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An Ensemble Classifier based Power Quality Disturbances Classification

Tiagrajah V. Janahiraman, Prakash Bala

Abstract: Evolution of the current modern era demands a huge and good power quality supply day by day. Power utility suppliers and power exchange specialist organizations face a noteworthy test in recognizing the kind of Power Quality Disturbances (PQD). Our research illustrates the technique of PQD classification by utilizing wavelet signal decomposition and Ensemble classification. A normal wave without disturbance and waves with PQD events of single-type and hybrid-type were generated using MATLAB using the mathematical model as per the definition and parameters outlined by IEEE 1159 and IEC61000 customary. Discrete Wavelet Transform (DWT) is pertained to decompose the signal form the generated PQD to get the illustration in time and frequency domain. In this research work, our database consists of 14000 generated signals of a normal wave and the PQDs, which were divided into 80% for the train set and 20% for the test set for each PQDs. An ensemble methodology for multiclass order was chosen as the classifier of the component vector for the PQD. Examinations were conjointly made with elective sorts of classifiers and different kinds of mother wavelet channel capacities to observe and investigate the exhibition qualification. The outcomes demonstrated that the blend of DWT and Ensemble Classifier delivers an optimal solution to recognize the class of PQD with a precision of 100% for each train and test set.

Keywords: Power Quality, Ensemble Method, Discrete Wavelet Transform.

I.INTRODUCTION

Excellent and uninterrupted power quality alludes to disturbance-free power fortune. In case of innovation improvement, extra and increasingly electronic gadgets are being associated with the framework, exacting potential disturbances and deviation from the provided voltage bending wave, which prompts instrumentality being exasperate or broken. Having as a top priority that power quality disturbances (PQD) are the wellsprings of voltage aggravations that can corrupt and potentially harm in fashionable gadgets. Power electronic devices such as thyristors, triac, gate turn-off thyristor, power transistor and MOS controlled thyristors may cause power quality degradation in the industrial applications [1]. Electrical inductive and capacitive loads have the potential to produce PQD such as sag, swell, harmonics and interruption. Inductive masses, conjointly known as insulant masses or inductive load banks, are AC masses that are preponderantly inductive in nature which causes electrical energy lag in the alternating voltage [2].

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* Correspondence Author
Tiagrajah V. Janahiraman, College of Engineering, Universiti Tenaga Nasional, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia
Prakash Bala, College of Engineering, Universiti Tenaga Nasional, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia

A very common electrical phenomenon load in installation could be a long line. There is shunt capacitance for any line, however, the worth is extremely little for brief and medium length lines, whereas for long lines, the capacitance value becomes considerably massive and significantly effects the ability of power systems performance [3]. The electrical phenomenon, photovoltaic (PV) solar oriented power, the most encouraging unpracticed vitality and lattice associated photovoltaic frameworks (GCPVs) have appeared premier development inside the world. PV control age straightforwardly changes over the sunlight-based power into electrical power. The conventional facility system is intended to give wattage from high or medium voltage systems to users through low voltage feeders. The normal system conduct with incorporation of star PV frameworks may be an adjustment like change in voltage profile with high PV entrance and high voltage near the heap against the free tumble from the supply to the heap in antiquated system. Reconciliation of star PV frameworks to the utility network offers specialized difficulties like voltage variances, sounds, responsive power, low power issue, load the executives and steadiness issues. [4].

There are several types of PQD present during the voltage distribution to the other end. Some are categorized as under voltage and overvoltage or commonly known as voltage sag and voltage swell. Voltage sag presents due to a fault in the ground line whereas voltage swell occurs due to large capacitor banks or switching off heavy loads. Transients are also another kind of PQD which normally takes place due to environmental effects. In addition, harmonics are also a kind of distortion in sinusoidal frequency wave with multiple fundamental signals produced by non-linear loads. Interruption occurs during a total power loss situation. Furthermore, there are also Hybrid PQDs where the power disturbances of two types present within the same cycle [5]. For example, harmonics with sag, flicker with swell and interruption with harmonics.

Multiple digital signal processing methods were utilized in the method of extraction which characterizes or models the PQD. Competing within them, Wavelet Transform (WT) has been used to the extend within past years. WT approach can present information concerning frequency contents of the stored signal and knowledge in partitions of the time domain. Rixing Huang et al [6] proposed to classify the power quality disturbance using waveform feature extraction using image processing algorithm. Rixing Huang et al analyzed 10 types of PQD.

In order to classify PQDs, the 1-D signal was converted to a 2-D image using an algorithm that contains image processing steps for PQD identification. Then, a new method referred to as T2DIAT1DSRA transforms a 2-D image into a 1-D signal and classified using Support Vector Machine (SVM). MarijaMarkovska et al [7] proposed to classify the PQD using DWT based features (SVM). MarijaMarkovska et al experimented on 7 types of PQD using three types of classifiers, Random Forest (RF), Decision Tree (DT) and SVM. Several wavelet-based features were used to classify the PQD and their efficiency was tested when they are used in multiple combinations to achieve the optimal extraction approach. Francisco M. et al [8] proposed a simulation-based work on PQD through Continuous Wavelet Transform (CWT), DWT, Short Time Fourier Transform (STFT) and Stockwell Transform (ST). Francisco M. et al stated, 6 types of PQD were analyzed and simulated. Francisco M. et al implemented an application in MATLAB which creates a simulation of different types of PQDs. It is also mentioned that after the denoised signal is evaluated, the application can be accessed from any electronic device via web service of RESTful and query for data in smart sensors. MahaveerMeena et al [9] proposed to detect and classify the complex PQD using ST and Rule-based Decision Tree (RDT). MahaveerMeena et al worked on 10 types of hybrid PQD which were decomposed to obtain S-matrix using S-transform. Features extracted from S-matrix will be plotted and input to RDT to classify its type. Zhen Lei et al [10] proposed to identify the PQD using

Improved Particle Swarm Optimizer (IPSO) and SVM. The author in [10] worked on 7 types of PQD which were classified using SVM. Mathematical morphology (MM) was used to denoise the signal to identify the PQD more precisely. The classification accuracy using SVM was improved using IPSO by optimizing its parameters. In our previous work [11], we used DWT to decompose a total of 12 PQD with several types of mother wavelet filter functions. Then, statistical features of first and second orders were calculated on the decomposed signals. These features were used for classification using SVM.

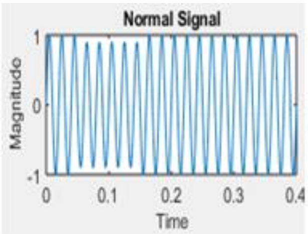
The figure of merit of this research is the experimentation of 14 types of PQD. The mathematical models of the PQD are given in this paper. When the number of PQD increases, the challenges will increase for the feature extractor and classifier to deliver the optimal solution. The signal decomposed using DWT were classified using five types of multiclass classifiers: Support Vector Machine (SVM), Tree, Linear Discriminant, and K-Nearest Neighbor (KNN) and Ensemble Method.

II. TYPES OF POWER QUALITY DISTURBANCES

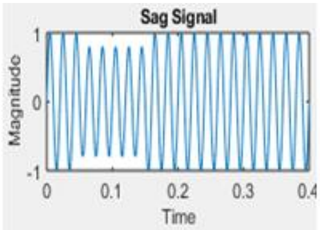
To obtain the disturbance signal samples, mathematical models as shown in Table 1, were used. In this research, 14 types of PQDs were generated which are: one type of normal wave without any disturbances, seven types of single PQDs and six types of hybrid PQDs. The PQDs are generated as per the definition and parameters outlined by IEEE 1159 [12] and IEC61000 customary [13]. The normal waveform and seven single types of PQD are depicted in Fig 1. Fig.2 shows the signal waveform of 6 types of hybrid PQD. The figures were plotted from $t = 0$ till $t = 0.4$s, with a step size of 0.001s.

Table. 1 Mathematical model for the PQDs

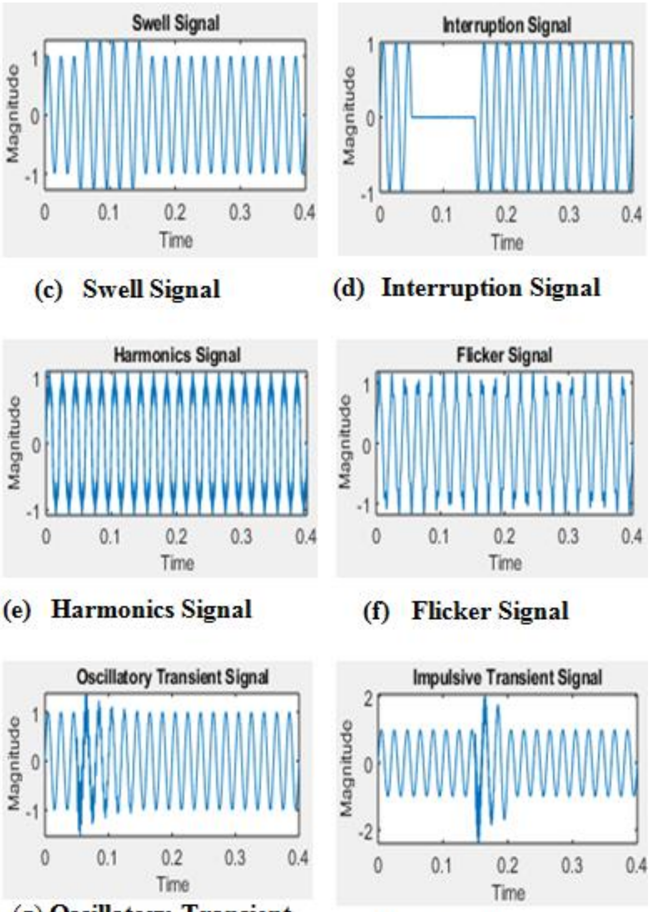
Label	Power Quality Disturbances	Mathematical equations	Parameters
C1	Normal	$y(t)=Z\,[1 \pm \Psi\,(u\,(t-t_1) - u\,(t-t_2))]\sin(\omega t)$	$\Psi \le 0.1; T \le t_2-t_1 \le 9T$
C2	Sag	$y(t)=Z\,[1 - \Psi\,(u\,(t-t_1) - u\,(t-t_2))]\sin(\omega t)$	$0.1 \le \Psi \le 0.9; T \le t_2-t_1 \le 9T$
C3	Swell	$y(t)=Z\,[1 + \Psi\,(u\,(t-t_1) - u\,(t-t_2))]\sin(\omega t)$	$0.1 \le \Psi \le 0.8; T \le t_2-t_1 \le 9T$
C4	Interruption	$y(t)=Z\,[1 - \Psi\,(u\,(t-t_1) - u\,(t-t_2))]\sin(\omega t)$	$0.9 \le \Psi \le 1.0; T \le t_2-t_1 \le 9T$
C5	Harmonics	$y(t) = Z\,[\Psi_1 \sin(\omega t) + \Psi_3 \sin(3\omega t) + \Psi_5 \sin(5\omega t) + \Psi_7 \sin(7\omega t)]$	$0.05 \le \Psi_3, \Psi_5 \le 0.15; \sum \Psi_i^2 = 1$
C6	Sag with harmonics	$y(t)= Z\,[1 - \Psi\,(u\,(t-t_1) - u\,(t-t_2))]\,[\Psi_1 \sin(\omega t) + \Psi_3 \sin(3\omega t) + \Psi_5 \sin(5\omega t)]$	$0.1 \le \Psi \le 0.9; T \le t_2-t_1 \le 9T$ $0.05 \le \Psi_3, \Psi_5 \le 0.15; \sum \Psi_i^2 = 1$
C7	Swell with harmonics	$y(t)= Z\,[1 + \Psi\,(u\,(t-t_1) - u\,(t-t_2))]\,[\Psi_1 \sin(\omega t) + \Psi_3 \sin(3\omega t) + \Psi_5 \sin(5\omega t)]$	$0.1 \le \Psi \le 0.8; T \le t_2-t_1 \le 9T$ $0.05 \le \Psi_3, \Psi_5 \le 0.15; \sum \Psi_i^2 = 1$
C8	Interruption with harmonics	$y(t)= Z\,[1 - \Psi\,(u\,(t-t_1) - u\,(t-t_2))]\,[\Psi_1 \sin(\omega t) + \Psi_3 \sin(3\omega t) + \Psi_5 \sin(5\omega t)]$	$0.9 \le \Psi \le 1.0; T \le t_2-t_1 \le 9T$ $0.05 \le \Psi_3, \Psi_5 \le 0.15; \sum \Psi_i^2 = 1$
C9	Flicker	$y(t)=Z\,[1 + \Psi_f \sin(\Phi\omega t)]\sin(\omega t)$	$0.1 \le \Psi_f \le 0.2; 5 \le \Phi \le 20$ Hz
C10	Flicker with harmonics	$y(t)=Z\,[1 + \Psi_f \sin(\Phi\omega t)]\sin(\omega t)\,[\Psi_1 \sin(\omega t) + \Psi_3 \sin(3\omega t) + \Psi_5 \sin(5\omega t)]$	$0.1 \le \Psi_f \le 0.2; 5 \le \Phi \le 20$ Hz $0.05 \le \Psi_3, \Psi_5 \le 0.15; \sum \Psi_i^2 = 1$
C11	Flicker with sag	$y(t)=Z\,[1 + \Psi_f \sin(\Phi\omega t)]\sin(\omega t)\,[1 - \Psi\,(u\,(t-t_1) - u\,(t-t_2))]$	$0.1 \le \Psi_f \le 0.2; 5 \le \Phi \le 20$ Hz $0.1 \le \Psi \le 0.9; T \le t_2-t_1 \le 9T$
C12	Flicker with swell	$y(t)=Z\,[1 + \Psi_f \sin(\Phi\omega t)]\sin(\omega t)\,[1 + \Psi\,(u\,(t-t_1) - u\,(t-t_2))]$	$0.1 \le \Psi_f \le 0.2; 5 \le \Phi \le 20$ Hz $0.1 \le \Psi \le 0.8; T \le t_2-t_1 \le 9T$
C13	Oscillatory Transient	$y(t)=Z\,[\sin(\omega t) + \Psi e^{-(t-t_1)/\tau} \sin(\omega_n)\,(t-t_1)\,(u(t_2) - u(t_1))]$	$0.1 \le \Psi \le 0.8; 0.5T \le t_2-t_1 \le 3T$ 8ms $\le \tau \le$ 40ms; $300 \le f_n \le 900$Hz
C14	Impulsive Transient	$y(t)=Z\,[1 + \Psi(u\,(t-t_1) - u\,(t-t_2))][\Psi e^{-(t-t_1)/\tau} \sin(\omega_n)\,(t-t_1)\,(u(t_2) - u(t_1))]$	$0 \le \Psi \le 0.814; T/20 \le t_2-t_1 \le T/10$ 8ms $\le \tau \le$ 40ms; $300 \le f_n \le 900$Hz



(a) Normal Signal



(b) Sag Signal



(c) Swell Signal (d) Interruption Signal

(e) Harmonics Signal (f) Flicker Signal

(g) Oscillatory Transient Signa (h) Impulsive Transient Signal

Fig. 1 Eight types of single PQD

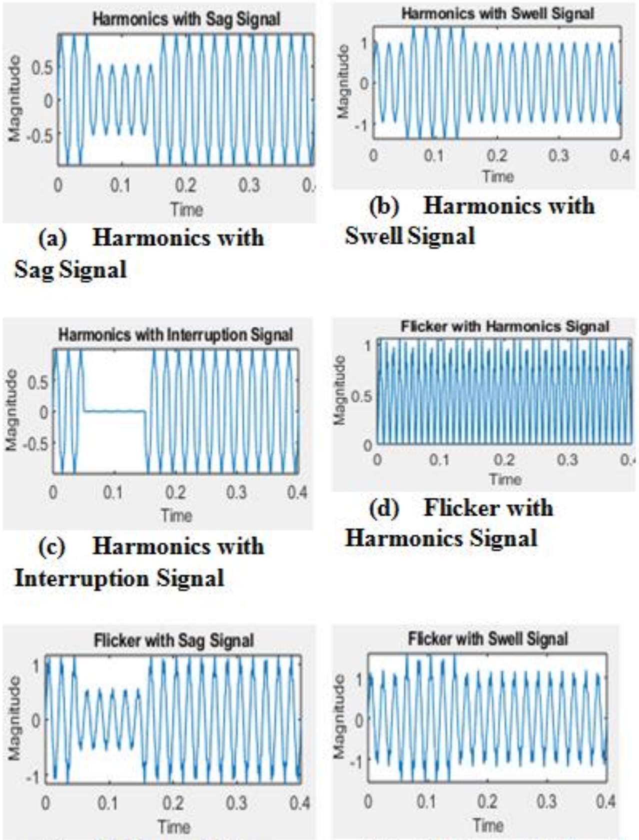
III.SIGNAL DECOMPOSITION USING WAVELET TRANSFORM

Wavelet Transform has the adaptability of breaking down a positioned signal and decay it to a totally various scales and dimensions of goals by widening a type of scientific connection. Partner in PQD instances of those dimension of deterioration is found in Fig. 2. Fourier transformation has the adaptability to clarify a proof in time area as an overall outline, whereas local time-frequency representation can be extracted by wavelet. Equation 1 represents the Continuous Wavelet Transform (CWT) for a given signal.

$$CWT(u,v) = \frac{1}{\sqrt{u}}\int_{-\infty}^{\infty} f(t)\,\Psi\left(\frac{t-v}{u}\right)dt, u,v \in R, u/=0 \quad \textbf{(1)}$$

The term u, that will be that the scale parameter, speaks to the length of wavelet and oscillating frequency. Term v speaks to the moving area. Be that as it may, for advanced registering examination some repetitive information are contained among CWT. Accordingly, DWT, depicted in condition 2, is alluring when contrasted with CWT.

$$DWT(u,v) = \frac{1}{\sqrt{a_o^u}}\sum_k f(k)\,\psi\left(\frac{v-kb_o a_o^u}{a_o^u}\right) \quad \textbf{(2)}$$



(a) Harmonics with Sag Signal (b) Harmonics with Swell Signal

(c) Harmonics with Interruption Signal (d) Flicker with Harmonics Signal

(e) Flicker with Sag Signal (f) Flicker with Swell Signal

Fig. 2 Six types of hybrid PQD

The Daubechies wavelets group of symmetrical wavelets process a different wavelet change and described by a biggest scope of disappearing minutes for a couple of given backings. All in all, the Daubechies wavelets are picked to claim the best range of disappearing moments, (this does not suggest the most straightforward smoothness) for given help expansiveness $N = 2A$, and possible arrangements the one is picked whose scaling channel has extremal part. Daubechies wavelets are wide utilized in goals and a wide differ of issues, for example self-closeness properties of a proof or structure issues, signal discontinuities, and so on. The Daubechies don't appear to be laid out regarding the following scaling and wavelet capacities; obviously, they're unfeasible to scribble down in shut sort [14].

The indicant refers to the amount N of coefficients. Every transform has many zero moments or vanishing moments up to 0.5 the number of coefficients. as an example, Db2 has one evaporating moment, Db4 has two, and so forth. An evaporating moment restrains the wavelet's capacity to speak to polynomial conduct or information in a signal. For instance, Db2, with one moment, just encodes polynomials of one constant, or steady signal parts. Db4 encodes polynomials with 2 coefficients, for example constant and direct signal segments and Db6 encodes three polynomials, for example, constant, direct and quadratic sign parts.

This capacity to compose signal is even so subject to the advancement of scale release, and thus the absence of move invariance, that emerge from the different moving task all through use of the adjust. Sub-arrangements that speak to straight, quadratic (for instance) signal parts are dealt with generally figuring on whether the focuses line up with even or odd numbered areas inside the succession. The deficiency of the imperative property of move invariance, has gem rectifier to the occasion of numerous totally various adaptations of a move invariant (discrete) WT [15].

Wavelet decomposition of one-dimensional signal forms a structure of one-dimensional coefficient by tangling with a wavelet or a combination of decomposition filters. In MATLAB, the function wavedec*(x, n, wname)* restores the disintegrated signal *x* at level *n* utilizing the mother wavelet function given in *wname*. The yield disintegration structure comprises of the wavelet decay vector *c* and the clerking vector *l*,that contains the decomposed coefficients as indicated by its dimension. The association of wavelet decomposition structure for 2 level decomposition of a Sag PQD signal is pictured in Fig. 3.

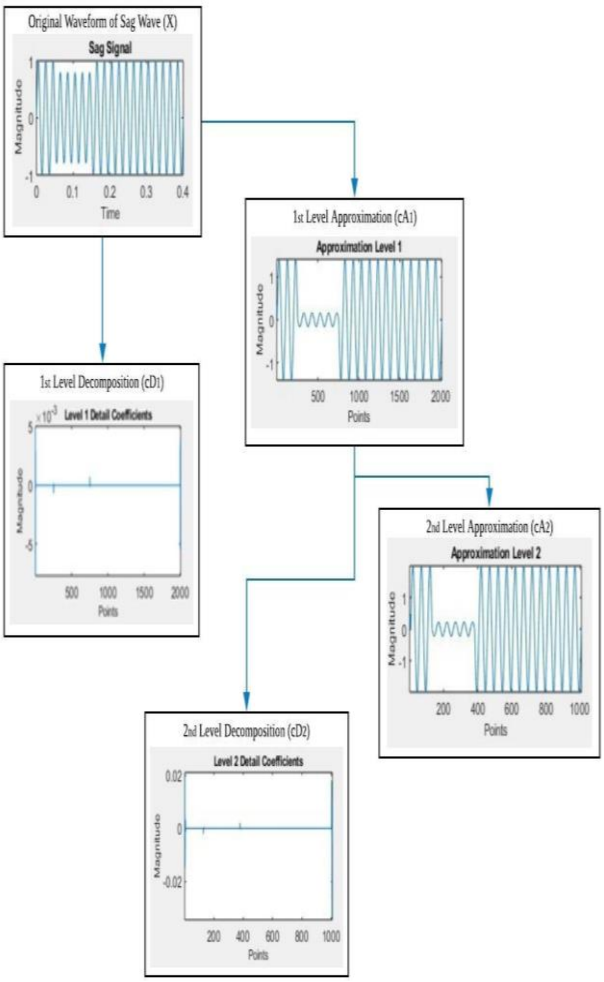


Fig. 3 Wavelet Decomposition Flowchart

The wavelet decomposition of the Sag signal *x* depicted at top level is decomposed into output level 1 approximation coefficients (cA1) and level 1 decomposition coefficients (cD1). From the cA1, level 2 approximation coefficients (cA2) and level 1 decomposition coefficients (cD2) are produced.

IV.CLASSIFICATION METHODS

Ensemble Classification

Ensemble classification brings together a group of trained weak learner models and knowledge of these trained learners. Prediction of ensemble response for brand spanking new knowledge by assuming predictions from its poor models. It keeps knowledge used for educating, figures out resubstituting predictions, and may resume training if desired. An ensemble is itself a supervised learning algorithmic rule, as a result of it may be trained, so accustomed create predictions. The prepared group, in this manner, speaks to one theory. This theory, in any case, isn't basically contained among the speculation place of the models from that its structured. Along these lines, groups might be appeared to have extra adaptability inside the capacities they'll speak to. This adaptability capacity, in principle, adjust them to over-fit the training learning of a normal model. In any case, in observe, some outfit systems will in general scale back issues related with over-fitting of the preparation information. Through exact perception, groups will in general yield higher outcomes once there's a noteworthy assorted variety among the models. A few outfit ways, in this way, get the chance to push assorted variety among the models they blend. Despite the fact that perhaps non-natural, extra irregular calculations (like arbitrary call trees) might be acclimated fabricate a more grounded gathering than terrible intentional calculations (like entropy-lessening choice trees). General theory of ensemble's algorithm was first proposed in an approach in the form of algebraic by Zhuravlev et al [16]. Based on Zhuravlev et al [16], the N basic algorithm's composition $h_t = C(a_t(x)), t = 1,...., N$ is taken to mean a superposition of recursive operators at $a_t : X \to R$, of a correction operation $F : R^N \to R$ and call rule $C : R \to Y$ like $H(x) = C(F(a_1(x),...., a_N(x)))$, where $x \in X$, X may be a house of objects, Ymight be a lot of answers, and R might be a place of appraisals. This method was referred to as boosting. Schapire et al [16] developed the primary obvious polynomial-time boosting of polynomial-time algorithmic program. It totally should change over powerless models into robust model by building associate degree ensemble of classifiers. Most plan of the boosting algorithmic program may be a stepwise strengthening of the ensemble's algorithm. One in every of the favored to implement this idea is Schapire's AdaBoost algorithmic program, that includes associate degree of ensemble's decision trees.

V.METHODOLOGY

A total of 14 Power Quality Disturbances has been simulated and analyzed. Fig. 4, shows the experimental design flowchart of this paper's methodology. For every PQD, 1000 samples were collected which contributes to a total of 14000 samples altogether. From the 1000 samples of each PQD, 800 samples (80%) were split for training, 200 samples (20%) were split for testing.

In any DWT applications, Haar, Morlet, Discrete Meyer, Daubechies, Coiflets and Mexicans are few sorts of fundamental wavelet filters that were utilized by scientist and engineers to break down the PQD. The selection of mother wavelet filter will influence the efficiency of the classifier. Mother wavelet filter functions of choices that were experimented in this paper are Daubachies (db), Discrete Meyer (dmey), Coiflets (coif), Fejer-Korovkin filters (fk), Symlets (sym), Boirthogonal (bior). Equation 3 is used to calculate the accuracy for both train and test sets.

$$Accuracy = \frac{No.of correct classification}{Total no.of samples} x\ 100 \qquad (3)$$

Ensemble classification was performed on 14 classes using multiclass ensemble classifier, which uses AdaBoostM2 method. The ensemble classifier was compared against other classifiers such as Tree, Linear Discriminant, SVM and KNN in terms of classification accuracy. Besides that, experiments were also carried out with different choices of mother wavelet filter function to determine which mother wavelet filter function delivers the most optimal results. Each mother wavelet filter functions were decomposed at both 4th and 8th levels.

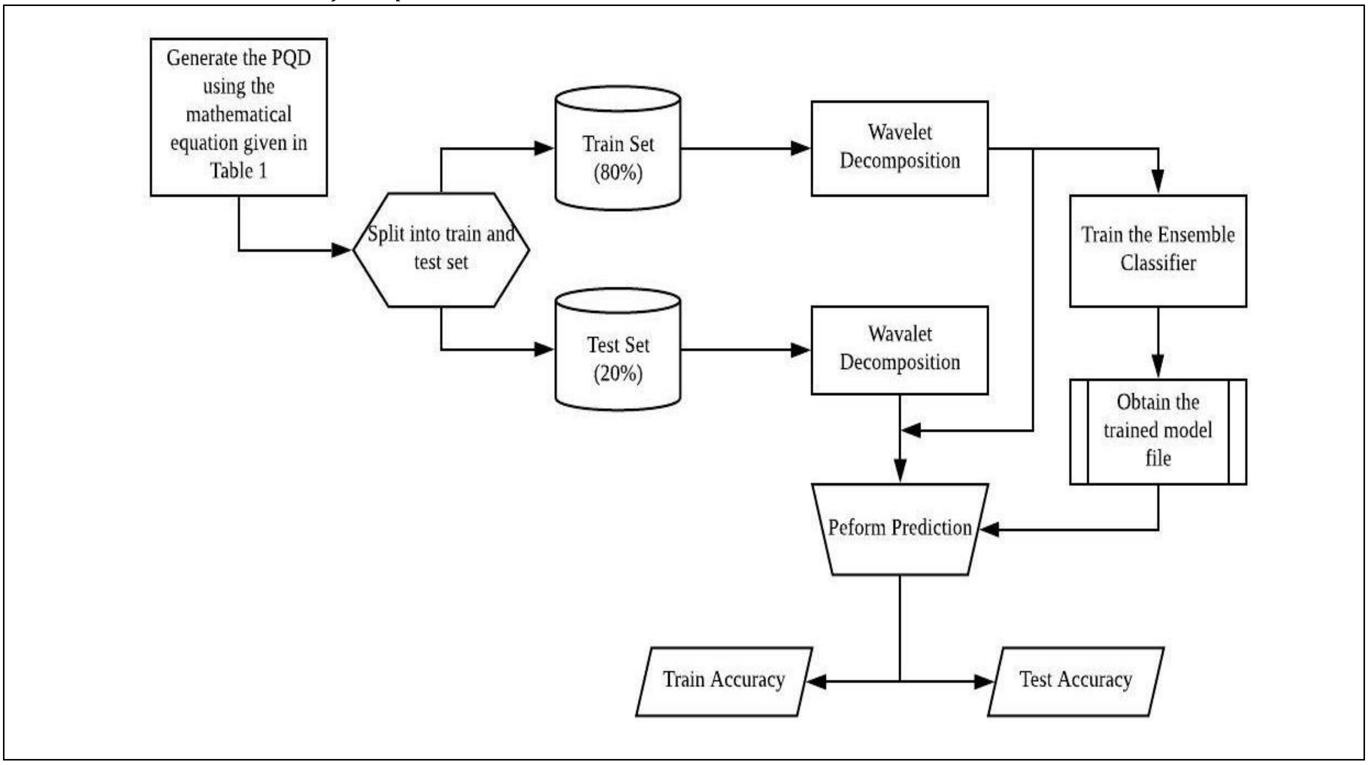


Fig. 4 Experimental Design Flowchart

VI.RESULTS

Table 2 tabulates the experimental result of the accuracy obtained from test and train set for different levels of wavelet decomposition, mother wavelet filter function and types of classifier.

The average accuracy for train and test set for each respective classifier with different mother wavelet filter functions are stated in the last column of Table 2. The Ensemble and Tree classifier outperformed other classifiers, Linear Discriminant, SVM and KNN, to achieve an overall maximum accuracy of 100% (highlighted in grey at the bottom of the table), for both train and test sets. For Ensemble classifier, the mother wavelet filter functions of type Coiflets, Fejer-Korovkin, and Biorthogonal at the 8th level of decomposition produced a consistent 100% accuracy (highlighted in green) whereas, for tree classifier, only a few particular mother wavelet filter functions produced an accuracy of 100% (highlighted in yellow color). Even though both classifiers can produce the same maximum accuracy of 100%, Ensemble classifier outperformed other classifiers by obtaining the highest overall average accuracy (highlighted in blue color) for both training set (99.38%) and testing set (98.52%). When compared to the Tree classifier, it produced an average accuracy of 99.24% for a train set and 97.84% for the test set, shown at the bottom of Table 2. Among different type of mother wavelet filter functions, the Symlets wavelet function of type sym12 produced the highest average accuracy of 97.2% for train and 97.1% for the test (highlighted in orange color in the last column of Table 2). Results in Table 2 concludes that Ensemble classifier produces the best classification accuracy with mother wavelet filter functions such as Coiflets, Fejer-Korovkin filters or Biorthogonal, at the 8th level of Wavelet Decomposition.

Table. 2 Accuracy of Train and Test Sets for different levels of Wavelet Decomposition, Mother Wavelet Filter Function and types of Classifier

Family	Type	Level	Type of classifier (%) Multiclass Tree		Linear Discriminant		Multiclass SVM		Multiclass KNN		Multiclass Ensembles		Train avg	Test avg
			Train	Test	Train	Test	Train	Test	Train	Test	Train	Test		
Daubachies	db2	4	98.7	97.0	88.9	87.1	97.9	95.9	100.0	90.8	99.0	97.9	96.9	93.8
		8	100.0	100.0	78.5	79.6	84.8	84.7	100.0	92.1	100.0	99.9	92.7	91.3
	db4	4	98.5	95.6	81.4	79.9	90.7	87.5	100.0	90.4	98.3	96.8	93.8	90.0
		8	100.0	100.0	87.8	87.5	91.2	91.4	100.0	99.3	100.0	100.0	95.8	95.6
	db6	4	98.3	93.6	80.7	77.3	90.4	85.5	100.0	89.8	99.0	96.3	93.7	88.5
		8	100.0	100.0	87.0	86.7	98.9	98.8	100.0	99.9	100.0	100.0	97.2	97.1
Discrete meyer	dmey	4	98.4	94.0	80.4	78.3	87.9	83.8	100.0	90.3	98.5	95.8	93.0	88.4
		8	100.0	99.9	83.6	84.1	87.9	87.6	100.0	99.9	100.0	100.0	94.3	94.3
Coiflets	coif1	4	98.8	98.2	88.0	87.1	96.4	94.4	100.0	90.5	98.8	98.1	96.4	93.7
		8	100.0	100.0	84.0	84.8	84.5	83.8	100.0	92.2	100.0	100.0	93.7	92.1
	coif3	4	98.3	94.5	78.7	76.3	89.3	86.4	100.0	91.0	98.2	96.5	92.9	88.9
		8	100.0	100.0	87.5	86.0	98.4	97.8	100.0	99.9	100.0	100.0	97.2	96.7
	coif5	4	98.4	94.9	80.6	77.2	87.5	84.4	100.0	89.7	98.6	95.9	93.0	88.4
		8	100.0	100.0	86.0	85.2	91.4	91.0	100.0	99.2	100.0	100.0	95.5	95.1
Fejer-Korovkin filters	fk4	4	99.0	99.1	88.4	88.2	95.8	93.8	100.0	93.2	100.0	99.7	96.6	94.8
		8	100.0	100.0	77.1	77.4	83.9	83.5	100.0	97.0	100.0	100.0	92.2	91.6
	fk8	4	98.3	94.8	88.4	88.6	96.4	94.8	100.0	90.5	98.8	97.5	96.4	93.2
		8	100.0	100.0	87.7	88.5	97.0	97.2	100.0	99.8	100.0	100.0	96.9	97.1
	fk22	4	98.3	93.9	81.4	77.1	91.8	87.7	100.0	89.9	98.7	95.3	94.0	88.8
		8	100.0	99.9	87.9	87.0	87.9	87.6	100.0	98.8	100.0	100.0	95.2	94.7
Symlets	sym2	4	98.6	97.1	88.5	86.6	97.8	95.5	100.0	90.8	98.8	98.1	96.7	93.6
		8	100.0	99.9	78.8	78.7	84.9	84.5	100.0	92.5	100.0	100.0	92.7	91.1
	sym8	4	98.1	94.6	79.7	77.4	90.5	87.1	100.0	90.4	98.0	96.4	93.3	89.2
		8	100.0	100.0	86.6	87.0	97.3	97.5	100.0	99.7	100.0	100.0	96.8	96.8
	sym12	4	98.3	95.1	81.1	77.3	89.4	85.4	100.0	90.4	98.6	95.5	93.5	88.8
		8	100.0	100.0	88.2	87.3	98.0	98.3	100.0	99.9	100.0	100.0	97.2	97.1
Biorthogonal	bior4.4	4	98.3	95.6	81.2	78.6	90.3	86.6	100.0	90.5	98.9	97.1	93.7	89.7
		8	100.0	100.0	86.3	86.0	94.6	94.1	100.0	98.1	100.0	100.0	96.2	95.6
	bior6.8	4	98.4	95.3	79.4	77.7	89.9	87.0	100.0	90.7	98.3	96.9	93.2	89.5
		8	100.0	100.0	87.3	87.4	97.2	97.4	100.0	99.3	100.0	100.0	96.9	96.8
		max	100.0	100.0	88.9	88.6	98.9	98.8	100.0	99.9	100.0	100.0	97.2	97.1
		avg	99.2	97.8	84.0	82.9	92.1	90.5	100.0	94.4	99.4	98.5	94.9	92.8

When compared to the Tree classifier, it produced an average accuracy of 99.24% for train set and 97.84% for test set, shown at the bottom of Table 2. Among different type of mother wavelet filter functions, the Symlets wavelet function of type sym12 produced the highest average accuracy of 97.2% for train and 97.1% for test (highlighted in orange color in the last column of Table 2). Results in Table 2 concludes that Ensemble classifier produces the best classification accuracy with mother wavelet filter functions such as Coiflets, Fejer-Korovkin filters or Biorthogonal, at 8th level of Wavelet Decomposition. Length of the feature vector is an important criterion and measurable property that need be observed since it affects the computational effort of the subsequent processes.

In this research, the length of feature vector of the best performing mother wavelet filter functions, Coiflets, Fejer-Korovkin filters and Biorthogonal, are given in Table 3.

Table. 3 Length of Feature Vector for corresponding level of Wavelet Decomposition and its respective Mother Wavelet filter function

Mother Wavelet Filter Functions		Length of Feature Vector	
		Level 4 Wavelet Decomposition	Level 8 Wavelet Decomposition
Coiflets	Coif1	254	20
	Coif3	266	32
	Coif5	277	44
Fejer-Korovkin Filters	Fk4	252	18
	Fk8	256	22
	Fk22	269	36
Biorthogonal	Bior4.4	258	24
	Bior6.8	266	32

Basically, the 8th level of decomposition produces a lesser number of features when compared to lower level Wavelet decompositions. The analysis in Table 3 shows that mother wavelet filter function of type Fk4 produced the smallest number of features of 18.

VII.CONCLUSION

This paper studies the classification of power quality disturbances (PQD), which degrades the properties of delivered power to the end user. The time domain PQD signal was decomposed using Discrete Wavelet Transform and classified using Multiclass Ensemble Method. Our experimental results, conducted using 14000 samples, proved that the proposed method was able to outperform other methods by achieving 100% in both train and test sets. This performance was attained using a minimal number of 18 features. As a part of future work, more PQDs can be used for analysis by generating several variants of hybrid PQD such as notch with sag, notch with swell and notch with harmonics. Deep learning-based classification can be used for further investigation.

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AUTHORS PROFILE

Tiagrajah V. Janahiraman, College of Engineering, Universiti Tenaga Nasional, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia

Prakash Bala, College of Engineering, Universiti Tenaga Nasional, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia