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Evaluating windowing-based continuous S-transform with neural network classifier for detecting and classifying power quality disturbances

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ABSTRACT

The aim of this paper is to evaluate the implementation of windowing-based Continuous S-Transform (CST) techniques, namely, one-cycle and half-cycle windowing with Multi-layer Perception (MLP) Neural Network classifier. Both, the techniques and classifier are used to detect and classify the Power Quality Disturbances (PQDs) into one of possible classes, voltage sag, swell and interrupt disturbance signal. For realizing evaluation, we proposed the methodology that include the PQD generation, the signal detection using windowing-based CST, the features extraction from S-contour matrices, PQD classification using MLP classifier. Then, we perform two type of assessments. Firstly, the accuracy assessment of chosen classifier in relation to three different training algorithms. Secondly, the execution time comparison of the training algorithms. Based on assessment results, we outline several recommendations for future work.

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1. INTRODUCTION

Power quality (PQ) is crucial in provisioning utilities for fulfilling the consumers need [1]. Nowadays, PQ problem has becoming a huge challenge as more consumers are demanding for the power quality. Electrical devices vulnerable to power quality or lack of quality is more suitable to be included in the domain of power appears limited. All electric devices are disposed to have a problem or damage when they are exposed to one or more power quality issues [1]-[7]. Electric motor, generator, computer, communication equipment, or household appliance are the examples of electrical devices that has a high chances to damage when exposed to PQ disturbances (PQDs). To date, the asset quality of power is quite expensive, so there is a need of monitoring systems that can detect PQD activities in order to reduce costs.

To improve the power quality in the system, there is a need to detect the presence of the disturbances, identify the sources of the problems and find the solution to overcome them. In previous research and studies, the researchers typically use multiple approaches to detect and classify the activity of PQDs. Among approaches used in past studies are S-Transform [2]-[5],[8], Wavelet Transform [9], Neural Network, Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT), and Support Vector Machine (SVM), a combination of any of them or others. Most approaches described before supervised PQ problems by changing from one domain to another domain of mathematics which provides additional detailed information.

The main scope of the study is categorized into two parts which are detection of PQ disturbance based on the use of S-Transform mathematical techniques to detect power quality disturbances and Neural

Network namely Multi Layer Perception Neural Network (MLPNN) has been chosen as a classification method of classification analysis performance for PQ disturbances. The detection of PQ disturbances have been conducted based on two difference approach namely; One-Cycle Windowing Technique (OCWT) and Half-Cycle Windowing Technique (HCWT). A mathematical codes are created approaches by using software MATLAB© to find initial period, the final period, the magnitude and duration of the PQ disturbance. Furthermore, this paper will gives a brief summary of an analysis of the PQ disturbances for the detection and classification based on CST for the distribution system by using the method of OCWT and HCWT with MLPNN.

2. PQDs SIGNAL GENERATION

The disturbances signal power quality are generated based on mathematical modeling programming in m-file/script of MATLAB© [10]. There are three types of signals involved, namely, sag, swell, and interrupt. The parameters required to generate the signals are the real time of signal duration and amplitude of disturbance signal voltage. Table 1 shows the parameters associated to each type of disturbance.

Table 1. Mathematical PQD Disturbance Signals Modeling

Disturbances	Model equation	Parameters
Sag	v(t)=1-*(u(t-t1)-u(t-t2))*sint(ωt+*ϕ)*□ *Note:* *α= Reduction level of rms voltage in p.u.* *t = 0.1 : 0.001 : 0.18* *t1 = Time of* V_{sag} *initiation* *t2 = Time of* V_{sag} *recovery or clearance* *ϕ = Phase-angle jump*	α= 0.5 t1 = 40ms t2 = 100ms ϕ = 90°
Swell	v(t)=1+*(u(t-t1)-u(t-t2))* sint(ωt+*ϕ)*□ *Note:* *α= Increasing level of rms voltage in p.u.* *t = 0.1 : 0.001 : 0.18* *t1 = Time of* V_{swell} *initiation* *t2 = Time of* V_{swell} *recovery or clearance* *ϕ = Phase-angle jump*	α= 0.5 t1 = 50ms t2 = 110ms ϕ = 45°
Interrupt	v(t)=1-*(u(t-t1)-u(t-t2))* sintωt *Note:* *α= Reduction level of rms voltage in p.u.* *t = 0.1 : 0.001 : 0.18* *t1 = Time of* $V_{interrupt}$ *initiation* *t2 = Time of* $V_{interrupt}$ *recovery or clearance*	α= 0.95 t1 = 50ms t2 = 110ms

2.1. PQDs Signal Detection using One-Cycle Windowing Technique (OCWT)

The cycles accordance with windowing technique of Continuous S-Transform (CST) is used for PQDs detection and feature extraction. Each cycle of each sample window of interference waveform signal is analyzed accordance with ST contour [3], [4]. The detection of PQD using OCWT is performed for every 20ms (one-cycle) of time duration of signals. The signal must in absolute condition to perform this detection. Figure 1-3 shows detection of PQDs based on CST using OCWT. The red line is represent the signal line of PQD in an absolute condition. The blue line represented detection line of signals. Then, S-contour matrices analyze the signal used to extract the features from the detection, for instance; i.e magnitude, standard deviation, mean, frequency and phase. These features are then used to support PQD classification process.

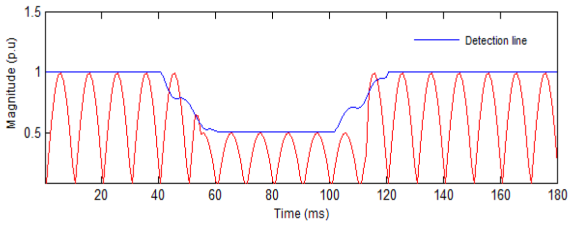

Figure 1. OCWT based on CST – Voltage Sag

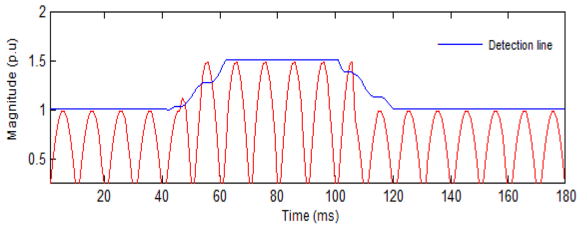

Figure 2. OCWT based on CST – Voltage Swell

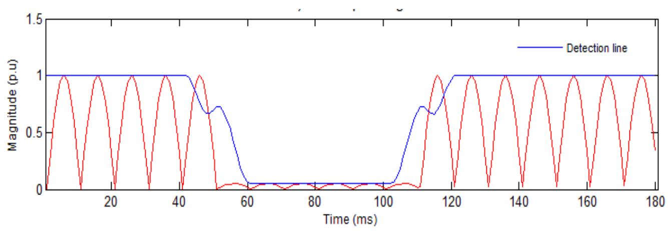

Figure 3. OCWT based on CST – Interrupt

2.2. PQDs Signal Detection using Half-Cycle Windowing Technique (HCWT)

HCWT represents a half duration of one-cycle for supporting the detection. A half-cycle is determined by 10ms. Thus, by using the same PQDs signal, the HCWT is utilized to limit the scope of the samples from the entire disturbance signal. Then, CST is applied to create the line detection which produces S-contour matrices, as shown in Figure 4-6.

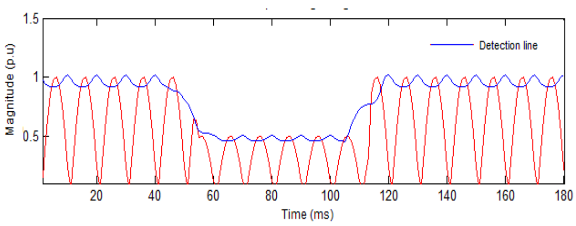

Figure 4. HCWT detection based on CST – Voltage Sag

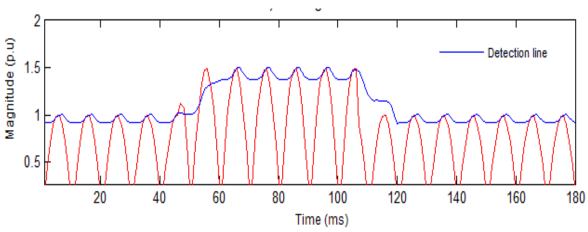

Figure 5. HCWT detection based on CST – Voltage Swell

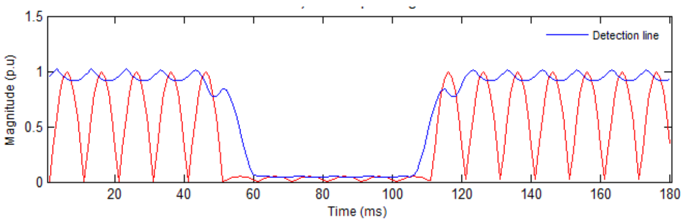

Figure 6. HCWT detection based on CST – Interrupt

2.3. PQDs Signal Classification using Neural Network classifier

In this paper, Multi-layer Perceptron (MLP) is used as NN classifier to classify from PQ disturbances signal [11], [12]. An MLP comprises of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Figure 7 shows the structure architecture of MLP for this paper.

3. RESULTS AND ANALYSIS

For the dataset preparation, 100 dataset is used as inputs to classify the voltage swell in PQDs signal. The inputs are partition into three parts, which are training, validation and testing datasets. Eight hidden layers are used to train the MLPNN and 1000 iteration is set for classification. Furthermore, this paper uses three different types of training algorithms for evaluating the classification performance, which are; Gradient Descent with Momentum and Adaptive LR 'traingdx' [13], Levenberg-Marquardt 'trainlm' [12]-[14] and BFGS Quasi-Newton 'trainbfg' [12], [15].

Table 2 shows the classification of Sample 1 using MLPNN classifier based on CST with OCWT. The results have shown that training algorithm Gradient Descent with Momentum and Adaptive LR 'traingdx' classified 98% of accurate classification. Meanwhile for Levenberg-Marquardt 'trainlm', the result of PQ disturbances classification is 100%, while for algorithm BFGS Quasi-Newton 'trainbfg'; it provided 97% of classification accurateness. Therefore, algorithm 'trainlm' has produced the higher accuracy of classification compared to other algorithms. As for the voltage swell classification, Levenberg-Marquardt ‘trainlm’ classified 100% of classification accuracy, more higher compared Gradient Descent with Momentum and Adaptive LR ‘traingdx’ and BFGS Quasi-Newton ‘trainbfg’ where they produced 98% of accuracy percentage.

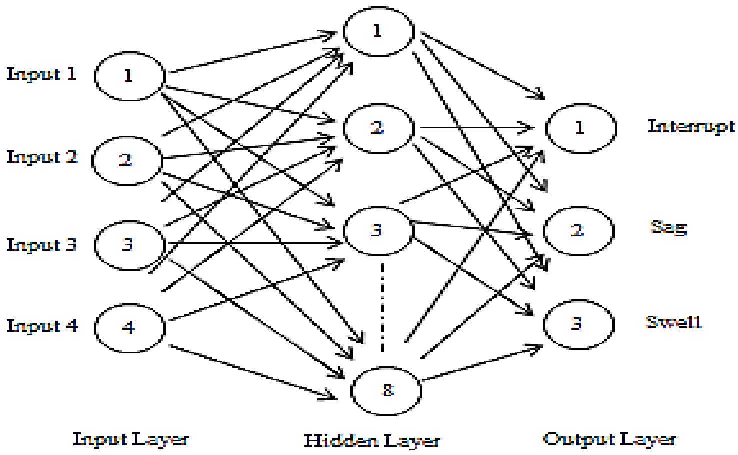

Figure 7. Architecture of MLP-NN

Table 2. Classification based on OCWT – Sample 1

Type of PQD	Test Set	Training Algorithm traingdx (%)	trainlm (%)	trainbfg (%)
Interrupt	10	90	100	90
Sag	40	100	100	97.5
Swell	50	98	100	98
Accuracy	100	98	100	97

Table 3 shows the classification of Sample 2 using MLPNN classifier with OCWT. From the PQDs classification, it was found that training algorithm Gradient Descent with Momentum and Adaptive LR ‘traingdx’ classified 97% of accuracy. Meanwhile for Levenberg-Marquardt ‘trainlm’, the result of PQDs classification is 99%, while for algorithm BFGS Quasi-Newton ‘trainbfg’; it provided 96% of classification accurateness. The ‘trainlm’ produced the highest accuracy of classification compared to other algorithms. As for voltage swell classification, Levenberg-Marquardt ‘trainlm’ classified 100% accurate of classification, more higher compared Gradient Descent with Momentum and Adaptive LR ‘traingdx’ and BFGS Quasi-Newton ‘trainbfg’ where they produced 97.8% of accuracy percentage.

Table 3. Classification based on OCWT – Sample 2

Type of PQD	Test Set	Training Algorithm traingdx (%)	trainlm (%)	trainbfg (%)
Interrupt	10	100	100	90
Sag	45	95.6	97.8	95.6
Swell	45	97.8	100	97.8
Accuracy	100	97	99	96

Table 4 shows the classification of Sample 3 using MLPNN classifier with OCWT. From the PQDs classification, it was found that training algorithm Gradient Descent with Momentum and Adaptive LR ‘traingdx’ classified 98% of accurate classification. Meanwhile for Levenberg-Marquardt ‘trainlm’, the PQDs classification is 99%, while for algorithm BFGS Quasi-Newton ‘trainbfg’; it provided 98% of accuracy. So, algorithm ‘trainlm’ produced the higher accuracy of classification compared to other algorithms. As for voltage swell classification, all type of training algorithms produced 100% of accuracy percentage.

Table 4. Classification based on OCWT – Sample 3

Type of PQD	Test Set	Training Algorithm		
		traingdx (%)	trainlm (%)	trainbfg (%)
Interrupt	10	100	100	100
Sag	50	96	98	96
Swell	40	100	100	100
Accuracy	100	98	99	98

Table 5 shows the comparison of accuracy Sample 1 for the classification of PQDs using MLPNN classifier with different training algorithms according to HCWT. From the analysis, training algorithm Gradient Descent with Momentum and Adaptive LR ‘traingdx’ provided 98% of an accuracy and BFGS Quasi-Newton ‘trainbfg’ also provided 98% for the classification of PQDs. While classification using Levenberg-Marquardt ‘trainlm’ algorithm provided the highest accuracy compared the others with 99% of correct classification of PQDs. As for voltage swell classification, all type of training algorithms produced 98% of accuracy percentage.

Table 5. Classification based on HCWT – Sample 1

Type of PQD	Test Set	Training Algorithm		
		traingdx (%)	trainlm (%)	trainbfg (%)
Interrupt	10	90	100	90
Sag	40	100	100	97.5
Swell	50	98	98	98
Accuracy	100	98	99	98

In Table 6 shows the comparison of accuracy Sample 2 for the classification of PQDs using MLPNN classifier with different training algorithms based on CST according to HCWT. From the analysis, training algorithm Gradient Descent with Momentum and Adaptive LR ‘traingdx’ provided 95% of an accuracy and BFGS Quasi-Newton ‘trainbfg’ provided 96% for the classification of PQD. While classification using Levenberg-Marquardt ‘trainlm’ training algorithm provided the highest accuracy compared the others with 97% of correct classification of PQDs. As for voltage swell classification, Levenberg-Marquardt ‘trainlm’ classified 100% of classification accuracy, more higher compared Gradient Descent with Momentum and Adaptive LR ‘traingdx’ and BFGS Quasi-Newton ‘trainbfg’ where they produced 97.8% accuracy.

Table 6. Classification based on HCWT – Sample 2

Type of PQD	Test Set	Training Algorithm		
		traingdx (%)	trainlm (%)	trainbfg (%)
Interrupt	10	90	90	90
Sag	45	93.3	95.6	95.6
Swell	45	97.8	100	97.8
Classification accuracy	100	95	97	96

In Table 7 shows the comparison of accuracy Sample 3 for the classification of PQDs using MLPNN classifier with different training algorithms based on CST according to HCWT. From the analysis, training algorithm Gradient Descent with Momentum and Adaptive LR ‘traingdx’ provided 97% of an accuracy and BFGS Quasi-Newton ‘trainbfg’ also provided 97% for the classification of PQD. While classification using Levenberg-Marquardt ‘trainlm’ training algorithm provided the highest accuracy compared the others with 98% of correct classification of PQDs. As for voltage swell classification, Levenberg-Marquardt ‘trainlm’ classified 97.5% accurate of classification, higher compared Gradient Descent with Momentum and Adaptive LR ‘traingdx’ and BFGS Quasi-Newton ‘trainbfg’ where they produced 95% of accuracy percentage.

In regards to the samples as shown in Figure 8, the highest accuracy of classification for individual disturbances is 100% by using CST OCWT for Sample 1, Sample 2 and Sample 3, while classification by using CST HCWT, NN classifier reach 98% for Sample 1, 100% for Sample 2 and 97.5% for Sample 3. On ther hand, Figure 9 shows the comparison in term of the effectiveness operating time taken using different training algorithms to complete the PQDs classification. By using eight nodes of hidden layer for the PQ disturbances classification, the Levenberg-Marquardt 'trainlm' algorithm completed the classification process faster compared to other algorithms and hence improvement in overall efficiency.

Table 7. Classification based on HCWT – Sample 3

Type of PQD	Test Set	Training Algorithm traingdx (%)	trainlm (%)	trainbfg (%)
Interrupt	10	100	90	100
Sag	50	98	100	98
Swell	40	95	97.5	95
Classification accuracy	100	98	98	97

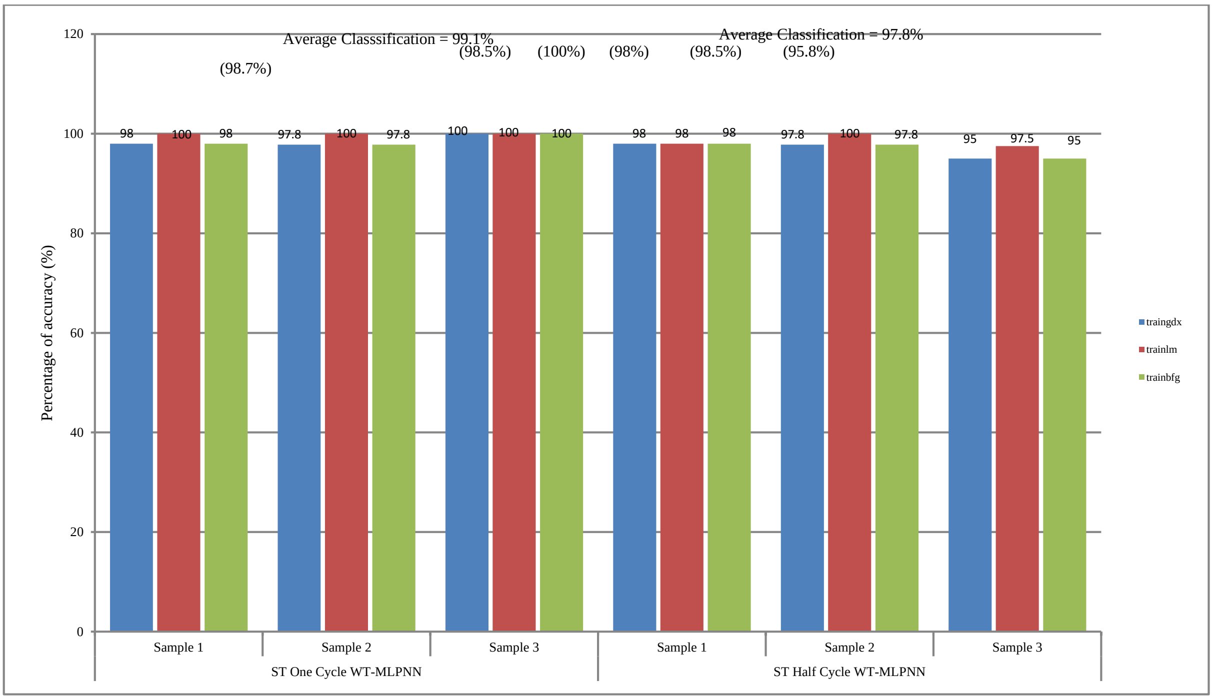

Figure 8. Analysis of voltage swells classification performance

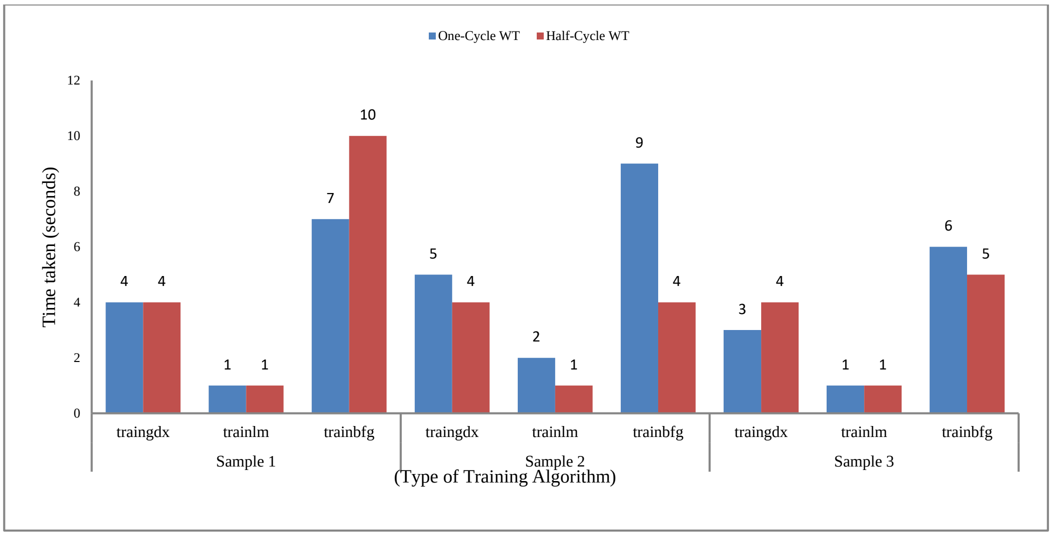

Figure 9. Operating time of PQ disturbance classification

4. CONCLUSION

We have presented the evaluation of the proposed methodology for detecting and classifying of PQD signals. The detection is based on CST with either OCWT or HCWT. Meanwhile, the classification is implemented using MLPNN. Furthermore, S-contour matrices are utilized to extract the relevant features of PQDs that server as a input for evaluating the PQD classification. Three different training algorithms were used to evaluate the accuracy of the PQD classification. The results have shown that, the training algorithm of Levenberg-Marquadt 'trainlm' outperformed others especially for classifying the voltage swell.

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