varying the parameters. The efficiency of classification has been achieved equal to 93%. The performance of proposed algorithm has been compared with the algorithms already reported in the literature to show the effectiveness of the algorithm.

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