A New Method for Detection and Classification of Power Quality Events Using Discrete Wavelet Transform and Correlation Coefficients

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A B S T R A C T

This paper presents a novel and simple approach to detecting and classifying a wide range of power quality (PQ) events based on the discrete wavelet transform (DWT) and correlation coefficient. For this purpose, two new indices are proposed and the type of PQ event is detected by comparing the values of the correlation coefficient between the value of these indices for the pre-stored PQ events and for a recorded indistinct signal. This algorithm enjoys the advantages of DWT and correlation coefficient and it does not suffer the disadvantages of neural networks or neural network-fuzzy based algorithms such as training and high dimension input matrices or the disadvantages of Fourier transform-based approaches such as unsuitability for non-stationary signals as it does not track signal dynamics properly due to the limitation of fixed window width. The effectiveness of the method tested by numerous PQ disturbance and simulation results confirms the competency and the ability of the proposed method in detection and automatic diagnosis of PQ disturbances. Compared with the other methods, the simulation under different noise conditions verifies the effectiveness of the noise immunity and the relatively better accuracy of the proposed method.

I. Introduction

Power quality (PQ) has become an important topic of research in recent years. PQ is a quality of service issue for customers and electric power service providers, and it covers a variety of transient electromagnetic phenomena in electric power distribution systems [1]. Today, the proliferation of power electronic devices and nonlinear loads in electric power networks has triggered a growing concern for power quality issues from both utilities and power users. A power quality problem usually involves a variation in the electric service voltage or current, e.g. sag, swell, DC offset, flicker, interrupt, notching, harmonic, and transient. These

disturbances can downgrade service quality and also cause different problems. Also, the recognition of the PQ event waveform is often bothersome because it includes a wide range of event categories or classes from dc offsets with low frequency to transients with high frequency.

Currently, some powerful tools are available to monitor and classify electrical PQ disturbances. Based on these tools, several methods have been suggested for PQ disturbance detection and classification in the last few years. A brief review of these methods is as follows.

So far, various methods have been proposed based on discrete wavelet packet and discrete wavelet transform for power quality disturbance identification [2-8].

Fuzzy logic has been used for PQ disturbance detection in several methods. In [9], both the Fourier transform and fuzzy approaches are suggested for PQ disturbance classification. Other fuzzy logic and discrete wavelet transform-based

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methods have also been presented [10,11]. Another methodology [12] uses a wavelet packet-based hidden Markov model for the detection and classification of PQ disturbances. It is noteworthy that this method employs the hidden Markov model to determine the existence of disturbance.

The neural network detection approach has been introduced in some methods [13-15]. In [13], the authors describe how a neural network, trained to recognize patterns of transmission line faults, has been incorporated in a PC-based system that analyzes data files from substation digital fault recorders. In [14], a real-time power quality monitoring scheme was implemented using an artificial neural network and Labview. In this method, the artificial neural network was used to detect and classify the voltage sag and swell in real time.

Hybrid schemes using an artificial neural network and DWT were presented in [16-23]. At first, the discrete wavelet transform provides the features of the events, and then, the artificial neural network classifies them. In [16], the features extracted from wavelet transform coefficients are inputted into a radial basis function (RBF) network for power quality disturbance pattern classification. Applications of the wavelet transform, fuzzy logic, expert systems, neural networks, and genetic algorithms in power quality detection and classification, in particular, are reviewed in [17]. The PQ event detection scheme in [19] was carried out in the wavelet domain using a set of multiple neural networks. With the configuration used in this reference, the classifier is capable of providing a degree of belief for the identified PQ disturbance waveform. In the method presented by Kanirajan et al., the features extracted by the wavelet are trained by an RBF neural network for the classification of PQ events [21]. Sridhar et al. presented a method for PQ disturbance classification. The PQ disturbances are first identified using discrete wavelet transform and they are, then, classified using ANN [22]. The overall performance evaluation of the method is more than 97%. In [23], DWT with a multi-resolution analysis was used for the feature extraction of the PQ events. The probabilistic neural network classifier was used as an effective classifier for the detection and classification of PQ disturbances.

Moreover, in [24-28], combined neuro-fuzzy methodologies were utilized to identify and classify PQ disturbances. In these approaches, the discrete wavelet transform decomposition was used to form feature vectors.

In [24], the input PQ waveforms were preprocessed by the wavelet transform for feature extraction, and the neural network outputs were not taken as the final classification but were used to activate the fuzzy-associative-memory recalling for identifying the most possible type that the input waveform may belong to. A two-stage PQ violation classification approach that uses the potentials of the wavelet transform and the adaptive neuro-fuzzy networks was presented in [25].

In [26], the selected features were extracted from amplitude, phase, and frequency and were instantly used as input to an adaptive neuro-fuzzy system for PQ disturbance classification. To extract PQ disturbance features, the energy distribution of the wavelet part at each decomposition level was introduced by Zhu et al. [27]. Based on these features (as an input), a neuro-fuzzy algorithm was used for the classification of PQ disturbances. Reaz et al. [28] employed a different type of univariate randomly optimized neural network combined with discrete wavelet transform and fuzzy logic in their method to have a better power quality disturbance classification accuracy.

Also, an approach based on a combination of genetic algorithm (GA) and artificial neural network was presented in [29]. A wavelet network-based PQ disturbance detection and classification method was introduced in [30]. The support vector machine (SVM) has also been applied for the detection of PQ events [31-32]. An approach presented in [31] used the histogram of oriented gradients for PQ event detection and SVM for PQ disturbance classification. Thirumala et al. presented a PQ disturbance detection method based on wavelet transform and dual multiclass support vector machines [32]. Ucar et al. proposed a PQ event detection and classification method using the DWT-based extreme machine learning (ELM) technique [33]. Fuzzy systems oriented by the particle swarm optimization algorithm are used for PQ event detection [34]. Recently, a novel detection and classification method for PQ using the least mean square (LMS) and neural network was proposed [35]. In [36], a PQ event detection algorithm using a balanced neural tree is introduced. In this method, the Hilbert-Huang transform is utilized to study non-stationary PQ disturbances. Generally, this technique is an amalgamation of two techniques including empirical mode decomposition and Hilbert transform. Biswal et al. proposed a PQ event detection method using hyperbolic S-transform for feature extraction and genetic algorithm-based fuzzy C-means for automatic recognition of PQ events [37]. Ray et al. presented a PQ disturbance classification technique using a combination of S-transform and SVM for PQ disturbance detection [38]. A fuzzy product aggregation reasoning rule classifier was adopted for the classification of PQ events in [39] in which the DWT technique was used as the feature extraction technique. The S-transform was combined with an extreme machine learning technique for automatic nonstationary power quality disturbance recognition in [40]. In [41], an approach was proposed for optimal placement of PQ meters in a power system on a seeker optimization algorithm.

The performance of a PQ event detection approach generally depends on the accuracy of the signal processing techniques.

Several signal processing approaches have been used for PQ events detection, such as discrete Fourier transform, fast Fourier transform, short-time Fourier transform, discrete wavelet transform, and Gabor-Wigner transform.

Discrete Fourier transform is mostly suitable for stationary PQ events. Since PQ events are generally nonstationary-type signals, it is unsuitable to sense the immediate variations in PQ disturbances, for example, their initial and finale points by using the discrete Fourier transform. The signal information, such as amplitude frequencies and phases,

cannot be acquired correctly by using the fast Fourier transform because of the leakage, aliasing effects, and picket fence formed by fast Fourier transform. It is hard to analyze nonstationary signals by short-time Fourier transform. The main drawback of this signal processing technique is the limited time-frequency resolution. Moreover, it cannot give the exact time and frequency info simultaneously to categorize the power quality events as stated by the IEEE-1159 standard. In the Gabor-Wigner transform, the computational burden directly depends on the sampling frequency. Moreover, the Wigner distribution will cause critical cross-interference, which promotes incorrect frequency components.

In contrast to Fourier and Gabor-Wigner transform, the wavelet transform can offer time and frequency information of a signal simultaneously. In other words, wavelet transform provides local representation in both time and frequency. Therefore, it is suitable where good time-frequency resolution is required.

The neural network-based PQ detection method has such disadvantages as its convergence speed, and the accuracy of the method depends on the network architecture as well as noise in the signal. Poor classification accuracy when training samples are minimum is the disadvantage of the support vector machine-based PQ detection method. In the fuzzy logic technique, the training set for every case is fixed, so it is not suitable for new disturbances.

This paper introduces a new algorithm based on the discrete wavelet transform and correlation coefficient for the PQ disturbance waveform recognition and classification. This algorithm has the advantages of DWT and correlation coefficient, while it does not have the disadvantage of neural network or neural network-fuzzy-based algorithms such as training and high dimension input matrices.

In the algorithm, the DWT is first used in an offline operation to de-noise and decompose the known power quality events signal, and for each event (8 types), the ratio of the sum of the absolute value of the detail coefficients of distorted the signal S(t) at decomposition levels 1 to 13 to the sum of the absolute value of detail coefficients of the pure sinusoid signal at the same decomposition levels is calculated and stored in the vector (totally 8 vectors are obtained for 8 events). Similarly, for the second index, the difference between the standard deviation obtained from the detail coefficients of the distorted signal S(t) at decomposition levels 1 to 13 and the standard deviation obtained from the detail coefficients of the pure sinusoid signal at the same decomposition levels is computed and stored in the vector. In the proposed algorithm (online operation), the unknown PQ voltage signal containing noise is first sampled by a 20-kHz sampling rate. Then, the signal is denoised by sym4 to get a higher SNR signal. Next, using sym4, the signal is decomposed into 13 decomposition levels and the proposed criterion is computed. Assuming that the condition is true, the proposed indices will be obtained. Then, the correlation coefficient between the first computed vector of pre-stored PQ violations and a recorded unknown signal will be calculated. So, eight numbers are achieved and the maximum

number is considered. The indistinct PQ event belongs to this group. If the number of maximum digits is two or more, the second index will be considered. This means that the correlation coefficient between the second computed vector of pre-stored PQ events and a recorded unknown PQ signal will be calculated. The maximum number will specify the PQ class. The results demonstrate that the proposed approach has excellent efficiency.

The rest of the paper is organized as follows. Section II introduces the proposed algorithm and shows how the two indices can be calculated by using DWT. In Section III, simulation results are demonstrated, and the concluding points are presented in Section IV.

II.   PROPOSED METHOD

The paper presents a new method for the detection and classification of PQ disturbances based on DWT and correlation coefficient.

The correlation between two variables X and Y is defined as [42]:

$$Corr(X,Y) = \frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}} \qquad (1)$$

The strength of the dependence between the two variables increases as the correlation moves further away from 0 to 1 or -1 [42].

The different steps of the proposed method are described below:

A. De-noising

In practice, signals sampled by measuring devices have noise. The presence of noise reduces the identification capability of the DWT-based PQ disturbance monitoring system. A DWT-based de-noising approach is used in the proposed algorithm to prevent the detrimental impact of noise and to improve the efficiency of discrete wavelet transform-based monitoring systems. The reconstructed signal is noise-free and has the same energy content.

The general de-noising procedure involves three steps as follows [43].

1. Decomposing
2. Threshold selecting
3. Reconstructing

The performance of a discrete wavelet-based denoising technique depends on two points: how to choose the appropriate threshold value (γ) and how to perform the thresholding.

There are two kinds of thresholding rules: hard thresholding and soft thresholding. Hard thresholding can be described as the usual process of setting the elements whose absolute values are lower than the threshold to zero. Soft thresholding is an extension of hard thresholding in which the elements whose absolute values are lower than the threshold value are first set to zero, and then the nonzero coefficients are shrieked towards zero [43]. We use soft thresholding in the paper.

But the main problem in statistical discrete wavelet

denoising is how to choose a proper threshold value (γ). Selecting a threshold with very large value will shrink almost all coefficients at higher frequency bands to zero, possibly resulting in a pure power quality waveform even in the presence of a disturbance. Conversely, choosing a threshold with a very small value would result in inefficient denoising.

So, the selection of a proper threshold value (γ) is the key to the success of the denoising technique. We use a mixture of Stein's unbiased risk estimate (SURE) approach and universal fixed thresholding method for the selection of a proper threshold value. As a result, if the signal-to-noise ratio is very small, the SURE estimate will be very noisy. So, in case this situation is identified, the fixed form threshold is utilized as follows:

$$\gamma = \left(\frac{\sum_{i=1}^{N_{d_j}} \left| d_j(i) \right|}{0.6745 \cdot 2^j \cdot N_{d_j}} \right) \cdot \sqrt{2 \log N_{d_j}} \qquad (2)$$

where N_{d_j} is the number of detailed coefficients at the desire resolution level j.

After denoising, the reconstructed signal is noise-free and has the same energy content.

B. *Proper Mother Wavelet selecting*

The proper mother wavelet selection has an important role in identifying and localizing different kinds of signal disturbances. Selecting the mother wavelet also depends on the essence and type of the application. For the detection of a low domain, short duration, rapid decaying, and oscillating type of signals, the most popular wavelets are Daubechies and Symlets family (Db2, Db3, ... and Sym2, Sym3,....). But, the Symlets were proposed by Ingrid Daubechies as modifications to the db family [44]. Furthermore, when the scale is increased, the accuracy of the event time localization will be decreased. Also, the width and smoothness of the mother wavelet depend on its number. So, we should be cautious to select the appropriate discrete wavelet family and its number. In this paper, after many examinations, the sym4 mother wavelet was selected.

Each PQ event is related to one or more discrete wavelet transform coefficients. For example, Figures 1-5 show voltage sag, swell, transient (capacitor bank switching) event, notching, flicker, and their detail coefficients at resolution levels 1, 2, and 3 using sym4, respectively.
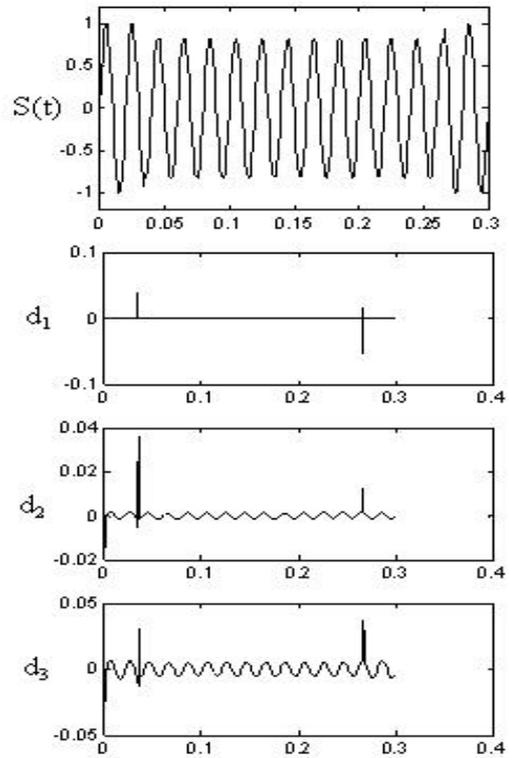

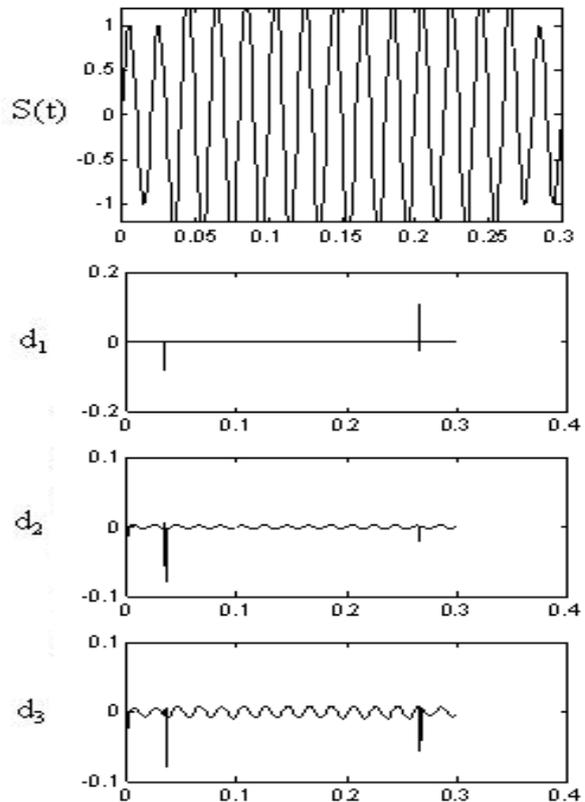**Fig. 1**. Voltage sag signal with its detail coefficients (d1, d2, d3).

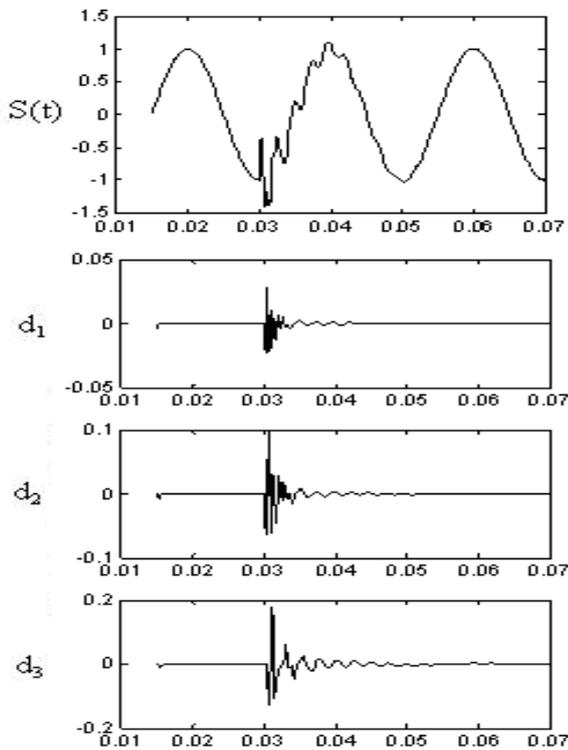**Fig. 2**. Voltage swell signal with its detail coefficients (d1, d2, d3).

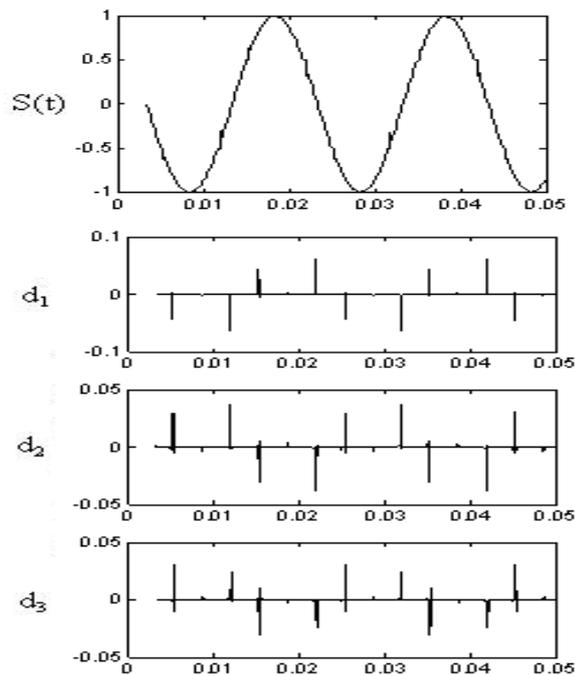**Fig. 3**. Capacitor bank switching signal with its detail coefficients (d1, d2, d3).

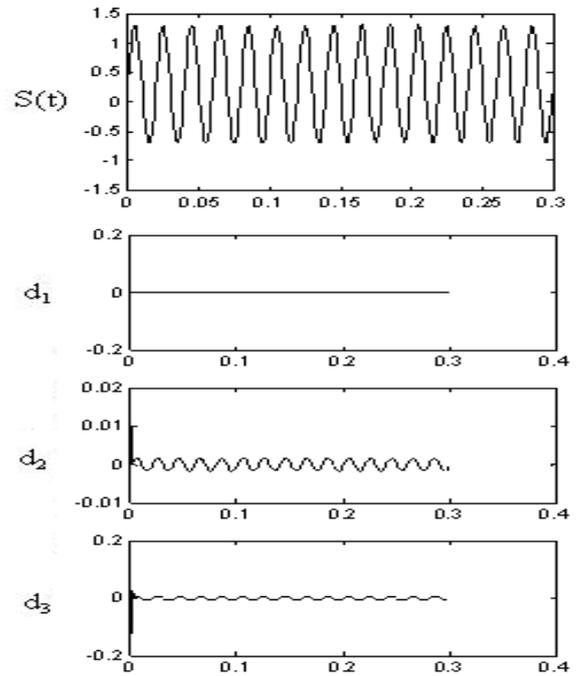**Fig. 4**. Notching signal with its detail coefficients (d1, d2, d3).

Fig. 5. DC offset signal with its detail coefficients (d1, d2, d3).

C. Proposed Algorithm Methodology

The paper presents a novel method for the detection and classification of PQ disturbances based on DWT and correlation coefficient.

For this purpose, DWT is first utilized in an offline operation to decompose the known power quality events signal. It is noteworthy that eight types of PQ disturbances (sag, swell, DC offset, flicker, interrupt, notching, harmonic, transient) are considered in the proposed method. Then, for each event (8 types), the ratio of the sum of the absolute value of detail coefficients of distorted signal S(t) at decomposition levels from 1 to 13, ($Sum\_absS_{d_j}^{Dist}(t) \quad j = 1,2,...,13$) to sum of the absolute value of detail coefficients of the pure sinusoid signal at the same decomposition levels ($Sum\_absS_{d_j}^{Sin}(t) \quad j = 1,2,...,13$) was calculated and stored in a vector (totally 8 vectors were obtained for 8 events). Similarly, for the second index, the difference between the standard deviation obtained from the detail coefficients of the distorted signal S(t) at decomposition levels 1 to 13 ($Std\_absS_{d_j}^{Dist}(t) \quad j = 1,2,...,13$) and the standard deviation obtained from the detail coefficients of the pure sinusoid signal at the same decomposition levels was computed ($Std\_absS_{d_j}^{Sin}(t) \quad j = 1,2,...,13$) and stored in the vector (In this case, 8 vectors were computed for eight PQ disturbances).

After proposing the vectors of the appropriate indices, we show how these proposed indices can be obtained.

Let's assume that signal S(t) was decomposed into N levels by discrete wavelet transform as follows:

$$S(t) = S_{c1}(t) + S_{d1}(t) + S_{d2}(t) + S_{d3}(t) + ... + S_{dN}(t) \quad (3)$$

$$S(t) = \sum_i c_0(i)\phi(t-i) + \sum_i \sum_{j=1}^{N} d_j(i) 2^{\frac{j}{2}} \psi(2^j t - i) \quad (4)$$

Also, we know that in a multi-resolution analysis, a set of involute subspaces Vj and Wj are denoted as:

$$V_N \supset V_{N-1} \supset V_{N-2} \supset ... \supset V_j \supset ... \supset V_2 \supset V_1 \quad (5)$$

$$V_{j+1} = V_j \oplus W_j \quad (6)$$

$$V_j \cap W_j = \{0\} \quad (7)$$

where $\oplus$ defines a summation of two subspaces.

Therefore, an input signal S(t) can be decomposed into their subset signals Sc1(t) and Sdj(t) in accordance with the subsets V1 and Wj, respectively as follows [45]

$$S_{c1}(t) = \sum_i c_1(i)\phi(t-i) \quad (8)$$

$$S_{dj}(t) = \sum_i d_j(i) 2^{\frac{j}{2}} \psi(2^i t - i) \quad (9)$$

where $\phi, \psi \in R$.

So, the sum of the absolute value of the detail coefficients of distorted signal S(t) at decomposition level j ($Sum\_absS_{d_j}^{Dist}(t)$) is obtained as follows:

$$Sum\_absS_{d_j}^{Dist}(t) = \sum_{i=1}^{N_{d_j}} |d_j(i)| \quad (10)$$

where

j = the level of decomposition

dj = the detailed coefficients at level j

N_{d_j} = the number of detailed coefficients at level j

$Sum\_absS_{d_j}^{Dist}(t)$ = the sum of the absolute value of detail coefficients of distorted signal S(t) at resolution level j

Accordingly, the abovementioned first index (the ratio between the sum of the absolute value calculated from detail coefficients of the PQ disturbances and pure sin) is defined as:

$$Index1 = \frac{Sum\_absS_{d_j}^{Dist}(t)}{Sum\_absS_{d_j}^{Sin}(t)} \quad j = 1,2,...13 \quad (11)$$

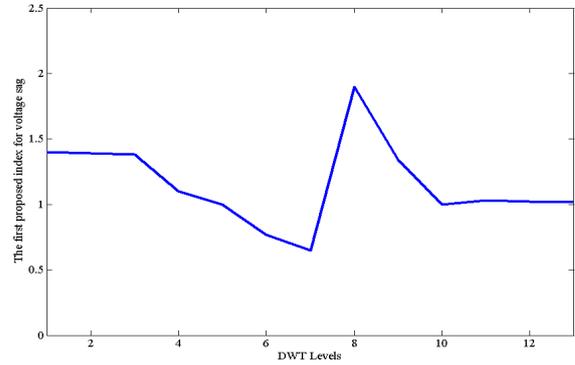The first index for some PQ events is shown in Figures 6-9.

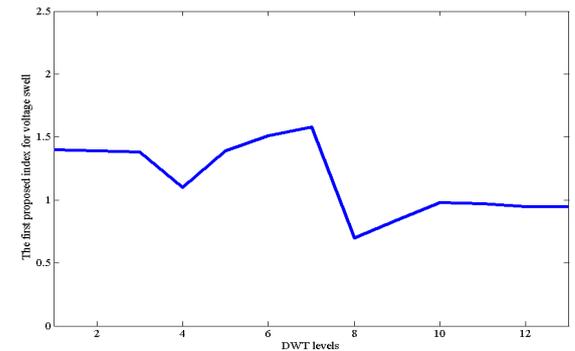**Fig. 6**. The first proposed index for the voltage sag signal

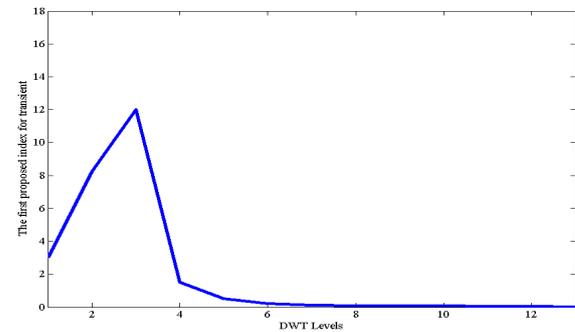**Fig. 7**. The first proposed index for the voltage swell signal

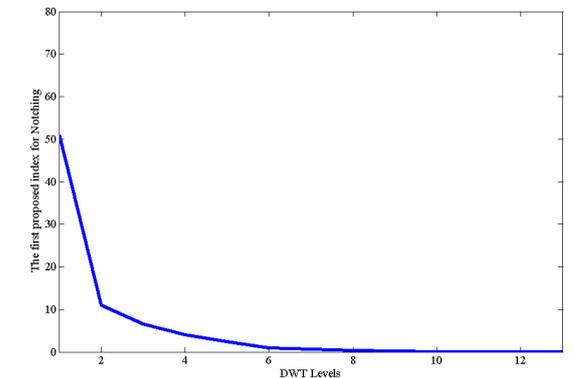**Fig. 8.** The first proposed index for transient

Fig. 9. The first proposed index for notching

The standard deviation of the absolute values of the detailed coefficients at decomposition level j ($Std\_absS_{d_j}(t)$) is:

$$Std\_absS_{d_j}^{Dist}(t) = \sqrt{\frac{1}{2^j N_{d_j}} \sum_i \left(\left|d_j(i)\right| - Mean\_absS_{d_j}(t)\right)^2} \quad (12)$$

Accordingly, the abovementioned second index (the difference between the standard deviation obtained from the detail coefficients of the distorted PQ voltage signal and the pure sinusoidal) can be shown as follows:

$$Index2 = Std\_absS_{d_j}^{Dist}(t) - Std\_absS_{d_j}^{Sin}(t) \quad j=1,2,\dots 13 \quad (13)$$

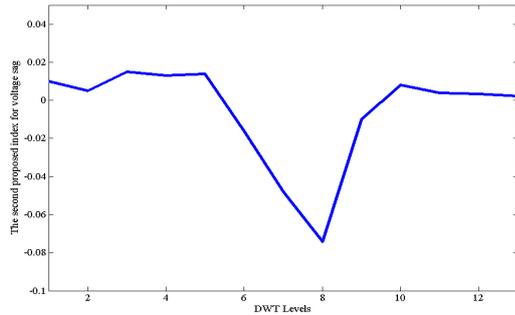The second index for some PQ events is shown in Figures 10-13.

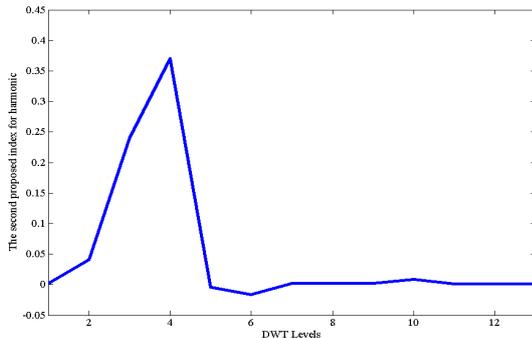
Fig. 10. The second proposed index for the voltage sag

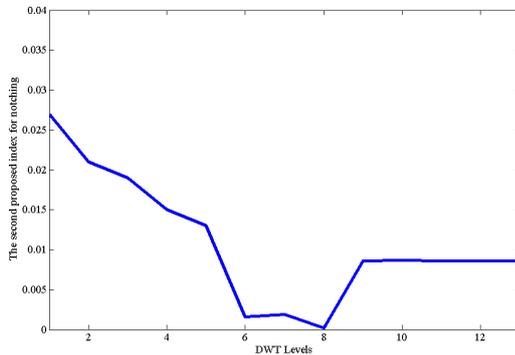**Fig. 11.** The second proposed index for harmonic

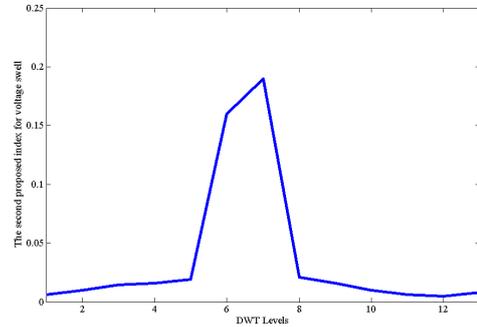**Fig. 12.** The second proposed index for the notching

Fig. 13. The second proposed index for the voltage swell

The online operation of the proposed detection method is defined below:

First, an unknown PQ voltage signal having noise is sampled at a 20-kHz sampling rate. Then, the signal is denoised by sym4 wavelet to get a signal with a higher signal-to-noise ratio. Next, using sym4 wavelet, the signal is decomposed into 13 levels and the following criterion is computed:

$$Cr = \sqrt{\frac{\sum_{j=1}^{N} 2^j \sum_{i=1}^{N_{d_j}} d_j^2(i)}{2^N \sum_{i=1}^{N_{d_N}} a_N^2(i)}} \quad (14)$$

Eq. (14) is the THD generalization in wavelet domains. In Eq. (14), N is the highest decomposition level (N is equal 12 in the algorithm), N_{d_j} is the number of detailed coefficients at level j, and aN is the approximated coefficients at level N.

It should be noted that only if Cr is greater than 1%, the proposed indices will be calculated by using Eq. (10)-(13). Otherwise (i.e. Cr < 1%), the procedure will not start. In other words, Cr indicates whether the captured signal is the disturbance or not.

Supposing that the condition (14) is correct, the proposed indices will be obtained. Then, by using the proposed algorithm, the kind of captured signal will be detected. The algorithm is as follows:

The correlation coefficient between the first computed vector of a pre-stored PQ event and a recorded indistinct signal will be computed from Eq. (1). So, eight numbers are achieved and the maximum number is considered. The unknown PQ event belongs to this group. If the number of maximum digits is two or more, the second index will be considered. This means that the correlation coefficient between the second computed vector of a pre-stored PQ event and a recorded unknown PQ signal will be calculated and the maximum coefficient will be computed. The unknown PQ event belongs to this group. The second index will increase the reliability of the proposed PQ detection algorithm.

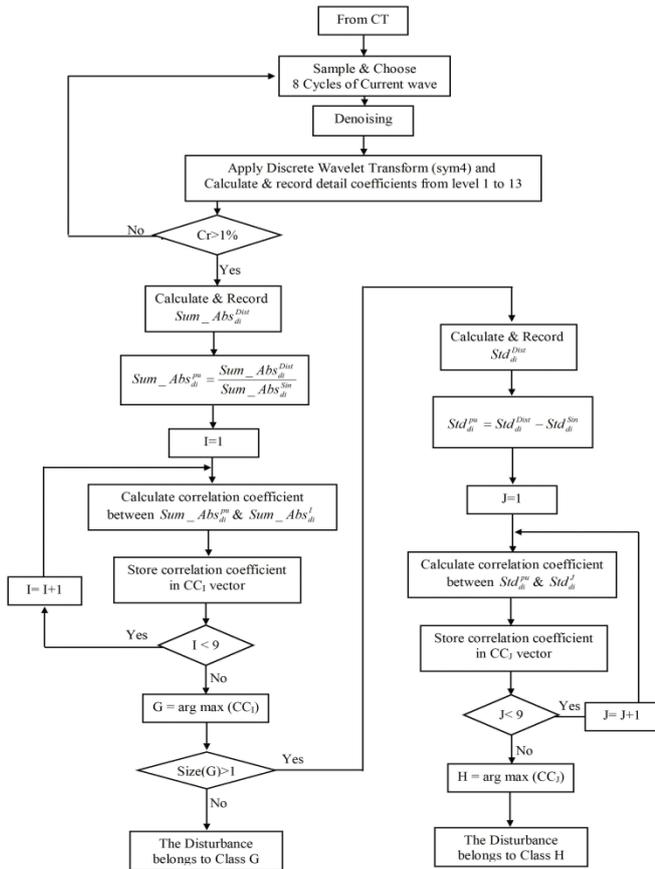Fig. 14 demonstrates a simplified flowchart of the proposed PQ detection and classification algorithm.

Fig. 14. The flowchart of the proposed algorithm

III. RESULTS

This section presents the simulation results of applying the correlation coefficient for recognizing and classifying PQ event types. The proposed algorithm was run in the MATLAB software. The signal randomly sampled out of 60 signals of each disturbance type is used to test the method accuracy. The combined discrete wavelet transform and correlation coefficient can detect and classify all 8 types for PQ disturbances as shown in Table I.

TABLE I
CORRELATION COEFFICIENTS VALUES FOR THE PROPOSED METHOD

Type of PQ disturbances	Representative vectors							
	DC offset	Flicker	Interrupt	Sag	Swell	Notching	Harmonic	Transient
DC offset	0.93	0.72	-0.42	-0.35	0.26	0.21	0.34	0.12
Flicker	0.67	0.96	-0.64	-0.79	0.81	-0.17	0.31	-0.27
Interrupt	-0.39	-0.69	0.95	0.77	-0.63	0.14	0.17	0.11
Sag	-0.43	-0.81	0.83	0.97	-0.74	0.27	-0.16	0.23
Swell	0.32	0.81	-0.79	-0.71	0.96	-0.32	0.12	-0.26
Notching	0.21	-0.14	0.19	0.25	-0.29	0.93	0.11	0.33
Harmonic	0.34	0.37	0.20	-0.13	0.09	0.07	0.89	0.43

| Transient | 0.08 | -0.21 | 0.13 | 0.18 | -0.16 | 0.29 | 0.38 | 0.98 |

TABLE II
CORRELATION COEFFICIENTS FOR THE PROPOSED METHOD WITH SNR=35DB

Type of PQ disturbances	Representative vectors							
	DC offset	Flicker	Interrupt	Sag	Swell	Notching	Harmonic	Transient
DC offset	0.91	0.73	-0.47	-0.39	0.27	0.24	0.31	0.19
Flicker	0.62	0.94	-0.62	-0.82	0.84	-0.23	0.39	-0.24
Interrupt	-0.39	-0.69	0.91	0.79	-0.60	0.17	0.21	0.14
Sag	-0.45	-0.85	0.83	0.93	-0.75	0.29	-0.19	0.27
Swell	0.34	0.82	-0.77	-0.73	0.92	-0.35	0.15	-0.28
Notching	0.28	-0.17	0.23	0.27	-0.31	0.88	0.14	0.34
Harmonic	0.30	0.41	0.25	-0.18	0.13	0.11	0.84	0.47
Transient	0.12	-0.26	0.17	0.22	-0.12	0.35	0.41	0.96

As can be seen in the test results, the proposed method can identify and classify the PQ disturbances correctly.

In order to demonstrate the robustness of the proposed method, the wavelet network was tested with different SNRs. The results with SNR=35 db are shown in Table II.

The percentage of classification accuracy (CA) of the proposed method are presented in Table III where the CA is defined as

Classification accuracy (%) = CA $= \dfrac{N_{correctly\ classified\ events}}{N_{total\ number\ of\ disturbances}}$ (15)

Table III
Classification accuracy rate of the proposed algorithm

	PQ events	$N_{disturbances}$	$N_{correctly\ identified}$	CA (%)
1	DC offset	60	60	100%
2	Flicker	60	59	96.67%
3	Interrupt	60	59	98.33%
4	Sag	60	59	98.33%
5	Swell	60	59	98.33%
6	Notching	60	58	96.67%
7	Harmonic	60	60	100%
8	Transient	60	59	96.67%
9	Total	480	473	98.54%

Table IV shows the impact of SNR on the performance of the proposed algorithm and demonstrates the robustness of the approach with different levels of signal-to-noise ratios. This is due to the proper selection of the de-noising method (using the

SURE method and Eq. 2). Therefore, the results indicate that satisfactory performance is achieved under different disturbances and noise backgrounds.

Table IV.
The robustness of the proposed algorithm with different SNRs

SNR (db)	CA (%)
35db	98.33
30db	98.12
20db	97.91
10db	97.50

The proposed method is compared with existing PQ disturbance detection techniques published in recent years. The results are shown in Table V where the PQ disturbance techniques are compared using several criteria, such as the type of data used (synthetic or real world), the number of PQ disturbance types studied, and performance in terms of accuracy (both noiseless and noisy environment). Unfortunately, some literature has not provided the information needed to extract all the criteria.

The proposed algorithm has higher accuracy than all other methods except for ref. [33], [39], and [40]. However, the proposed algorithm is robust for different signal-to-noise ratios and capable to classify more PQ disturbance types. The utilization of a new de-noising approach (using the SURE method and Eq. 2) and an identification criterion (Eq. 14) to detect non-disturbance events to accelerate the solution procedure and prevent extra calculations is another advantage of the proposed method.

Table V.
The comparison of the proposed algorithm performance with other methods

Reference	Year	CA (Without noise)	CA (With noise 30db)	Number of disturbance types	Data
33	2018	100	-	6	Synthetic
34	2010	98.5	-	8	Synthetic
35	2018	96.71	-	7	Synthetic
36	2014	97.9	-	8	Synthetic
37	2009	95.75	-	7	Synthetic
38	2012	97.33	-	8	Synthetic
39	2010	98.75	90.61	8	Synthetic
40	2014	99.5	-	5	Synthetic and real time
Proposed method		98.54	98.12	8	Synthetic

IV.   CONCLUSION

A new method for PQ disturbance recognition and classification is introduced in the paper. The proposed algorithm is based on the discrete wavelet transform and correlation coefficient.

This algorithm has advantages of discrete wavelet transform and correlation coefficient, but it does not have the disadvantages of artificial neural networks or neuro-fuzzy-based algorithms such as training and high dimension input matrices. It is not suffering from the disadvantages of Fourier transform-based approaches such as unsuitability for non-stationary signals as it does not track signal dynamics properly due to the limitation of fixed window width either. The existence of the criterion (Eq. 14) is another advantage of the method. This criterion prevents extra calculations, whenever the captured signal is not PQ disturbance. The proposed algorithm compared with the other methods has relatively higher accuracy and capability to classify more PQ disturbance types. The use of a new de-noising approach (the SURE method and Eq. 2) is another advantage of the proposed method. The simulation results at different noise conditions verify the effectiveness of the noise immunity of the proposed method.

V.   REFERENCES

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