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Comparison analysis of different classification methods of power quality disturbances

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ABSTRACT

Good power quality delivery has always been in high demand in power system utilities where different types of power quality disturbances are the main obstacles. As these disturbances have distinct characteristics and even unique mitigation techniques, their detection and classification should be correct and effective. In this study, eight different types of power quality disturbances were synthetically generated, by using a mathematical approach. Then, continuous wavelet transform (CWT) and discrete wavelet transform with multi-resolution analysis (DWT-MRA) were applied, which eight features were then extracted from the synthesized signals. Three classifiers namely, decision tree (DT), support vector machine (SVM) and k-nearest neighbors (KNN) were trained to classify these disturbances. The accuracy of the classifiers was evaluated and analyzed. The best classifier was then integrated with the full model, which the performance of the proposed model was observed with 50 random signals, with and without noise. This study found that wavelet-transform was effective to localize the disturbances at the instant of their occurrence. On the other hand, the SVM classifier is superior to other classifiers with an overall accuracy of 94%. Still, the need for these classifiers to be further optimized is crucial in ensuring a more effective detection and classification system.

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1. INTRODUCTION

Good power quality is such a critical element of power delivery in the electrical system. Due to the fact that electrical equipment has become more sensitive to voltage disturbances, utilities providers all over the world have been working hard to ensure a stable and continuous power flow, where its frequency and voltage can be controlled within certain limits. Achieving a favorable power quality itself is a tough challenge as there are a lot of different types of power quality disturbances (PQD) that have been discovered. Some of the most common PQD include sag, swell, interruption, transients, and harmonics. Harmonics distortion is said to be the most common PQD due to the increasing invention of electronic and non-linear loads such as adjustable-speed drives, arc furnaces, and induction furnaces [1]. It is deduced that a lot of different elements can cause these PQD occurrences. For instance, the proliferation of the grid integrated renewable energy (RE) which often requires power electronic-based converters could affect largely on the power quality [2]. Other sources of these power quality phenomena include poor wiring, faults occurrence and lightning strike. These disturbances not only affect the reliability and continuity of the electric supply, they have also brought serious problems to the economy, industrial production and resident life [3]. Thus, it is no doubt that continuous counter measures should be taken into action.

Different PQD have equally different and unique mitigation techniques. Before any action could be taken, it is crucial for these disturbances to be correctly detected. According to a comprehensive review [4], up to 2018, around 241 research studies have been conducted, where a lot of different approaches to PQD detection and classification methods have been discussed. There are even more approaches now. What used to be only three types of methods have been integrated into more than ten methods, using different algorithm and approaches. The accuracy of these methods affects greatly on the effectiveness of the mitigation approach. It is even more favorable if these methods can be performed automatically in order for the PQD to be detected and classified at the instance of its occurrence. The higher the accuracy of the methods, the more likely the countermeasure to be successful.

Wavelet transform (WT) is famously known as the upgraded and better continuation of Fourier transform (FT). In comparison, FT is only applicable for a stationary signal in which the frequency component does not change with time [5], while WT has been proven to be reliable for both time or frequency domain analysis. The availability of a wide range of derivatives of wavelets is a key strength of wavelet analysis [6]. Wavelet-based transform often being categorized into continuous wavelet transform (CWT) and discrete wavelet transform (DWT). It is said that CWT requires higher computing power than DWT [7] and that it needs an infinite number of inputs resulting in the redundancy of provided information [8]. Most of the time, researchers combine DWT with multi-resolution analysis (MRA) to increase their effectiveness in detecting PQDs [8]. A study in 2016 used maximum overlap discrete wavelet transform [9]. In contrary, a study in 2008 proposed wavelet-packet transform as the PQD detection method [10]. All in all, researchers concluded that wavelet-based transform is indeed a reliable PQD detection method. On the other hand, the classification of power quality disturbances often used implementation of the concept of artificial intelligence such as support vector machine (SVM) [8], [11], extreme machine learning (ELM) [5], decision tree (DT) [12], [13], neural network (NN) [14], [15] and random forest (RF) [16]. This paper will compare and study three different classification methods namely, DT, SVM and k-nearest neighbors (KNN). Through this study, involved methods will be critically analyzed by using statistical analysis, in order to better secure the reliability of the results.

2. METHOD

2.1. Generation of PQD

Researchers include different types of single and hybrid PQD in their analysis [5], [8], [11], [17], [18]. These signals were mostly synthetically generated by using mathematical or simulation approach. It was said that the mathematical approach can provide more varied signals within the control range, especially if a great amount of signals were to be generated [19]. Nevertheless, both methods are equally reliable as they produce generated signals that appear to be very similar to the actual signals [19]. In this paper, synthetic PQD signals were generated by using parametric equations as shown in Table 1, by taking into account the guidelines provided by Categories and Characteristics of Power System Electromagnetic Phenomenon, IEEE STD 1159-2009 [20]. 400 arbitrary sample cases for each of eight most common PQ disturbances namely, sag, swell, interruption, flicker, harmonics, sag with harmonics, swell with harmonics, and interruption with harmonics were generated with frequency and amplitude being fixed at 50 Hz and 1 V respectively. In order to achieve a signal close to the actual PQD signals, every 50 signals of each PQ disturbances will include the noise of 20 dB and 30 dB.

Table 1. Parametric equation of PQD signals

	PQ Disturbance	Equation	Parameter variation
C1	Sag	$f(t)=A(1-\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.1\leq\alpha\leq0.9$, $T\leq t_2-t_1\leq 9T$
C2	Swell	$f(t)=A(1+\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.1\leq\alpha\leq0.9$, $T\leq t_2-t_1\leq 9T$
C3	Interruption	$f(t)=A(1-\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.9\leq\alpha\leq1$, $T\leq t_2-t_1\leq 9T$
C4	Flicker	$f(t)=(1+\alpha\sin(\beta\omega t))\sin(\omega t)$	$0.1\leq\alpha\leq0.2$, $5\leq\beta\leq10$,
C5	Harmonics	$f(t)=A(\alpha_1\sin(\omega t)+\alpha_3\sin(3\omega t)+\alpha_5\sin(5\omega t)+\alpha_7\sin(7\omega t))$	$0.05\leq\alpha_3,\alpha_5,\alpha_7\leq0.15$, $\sum\alpha_i^2=1$
C6	Sag+Harmonics	$f(t)=A(1-\alpha(u(t-t_1)-u(t-t_2)))(\alpha_1\sin(\omega t)+\alpha_3\sin(3\omega t)+\alpha_5\sin(5\omega t)$ $+\alpha_7\sin(7\omega t))$	$0.1\leq\alpha\leq0.9$, $T\leq t_2-t_1\leq 9T$, $0.05\leq\alpha_3,\alpha_5,\alpha_7\leq0.15$, $\sum\alpha_i^2=1$
C7	Swell+Harmonics	$f(t)=A(1+\alpha(u(t-t_1)-u(t-t_2)))(\alpha_1\sin(\omega t)+\alpha_3\sin(3\omega t)+\alpha_5\sin(5\omega t)$ $+\alpha_7\sin(7\omega t)$	$0.1\leq\alpha\leq0.9$, $T\leq t_2-t_1\leq 9T$, $0.05\leq\alpha_3,\alpha_5,\alpha_7\leq0.15$, $\sum\alpha_i^2=1$
C8	Interruption+Harmonics	$f(t)=A(1-\alpha(u(t-t_1)-u(t-t_2)))(\alpha_1\sin(\omega t)+\alpha_3\sin(3\omega t)+\alpha_5\sin(5\omega t)$ $+\alpha_7\sin(7\omega t))$	$0.9\leq\alpha\leq1$, $T\leq t_2-t_1\leq 9T$, $0.05\leq\alpha_3,\alpha_5,\alpha_7\leq0.15$, $\sum\alpha_i^2=1$

2.2. Wavelet transform

Detection of PQD is often being relate to feature extraction. By synthesizing the signals, feature extraction can be done rather efficiently. Some of the detection methods include Stockwell transform, Gabor transform and Hilbert-Huang transform. Wavelet transform (WT) is one of the most powerful methods being used by a lot of academic investigators to characterize and classify different PQD [4]. Wavelet is often defined as a rapidly decaying wavelike oscillation with a mean of zero where it exists for only a finite duration. Representation of CWT in mathematical expression is as (1).

$$CWT(c,d) = \frac{1}{\sqrt{c}}\int_{-\infty}^{\infty} x(t)\varphi\left(\frac{t-d}{c}\right)dt \tag{1}$$

In (1), $\varphi(t)$ is a continuous function in both frequency and time domain which is often called a mother wavelet. In this paper, the mother wavelet of Daubechies4 from the Daubechies family is used. Based on (1), c is the scaling factor while d is the translational factor. The scale factor, c determines the compression or dilation of the wavelet. A compressed wavelet is useful to capture a high-frequency signal, while stretched wavelet is useful to capture a low-frequency signal. The translational factor will capture information regarding the time of the occurrence of the disturbances. On the other hand, the mathematical representation of DWT is given in (2).

$$DWT(m,n) = \frac{1}{\sqrt{c_0^m}}\sum_k x(k)\varphi\left(\frac{n-kd_0c_0^m}{c_0^m}\right) \tag{2}$$

Different from CWT, c_0 and d_0 are the discrete scaling and translational factors respectively, where oftentimes, they are fixed to be $c_0=2$ and $d_0=1$. M and n are the integers, representing frequency localization and time localization, correspondingly [8]. In DWT, high frequency signals will be passed through high pass filters, while low frequency signals will be passed through low pass filters. By implementing MRA, signals will be decomposed up to a few levels where the frequency resolution will be increased in order to get coefficient and detailed approximate n waveform. Figure 1 shows the decomposition process of discrete wavelet transform with multi-resolution analysis (DWT-MRA).

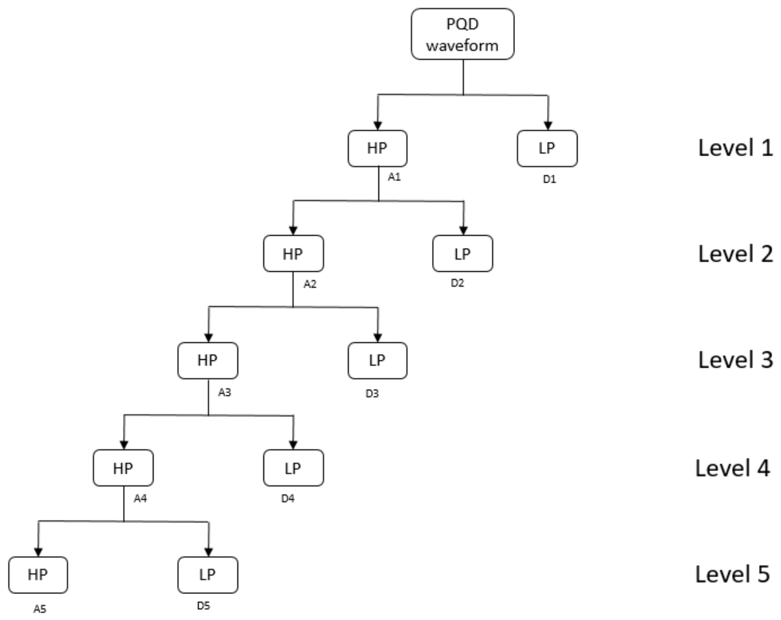

Figure 1. Five level of decomposition of DWT-MRA

2.3. Feature extraction

Feature extraction is really significant in assuring the classification process to have better accuracy. The feature extracted will be the guidance for the classifier to classify different PQD. Table 2 shows 8 different features that were used to extract the signals.

Table 2. Feature extraction formula

Feature	Equation
Mean	$\overline{x} = \frac{1}{t_a - t_b}\int_{t_a}^{t_b} x(t)dt$
Variance	$\sigma^2(t_a, t_b) = \int_{t_a}^{t_b} (x(t) - \overline{x})^2 dt$
Standard deviation	$\sigma(t_a, t_b) = \sqrt[2]{\int_{t_a}^{t_b} (x(t) - \overline{x})^2 dt}$
Skewness	$S(t_a, t_b) = \frac{\int_{t_a}^{t_b} (x(t) - \overline{x})^3}{\sigma^3}$
Kurtosis	$K(t_a, t_b) = \int_{t_a}^{t_b} (\frac{x(t) - \overline{x}}{\sigma})^4$
Total harmonic distortion (THD)	$THD = \frac{\sqrt{V_2^2 + V_3^2 + V_4^2 + \cdots}}{V_1}$
Energy	$ED_i = \frac{1}{n}\sum_{i=1}^{n} \lvert P(x_i)\rvert$
Entropy	$ENT = \sum_{i=1}^{n} P(x_i) log_2 P(x_i)$

2.4. Decision tree

A decision tree is a tree-like structure that can be designed top to down, bottom to up, and other special approaches [9]. A study conducted in 2016, where DT and SVM classifiers were compared, it is found that DT gave better classification accuracy with and without noise [9]. In a recent study where DT is implemented, an accuracy of 99.14% and 98.20% were obtained for unnoisy and 20 dB of noise signal respectively 21 [21]. In general, the decision tree can simply be seen as a branched analysis where it consists of nodes, known as leaf nodes that carry the response of the tested data. Decision tree will recursively split the data set until a pure leaf node is achieved or in this case, until a response consists of only a single PQ disturbance is achieved. The maximum number of splits used in this research study is set to be 100. The basic principle of the decision tree is shown in Figure 2.

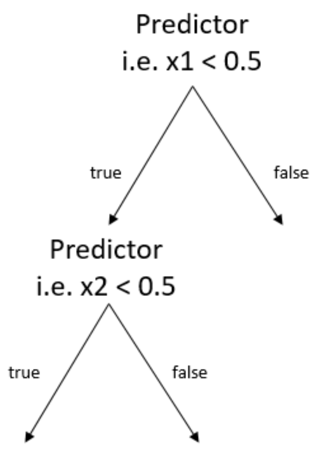

Figure 2. Basic principle of decision tree

2.5. Support vector machine

In SVM classifier, hyperplane contributes the most in ensuring the efficiency of the classification process, where it separates data into classes. Wrong choice of decision boundary could result in higher misclassification of new data. The best hyperplane is usually the one that results in the same distance of D+ and D-. D+ and D- are measured from the shortest distance of features or variables from the hyperplane. In some cases, the support vectors of the different classes were in the straight line. Figure 3 shows the principle of SVM. In order to make mathematics possible, SVM uses Kernel functions to systematically find the support vector classifiers in higher dimensions. In some cases where the different points are linear, hyperplane cannot be determined. Thus, additional features such as quadratic features can be added to transform the linear data into quadratic data. This is called as SVM of Kernel quadratic, which has been implied in this research study. With the help of the Kernel function, the accuracy of the classifier can be improved.

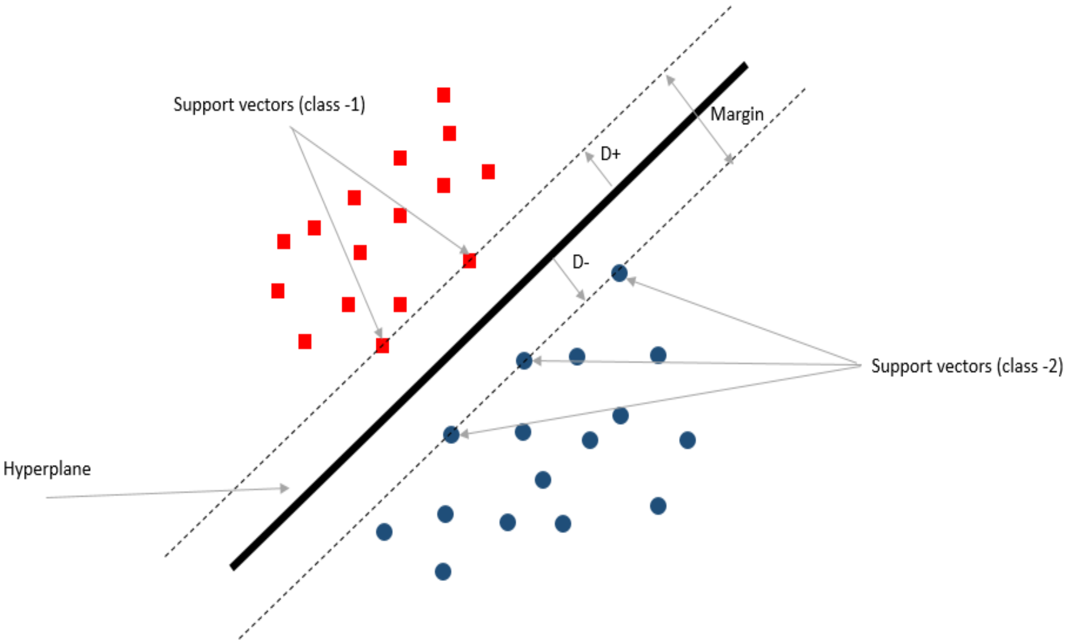

Figure 3. Basic principle of SV

2.6. K-nearest neighbor

K-nearest neighbor uses k distance or also called Euclidian distance to mines for samples that are nearby or adjacent to the unknown samples of the classification process as its main component in classifying data [16]. The majority class within the radius of the unknown sample will be chosen as the classification results. Thus, it can be said that this classification method is greatly dependent on the value of k where if the k is too large, the classifier might get confused with different samples surrounding the unknown sample. Figure 4 shows the basic principle of the KNN classifier. In order to improve the classification accuracy, weighted KNN is applied where the main concept is to give more weight to the nearby points and less weight to the further points. The weight usually uses Kernel function, namely squared inverse function. This will give better accuracy compared to a pure KNN classifier. In a study conducted in 2013, a KNN classifier was applied [22]. As a result, an accuracy of 94.44% was obtained. KNN classifier might be one of the simplest classifiers as it characterizes a signal best on the majority class within a specific distance from the tested signal. In [23], fuzzy KNN was introduced, with an accuracy of 98.3%.

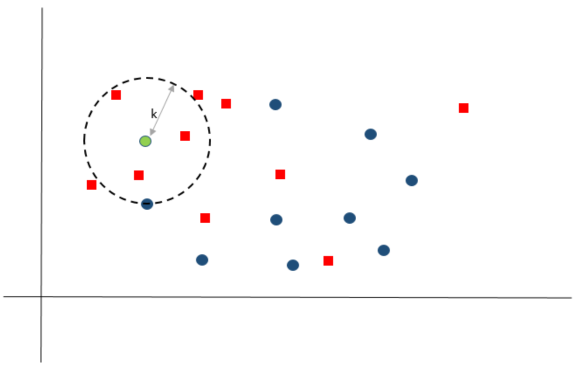

Figure 4. Basic principle of SVM

3. RESULTS AND DISCUSSION

3.1. Generation of PQD

By using MATLAB software, a total of 400 signals for every 8 different types of PQD were synthetically generated using parametric equation. The 400 signals consist of 200 signals with no addition of noise, 100 signals with the addition of 20 dB of noise while the remaining 100 signals are signals with 30 dB of noise. Overall, 3,200 signals were generated for the analysis purpose. The sampling frequency of the signals was set to be at 12.5 kHz with 128 samples per cycle. The voltage of the signals was fixed at 1 p.u while the frequency was set to 50 Hz, following Malaysia's nominal frequency. When comparing the generated signals with the actual signals, it was observed that generated signals do have a close similarity with the actual signals.

3.2. Detection of PQD

Detection of PQ disturbances was performed using MATLAB wavelet Toolbox, in which one-dimensional DWT and CWT were chosen. In wavelet transform, there are a lot of different types of mother wavelet that can be used. The choice of mother wavelet is crucial in ensuring the detection process to be performed correctly. In this study, it is found that Daubechies4, up to five levels of decomposition gave the best performance. This is due to the fact that it can correctly detect the disturbances while at the same time, reconstruct the decomposed signals that can mimic the original signal. Figure 5 shows the results obtained from the DWT of five levels of decomposition. As can be observed from the wavelet coefficients, d1, d2, d3, d4, and d5, Db4 can detect the disturbance at the instant of its occurrence, where in this case, during the fifth period. The reconstructed signals also mimicked the original signal well. Not only that, by using the synthesized signals, it will be easier for the feature extraction to be done.

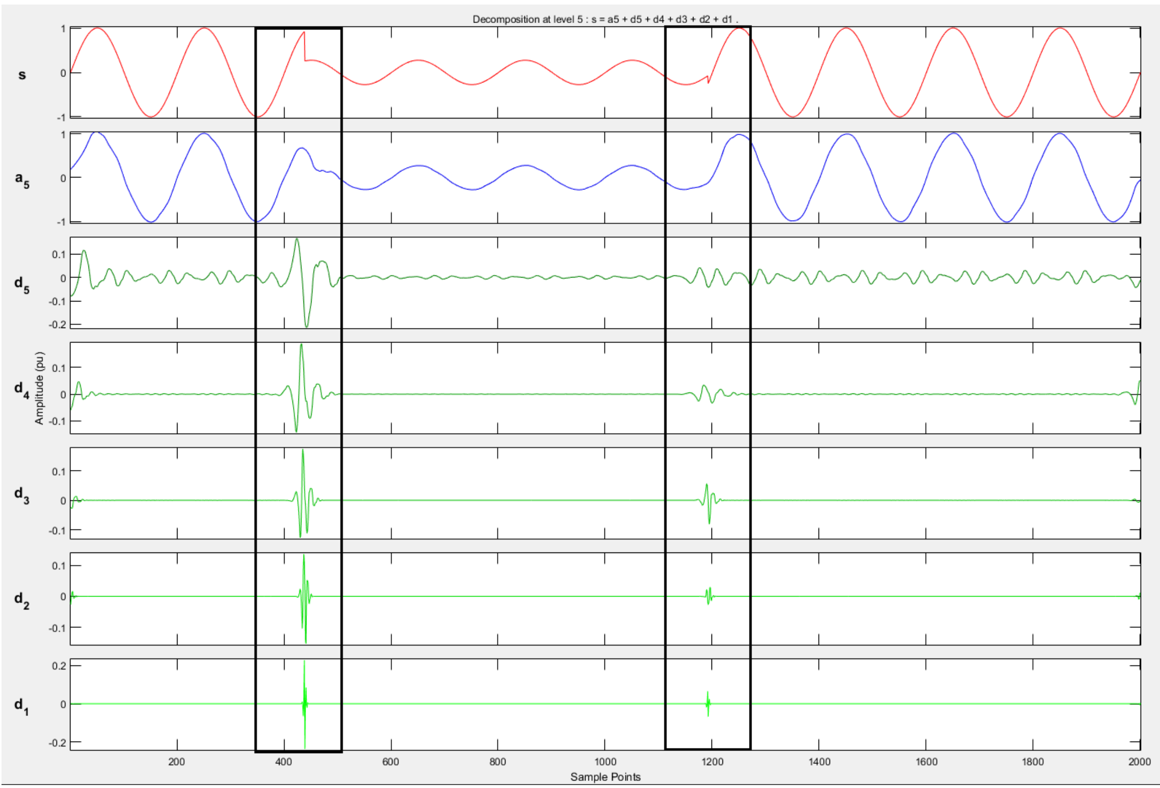

Figure 5. Result of detection for DWT of five decomposition level

Different from DWT, CWT is mostly used to localize or detect continuous signals with uniform frequency. As the generated signals are discrete in nature, the effectiveness of CWT is rather hard to be further analyzed. This is because, compared to DWT, CWT has the ability to detect the disturbances with varying frequency, where the mother wavelet can be shrunk or expanded, according to the frequency of the signals. Nevertheless, it can be seen from the spectrogram shown in Figure 6, that the disturbance can be detected correctly during the time of its occurrence.

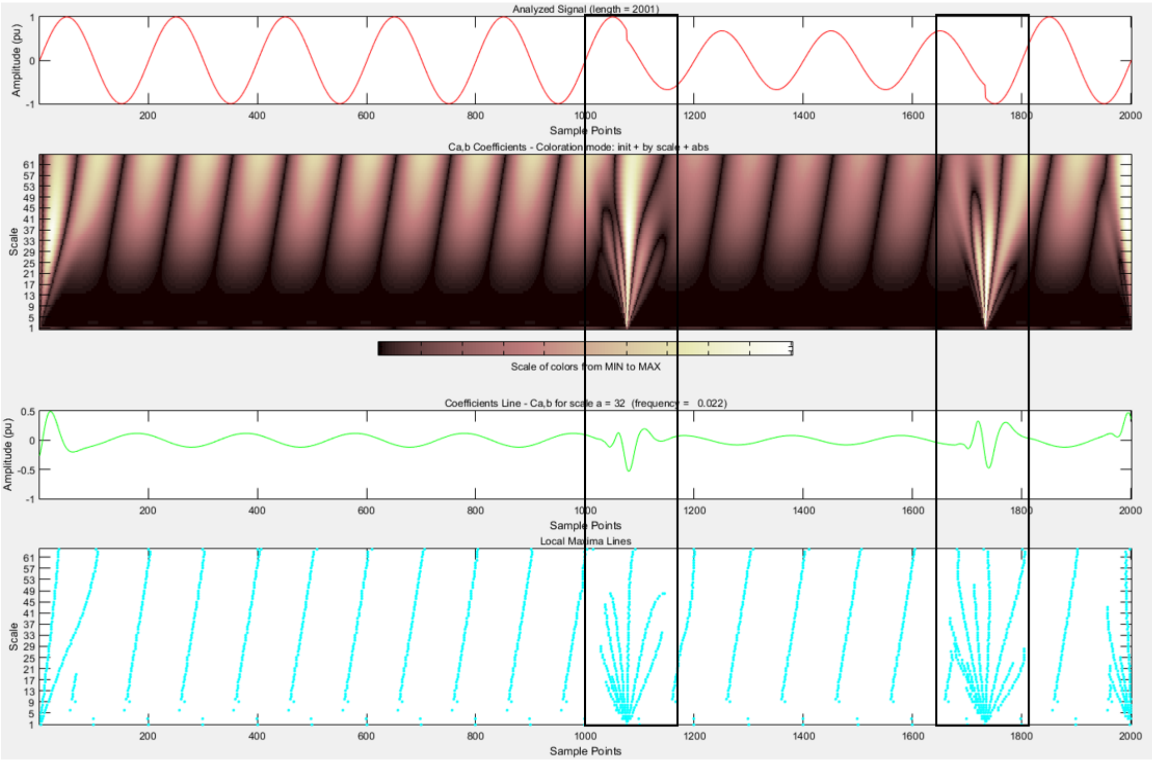

Figure 6. Result of detection for CWT by using Daubechies4

3.3. Classification of PQD

By using Classifier Learner App in MATLAB, three classifiers, namely DT, SVM and KNN are trained by using signals of each PQD where 100 of them are of signals with no noise while the remaining 100 signals are of signals with 20 dB and 30 dB of noise equally. The trained models were tested to classify another 200 signals of each PQ disturbances with the same amount of the number of noisy signals as mentioned previously. It is found that the training time of DT, SVM and KNN are 11.587 s, 11.592 s and 9.3955 s respectively. Table 3 shows the accuracy results of the involved classifiers.

Table 3. Classifiers results

PQD		Classifier Accuracy								
			DT			SVM			KNN	
		0 dB	20 dB	30 dB	0 dB	20 dB	30 dB	0 dB	20 dB	30 dB
C1	Sag	92%	50%	52%	94%	48%	68%	92%	20%	16%
C2	Swell	91%	66%	62%	97%	74%	60%	91%	42%	42%
C3	Interruption	76%	44%	38%	94%	48%	46%	71%	40%	50%
C4	Flicker	100%	64%	70%	100%	76%	88%	100%	68%	54%
C5	Harmonics	100%	74%	82%	100%	66%	80%	100%	58%	70%
C6	Sag+Harmonics	74%	36%	44%	88%	66%	70%	79%	42%	48%
C7	Swell+Harmonics	89%	50%	74%	95%	60%	70%	89%	40%	52%
C8	Interruption+Harmonics	79%	50%	40%	92%	46%	52%	73%	20%	26%
Overall Accuracy		87.625%	54.25%	57.75%	95.0%	60.5%	66.75%	86.875%	41.25%	44.75%
Average Accuracy			66.54%			74.08%			57.625%	

It can be seen that flicker and harmonics were being correctly classified for most of the time for all three classifiers. This might be due to their distinct features that do not confuse the classifiers. Most of the misclassified signals are the ones with the same features such as sag and sag with harmonics. The optimization of the classifier and features used can increase the reliability of the PQD classification. From the table, SVM is undoubtedly has given the best performance in classifying different PQ disturbances with and without the addition of noise. Thus, in order to further analyze the efficiency of this classifier, the SVM model is implemented in the full model where 50 random signals consisting of different PQ disturbances ranging from 0 dB, 20 dB and 30 dB of noise were being put into test with the full model.

For signals with the addition of 20 dB and 30 dB of noise, wavelet de-noising by using a threshold value of 2.172, 1.945, 2.045, 2.468, and 1.932 for the first, second, third, fourth, and fifth level of decomposition was applied. The overall accuracy of the full model was calculated to be 94% with only three signals being misclassified. Two of the three misclassified signals were sag and harmonics disturbances, in which the signals were misclassified as sag disturbance only. One of the signals was misclassified as harmonics instead of sag with harmonics. Nevertheless, with an accuracy of 94%, this signifies that the proposed model is reliable in detecting different PQ disturbances, with and without noise.

In a study conducted in 2013, four classifiers namely SVM, probabilistic neural network (PNN), radial basis function (RBF) and multi-layer perceptron (MLP) were compared and it is proven that SVM is superior to other methods with the accuracy of 99.06% [24]. In addition, in a study conducted in 2013, by also implementing an SVM classifier with the integration of Gaussian kernel, authors obtained an accuracy of 94% [8]. In a study conducted in 2009, by using an SVM classifier, an accuracy of almost 100% was obtained for no-noise condition and 95.6% and 98% for 20 dB and 30 dB of noise respectively [25]. It is said that SVM can handle large data well, without affecting the classification accuracy. It also claimed that it has good generalization properties that are able to distinguish different classes well which results in minimum misclassification risk [25]. In a study conducted in 2019, by implementing DWT-MRA and SVM, authors also obtained an accuracy of 94%, with oscillatory transient being the least accurate classified signals [8]. Though the authors did not include any noise in their analysis, it seems like the presence of the noise will not affect the performance of the chosen classifier.

It can be said that, when dealing with noisy signals, the de-noising stage contributes the most to the accuracy of the model. Through this research study, wavelet de-noising is implied. It is also found that Db4 provides better de-noising results compared to the other wavelets such as Db6, Db10, sym4, and Coif4 [26]. Figure 7 represents the sample of a de-noised signal where a sag with harmonics disturbance was being injected with 20 dB of noise. Though the de-noised signal does represent about 75% of the original signal, it would be more favorable if it can fully replicate the original signal. As can be seen from the figure, the harmonics part of the original signals was being de-noised as well. This occurrence can be called overly de-noised, in which the disturbances were confused with the noise, resulting in the loss of information in the de-noised signals.

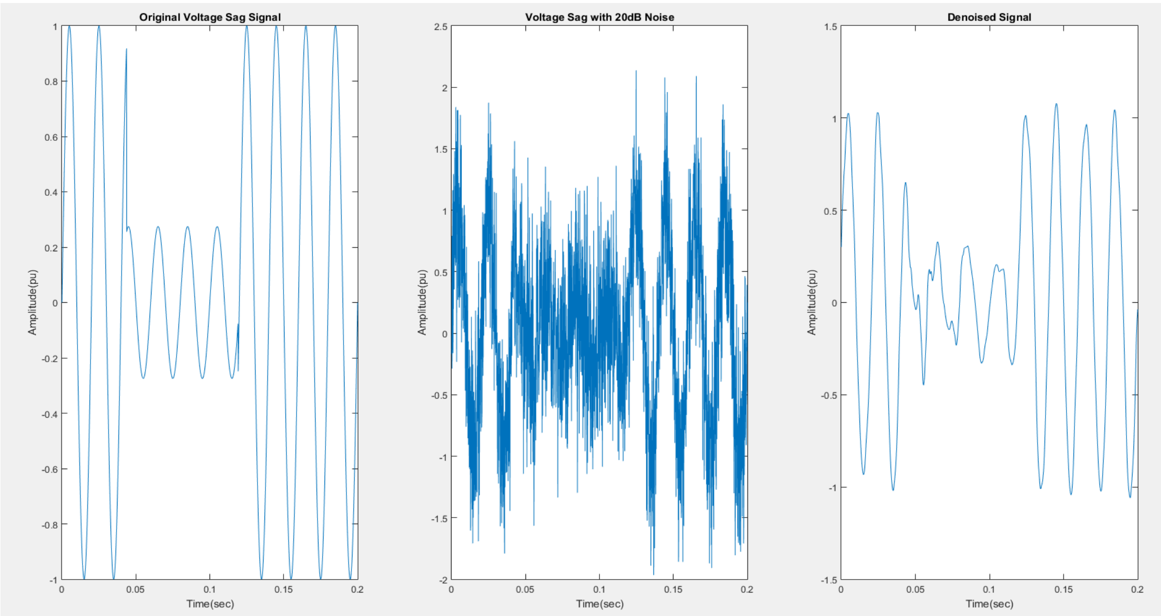

Figure 7. Sample of denoised signal

Looking at the feature extraction stage, it is found that amount and type of features used were adequate in training the classifiers. This is because, with regard to unnoisy signals, all classifiers achieved an accuracy of more than 80%, which is considered quite high. In a study conducted in 2018, more complex features, namely relative mode energy ratio (RMER) and number of zero crossing were applied [12]. The authors obtained an accuracy of around 99% for the proposed methods. Nevertheless, the features used in this study are enough to produce good results.

4. CONCLUSION

In this research study, eight different types of PQ disturbances were generated by using a mathematical approach. It is found that the generated signals have such a close representation to the actual signal. In addition, with the use of the parametric approach, it is easier to vary the parameter of the signals and that the signals can be generated in a huge amount. Overall, 3,250 signals were generated. Both wavelet-based transform, CWT and DWT-MRA are proven to be effective in correctly detecting the PQD at the instant of their occurrence. From the synthesized signals, 8 features were extracted where they then be used to train the DT, SVM and KNN classifiers. With an accuracy of 94%, SVM classifier gave the best performance in correctly classifying different PQ disturbances. Not only that, with the inclusion of 20 dB and 30 dB of noise, it is no doubt that the proposed model is efficient in both unnoisy and noisy conditions. Further study on these classifiers should be taken in order to develop a new system that can give an accuracy of almost 100%. In addition, this system should be considered to be integrated with hardware applications in order to automatically monitor the PQ disturbances. Through this research study, an understanding of PQD alongside their detection and classification methods is acquired.

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