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A New Method of Detection & Classification of Power Quality Disturbances Using Wavelet Transform Based on Selective Wavelet

[1]M. Mohammadi, [2]R. Ebrahimi

[1]Department of Engineering, Borujerd Branch, Islamic Azad University, Borujerd, Iran.
[2]Department of Engineering, Bushehr Branch, Islamic Azad University, Bushehr, Iran.

Abstract: This paper presents a novel method to detect and classify power quality disturbances using wavelets. The proposed algorithm uses different wavelets each for a particular class of disturbance. This method uses particular mother wavelet to detect each of power quality disturbances and compound of particular mother wavelet associated with selective method among of energy criteria or deviation standard criteria to classify them. A qualitative comparison of results shows the advantages and drawbacks of each wavelet when applied to the detection of the disturbances. This method is tested for a large class of test conditions simulated in MATLAB. Power quality monitoring together with the ability of the proposed algorithm to classify the disturbances will be a powerful tool for the power system engineers.

Key words: Wavelet transforms power quality disturbances, voltage sag, voltage swell

INTROUDUCTION

Electric power quality is an important issue in Power systems nowadays .The demand for clean Power has been increasing in the past several years. The reason is mainly due to the increased use of microelectronic processors in various types of equipments such as computer terminals, programmable logic controllers and diagnostic systems. Most of these systems are quite susceptible to disturbances in the supply voltage. For example a momentary power interruption or thirty percent voltage sag lasting for hundredth of a second can reset the PLCs in an assembly line. The amount of waveform distortion has been found to be more significant nowadays due to the wide applications of nonlinear electronic devices in power apparatus and systems.

Without determining the existing levels of power quality, electric utilities cannot adopt suitable strategies to provide a better service. Therefore an efficient approach of justifying these electric power quality disturbances is motivated. Several research studies regarding the power quality have been conducted. Their aims were often concentrated on the collection of raw data for a further analysis, so that the impacts of various disturbances can be investigated. Sources of such disturbances can be located or further mitigated.

However, the amount of acquisition data was often massive in their test cases. Such an abundance of data may be time consuming for the inspection of possible culprits. A more efficient approach is thus required in the power quality assessment.

The implementation of the discrete Fourier transform by various algorithms has been constructed as the basis of modern spectral analysis. Such transforms were successfully applied to stationary signals where the properties of signals did not evolve in time. However, for those non-stationary signals any abrupt change may spread over the whole frequency axis. In this situation, the Fourier transform is less efficient in tracking the signal dynamics. A point –to point comparison scheme has been proposed to discover the dissimilarities between consecutive cycles. This approach was feasible in detecting certain kinds of disturbances but fail to detect those disturbances that appear periodically. With the introduction of new network topologies and improved training algorithms, neural network technologies have demonstrated their effectiveness in several power system applications .once the networks have been well trained, the disturbances that correspond to the new scenario can be identified in a very short time .This technique has also been applied in the power system applications. However, it can only be applied to detect a particular type of disturbance. When encountering different disturbances, the network structure has to be reorganized, plus the training process must be restarted. A method of detecting power quality disturbances based on neural networks and wavelets has been proposed .In this method, the fundamental component is removed using wavelets and the remaining signal corresponding to disturbances is processed and given as input to ANN. However, this method fails to detect voltage sag/swell and also new ANN's have to be developed for different rated load voltages and sampling frequencies. Recently

Corresponding Author: Mohammad Mohammadi,Department of Engineering, Borujerd Branch, Islamic Azad University, Borujerd, Iran.
E-mail:Mohamadi.m@iaub.ac.ir

with the emergence of wavelets it has paved a unified framework for signal processing and its applications. Fourier transforms rely on a uniform window for speeded frequencies. Wavelet transforms can apply various lengths of windows according to the amount of signal frequencies. Characteristics of non stationary disturbances were found to be more closely monitored by wavelets. The transient behavior, cavities and discontinuities of signals can be all investigated by wavelet transforms. For example, if there is an instantaneous impulse disturbance, which happens at a certain time interval it may contribute to the Fourier transform, but its location on the time axis is lost. However, by wavelets both time and frequency information can be obtained. In other words, the wavelet transform are more local. Instead of transforming a pure 'time domain' in to a pure' frequency domain ', the wavelet transforms find a good compromise in time - frequency domain. This paper presents novel algorithm, which overcomes all these difficulties and can accurately detect and classify the disturbances present in the signal. This method is independent of the load voltage and can be easily customized for different sampling frequencies. In this approach, for detecting each disturbance a particular wavelet is used. In classification of disturbances special method is also used so that the best result is produced.

The performance evaluation of different wavelets in the proposed method shows the capability of a particular wavelet in detecting and classifying particular disturbance.

MATERIALS AND METHODS

1. Choice of Mother Wavelet:

In the fast transient case, the waveforms are marked with sharp edges, abrupt and rapid changes and a fairly short duration in time. In this case Db3 and Db4 are particularly good in detecting these disturbances. In slow transient case, the waveforms are marked with a slow change or smooth amplitude change. Db3 and Db4 cannot catch those disturbances because the time interval integral is very short.

However if Db8, Db10 and sym 8 are used the time interval integral is long enough and thus such wavelets can sense the slow changes. Thus in detecting sags which are not sudden Db10, sym8 and Db8 can be used. For detecting harmonics Dmey gives best results and for transients Db3 can be used.

For example as shown in figures 1,2 and 3 in this study two high frequency and low frequency disturbances are considered and in following three mother wavelets have been are considered to detect these disturbances. The square of details of the first four levels of transformation of each signal are shown in fig. 1,2and 3. the disturbance signal with their square of details factors d1,d2,d3 and d4 for Db4,Db12 and Db20 respectively are shown in fig. 1,2 and 3. it is obviously that in the first level of transformation, Db4 respect to other wavelets designates the disturbance better whenever two other wavelets cannot designate second disturbance (low frequency disturbance).this shows that Db4 respect to other wavelets designates low frequencies with more speed . It is also clear that in each of four levels Db4 correctly designates the start time and stop time as well as the properties of disturbance signal whenever two other wavelets designate it only in first two levels of transform and cannot correctly show it in the third and forth level.

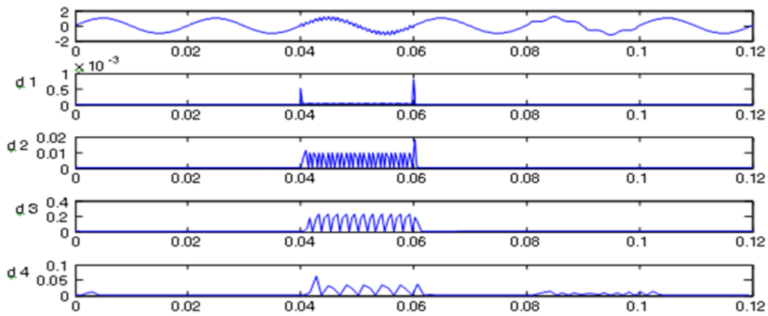

Fig. 1: Details Factors d1, d2, d3 and d4 of Signal with Db4

Therefore as mentioned in above it is not necessary to analyze the all levels of transformation to detect disturbance and it is enough to investigate only two first levels of transformation.

For example in this study for voltage sag and voltage swell with using mother wavelet Db4 the figures of signals and their details factor in first and second levels and also square of first level are shown in figures 4, 5.

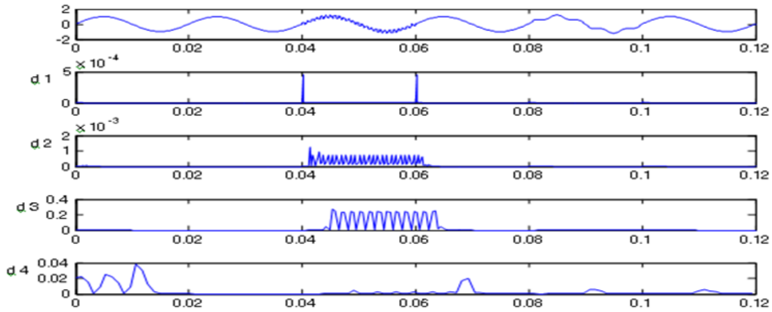

Fig. 2: details factors d1, d2, d3 and d4 of signal with Db12

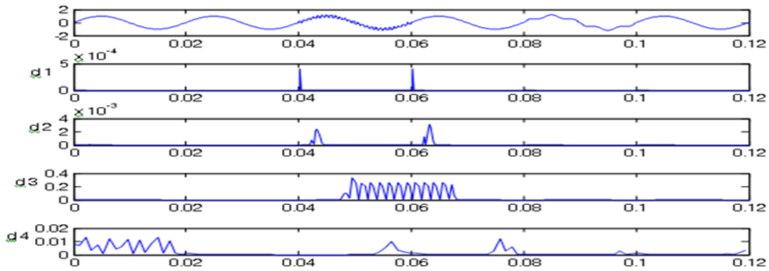

Fig. 3: details factors d1, d2, d3 and d4 of signal with Db20

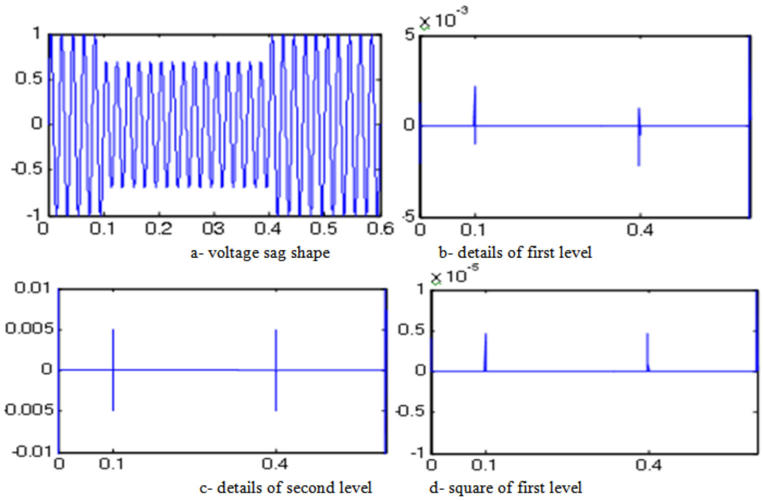

Fig. 3: Analyze of Voltage Sag

From figures (4-b),(4-c) and (5-b),(5-c) it is obvious that details of first level clearly designates the start and stop time of accuracy of disturbance and details of second level precisely shows the properties of signal. Therefore in detecting of disturbance details of two first levels are enough and this reduce the volume of calculation.

2. Classification of Disturbances:

In previous method based wavelet transform for classifying disturbances two method often had been used. This old methods are energy and deviation standard so that for all disturbance of power quality one method had be used. But in the present method several mother wavelet and both energy and deviation criteria are used. In order to study and investigate the effect of type of mother wavelet and type of designating criteria two precision coefficient must be defined. This two precisions factor contains, ‘frequency precession coefficient’, and, ‘designating precisions factor’.

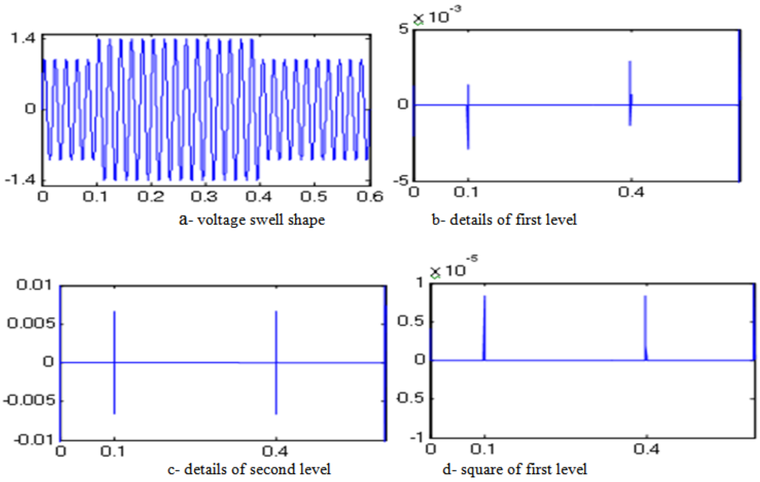

Fig. 4: Analyze of Voltage swell

Frequency Precession Coefficient:

This factor is capability of designating a particular disturbance respect to other disturbances in order to classifying it. in other words in this state the magnitude of dp of indicating level or levels of a particular disturbance is considered that dp is defined as:

$$dp(j) = \left| \frac{Div_{dis(j)} - Div_{ref(j)}}{Div_{ref(indicating)})} * 100 \right| \tag{1}$$

That concept of this definition is difference of deviation criteria between disturbance signal and sinusoidal signal in j_th level.

Designating Precisions Coefficient:

This precession defied as:

$$Acc_{Freq}(\%) = \left(\frac{\sum_{i=1}^{10, i \neq k} |dp(i)|}{|dp(k)|} \right) * 100 \tag{2}$$

This precession is capability of detecting all frequencies of disturbance signal in indicating level or levels of a particular disturbance without interface with another level of transformation of signal.

RESULTS AND DISCUSSION

For test this new method four mother wavelet is studied.

For each of mother wavelet two signals contains off sag and swell with two criteria contain energy and deviation is analyzed.

Figures 5-6 show this result for voltage sag disturbance with deviation and energy criteria respectively. The two precession coefficients that defined as above are calculated for this result and tables 1-2 indicates this results.

Table 1: Result of Calculated Precessions for Each Wavelet for Voltage Sag with Energy Criteria

Type of wavelet	Designating precessions (%	Frequency Precession (%)
Sym8	98.22	92.81
Dmey	100	99.57
Db4	99.65	81.14
Db20	99.36	99.51

Table 2: Result of Calculated Precessions for Each Wavelet for Voltage Sag with Deviation Criteria

Type of wavelet	Designating precessions (%)	Frequency Precession (%)
Sym8	55.03	70.86
Dmey	53.79	94.75
Db4	53.67	38.99
Db20	53.47	93.05

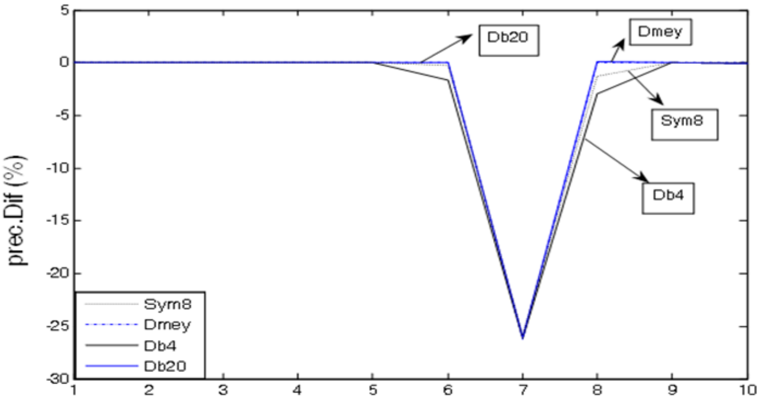

Fig. 5: Result of Energy Criteria for Voltage sag with Db4, Db20, Sym8, Dmey

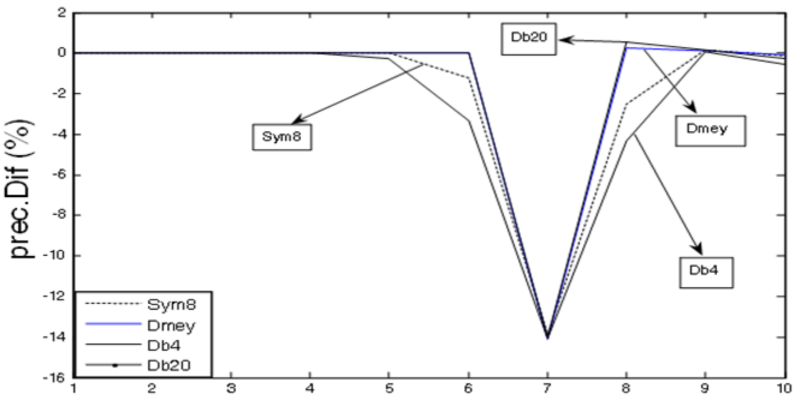

Fig. 6: Result of Deviation Criteria for Voltage sag with Db4, Db20, Sym8, Dmey

As shown in fig.6 in deviation criteria method the designating precession of various wavelets are similar and approximately is equal of half values of energy criteria.

But in frequency precession there is the most different among them, however this precession is better than energy criteria.

In second method i.e. in energy criteria the values of frequency and designating precessions are near to each other and are very high and overall it is understated that for voltage sag disturbance the energy criteria with mother wavelet Dmey is the best method for designating this disturbance in signal. Although the achieved result with Db20 is nearly similar to Dmey

This results for swell disturbance shown in figures 7-8 and tables 3-4 as well..

Table 3: Result of Calculated Precessions for Each Wavelet for Voltage Swell with Deviation Criteria

Type of wavelet	Designating precessions (%	Frequency Precession (%)
Sym8	98.69	93.96
Dmey	100	99.53
Db4	99.8	82.14
Db20	99.45	99.36

Table 4: Result of Calculated Precessions for Each Wavelet for Voltage Swell with Energy Criteria

Type of wavelet	Designating precessions (%	Precession (%) Frequency
Sym8	44.31	63.94
Dmey	45.04	96.53
Db4	44.9	32.72
Db20	44.78	93.98

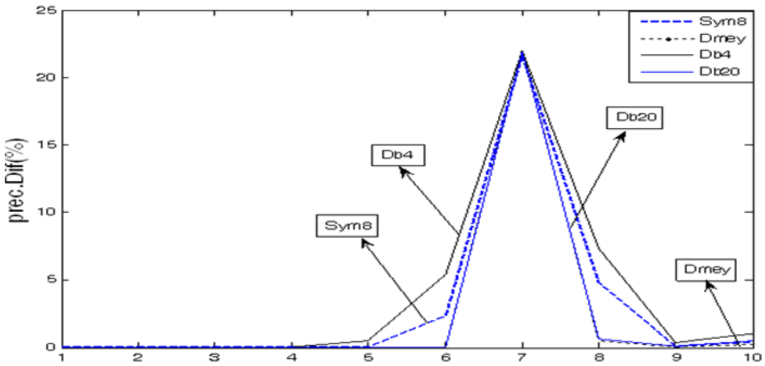

Fig. 7: Result of Deviation Criteria for Voltage Swell with Db4، Db20، Sym8 و Dmey

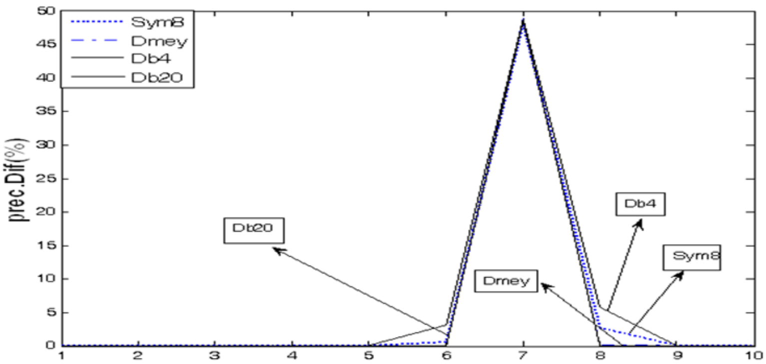

Fig. 8: Result of Energy Criteria for voltage Swell with Db4، Db20، Sym8 و Dmey

From these results it is found that designating precession of deviation criteria for swell is 10% less than sag. It is clear that the best method for designating swell is Demy with energy criteria .although similar sag the result of Db20 is near to Demy.

This method has been performed for various power qualities and the best methods have been listed in Table.5.

Table 5: The Selective Methods for classifying various Power Qualities

Type power quality disturbance	The best and selective method
Sag	Energy criteria-Dmey
Swell	Energy criteria-Dmey
Flicker	Energy criteria-Dmey
Harmonic	Deviation critera-Db4
Switching capacitor	Deviation criteria-Dmey
Interruption	Energy criteria-Dmey
Short-circuit	Energy criteria-Db20

Conclusion:

Power system events may be classified by quantity and duration of power quality disturbances. This paper has presented a novel method to detect and classify disturbed voltage which works for any number of cycles and can be customized for any sampling rate. This novel detection algorithm shows promise for the future development of fully automated monitoring systems with classification ability. A detailed comparative evaluation of the performance capabilities of different wavelets using the proposed algorithm is also done.

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