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PQ EVENT DETECTION AND CLASSIFICATION BASED ON DUAL TREE COMPLEX WAVELET AND COARSER-FINE TWO STAGE ANN CLASSIFIER

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ABSTRACT

Dual Tree Complex Wavelet Transform (DTCWT) is shift invariant and has 2^m redundancy as compared with Discrete Wavelet Transform. In this paper, DTCWT is used to obtain non-redundant sub bands energy levels representing PQ events in different and unique sub bands. The sub bands are quantized and thresholded to retain 95% of information that will improve classification process. Two stage FFNN architecture is designed to classify six possible PQ events by performing coarse and fine classification process. The two stage classifier with 10 neurons in each FFNN architecture and 4 neurons in the second stage achieves 97.5% of classification accuracy. The develop algorithm is suitable for real time applications in smart meters.

Keywords: *PQ event, DTCWT, Neural Network, Two Step Classifier, Smart Meter*

1. INTRODUCTION

Power Quality (PQ) disturbances like Voltage sag, Voltage swell, Harmonics and Interrupts are caused due to power system fault and the faults depends upon environment, age of equipment and use of power electronic devices leading to nonlinear and time-variant loads. In addition the emergence of smart grids that use the power grid for communications, control and monitoring are interfaced with large number of electronic systems that causes non-linear loads. Electronic gadgets require high quality power supplies and it is been reported by Electrical Power Research Institute (EPRI) that loss of $24 billion in US economy due to PQ phenomena [1]. Power system transient fault recognition using Wavelet Multi-Resolution Analysis (MRA) technique integrated with Neural Network. The proposed method requires less number of features as compared to conventional approach for the identification. The feature extracted through the wavelet is trained by a Probabilistic Neural Network for the classification of events. The accurate ratio is achieved about 95.5%.[2]. DWT coefficients based approach for the energy contents in the different frequency zone is proposed for the classification of PQ disturbances. Classification is done on the basis of DWT and MSD with these extracted features. The analysis and results presented are indicated the lowest and highest energy content in respective frequency zone [3].In [4] 8-level DWT and 50 neuron ANN are used for classifying 10 PQ event with an accuracy of 90%. In [5] empirical wavelet transform is used to extract five features and ANN classifier based on is used achieving 94% accuracy in classification. PQ events such as harmonics and interrupts lead to non-stationary characteristic of power signal. Use of Discrete Time Complex Wavelet Transform which supports shift invariance property instead of DWT gives rise to extraction of significant features and improves classification accuracy. In [6] 10-level DTCWT is computed to extract features and ANN is used for classifying demonstrating 96.8% accuracy. Wavelet decomposition of input data into multiple levels decomposes the signal based on frequency composition. Considering sampling frequency of Fs, each sub band with frequency range $\{Fs/2^n – Fs/2^{n-1}\}$, PQ events will be captured in more than on sub bands and more than one PQ event will appear in one sub band. Smart meters in smart grid environment constantly monitor power signal and PQ event can occur instantaneously and hence the PQ detector need to be designed to process more than 100 cycles of data to be more robust. In this work, real time test signals from 40 smart meters are captured by data logging for one week. A novel decomposition algorithm based on DTCWT is designed to capture the events in different sub bands so as to achieve localization. The features are classified using multi-stage multi-layered ANN. Section II discusses proposed classifier algorithm with validation logic, Section III discusses novel DTCWT feature extractor, Section IV discusses ANN classifier, Section V presents the results and conclusion is presented in Section VI.

2. PROPOSED METHODOLOGY

The PQ classifier algorithm is presented in Figure 1 for classification of synthetic power signal with six events. The algorithm comprises of two stages: feature detector with DTCWT and classifier using ANN. PQ events such as sag, swell, harmonics, interrupts, sag with harmonics and swell with harmonics are generated using parametric equations that are considered as reference event and are denoted by $PQ_{sag}Ref$, $PQ_{swell}Ref$, $PQ_{har}Ref$, $PQ_{intr}Ref$, $PQ_{sghar}Ref$ and $PQ_{swhr}Ref$ respectively. PQ events that are modeled using parametric equations are used to generate 10 different types of disturbances in terms of voltage, frequency and power variations with regard to PQ reference events. The modified PQ events generated from reference is denoted by $PQ_{sag}Ip$, $PQ_{swell}Ip$, $PQ_{har}Ip$, $PQ_{intr}Ip$, $PQ_{sghar}Ip$ and $PQ_{swhr}Ip$ and are considered as input signal. The proposed algorithm first computes the DTCWT sub bands of both the reference and input signal. From the DTCWT sub bands appropriate sub bands are selected and energy levels of selected sub bands are computed. Novel algorithm for selection of DTCWT sub bands for PQ events is presented in next section. Energy levels of undistorted PQ signal (sine wave), PQ events (reference) and PQ event (input) are computed. Feed Forward Artificial Neural Network (FFANN) is designed and trained to classify the DTCWT energy features.

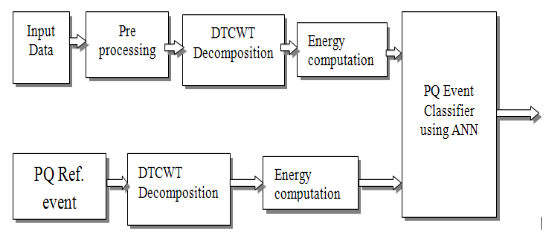

Figure 1 Proposed PQ Classifier Block Diagram

Figure 2 presents the FFANN classifier algorithm. The algorithm comprises of two FFANN classifiers. The classifier on the top is trained to classify the PQ events generated using parametric models. The classifier at the bottom denoted as “RANN” is trained to classify real time PQ event. The quantizer module is designed to scaling of PQ event before being processed by the classifier. The FFANN classifier is trained to classify two events undistorted PQ event and actual PQ event (reference). The quantized energy levels of sine wave and the corresponding PQ event (for ex. Sag event denoted by $PQ_{sag}Ref$) are used as input data for training the FFANN. The network is designed with 16 hidden layer neurons and 4 output neurons. The network function in both layers is selected to be tansig. As the network is designed to have four outputs, the target for sine wave denoted as “$Sine_{Reftarget}$” is set to {0.2, 0.2, 0.2, 0.2} and the target for $PQ_{sag}Ref$ denoted as “$Sag_{Reftarget}$” set as {0.8, 0.8, 0.8, 0.8}. The FFANN network is initially trained to classify the undistorted PQ event and the reference PQ events (Sag). After initial training is completed, with the obtained weights and biases of the network, the second level of training is carried out by considering three input signals {$PQ_{sine}Ref$, $PQ_{sag}Ref$ and $PQ_{sag}IP$} with corresponding targets {0.2, 0.8, 0.8}. By performing two levels of training it is identified that the network is able to reach its global minima point and optimum weights and biases are identified for classification. The optimum weight and bias matrix obtained is recorded and stored for the trained network for the corresponding PQ event classification. The above process is continued for classification of all six events considered and thus six ANNs are trained to obtain corresponding weights and biases.

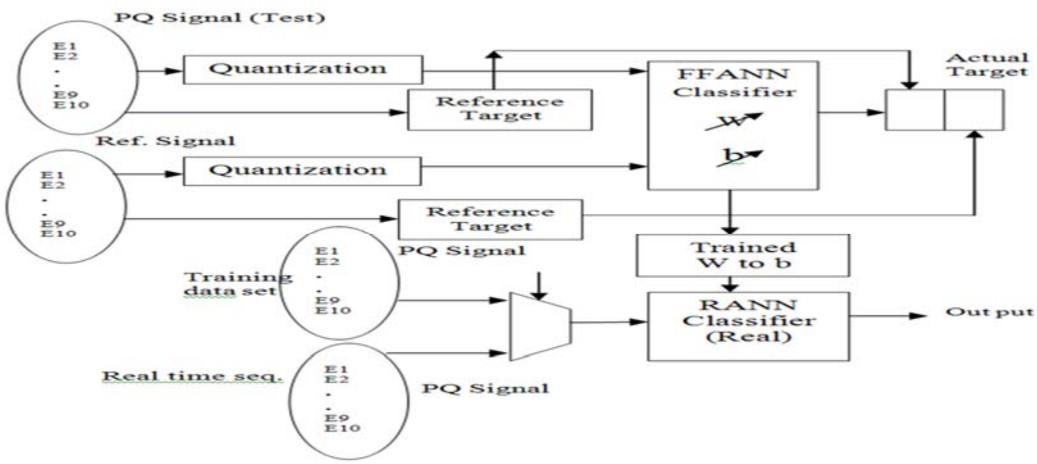

Figure 2 Proposed Real-Time PQ Classifier With Validation Logic

The RANN classifier comprises of six FFANN classifiers with each consisting 16 hidden layers and 4 output layers. Each of the networks designed and assigned with corresponding weights and biases obtained from the training process. The RANN classifier is trained to classify six PQ events generated based on parametric equations. The trained RANN is used for classification of real time PQ events. The multiplexer unit selects the PQ event to be classified. A detailed discussion on RANN working is presented in next section. Manuscripts must be in English (all figures and text) and prepared on Letter size paper (8.5 X 11 inches) in two column-format with 1.3 margins from top and .6 from bottom, and 1.25cm from left and right, leaving a gutter width of 0.2 between columns.

3. DTCWT FEATURE EXTRACTOR

10-tap eight-level DTCWT is used for decomposes input signal into multiple sub bands, each of these sub bands represents information in different frequency ranges varying from Fs to $Fs/2^N$. PQ disturbances such as swell, sag, harmonics and interrupts will have voltage fluctuations as well as frequency differences. Table 1 shows the frequency range in which PQ disturbances would appear.

Table 1: PQ Disturbance Frequency Range

PQ Disturbances	Frequency Range
Sag	50 Hz ±10 Hz
Swell	50 Hz ±10 Hz
Harmonics	100Hz-500 Hz
Interrupts	> 500 Hz

The PQ signal undistorted will be 50Hz signal assuming a noise moving of 10% the frequency of the PQ signal will be in the range of 45 Hz -55 Hz. PQ disturbances such as Voltage sag and swell causes amplitude changes and hence lead to frequency fluctuations, thus the undistorted PQ signal, voltage sag and swell will also occur in the frequency band of PQ undistorted signal. The disturbances such as harmonics and interrupts will always fall in higher frequency bands. In the novel algorithm shown in Figure 3, DTCWT decomposition is carried out to capture these signals accurately.

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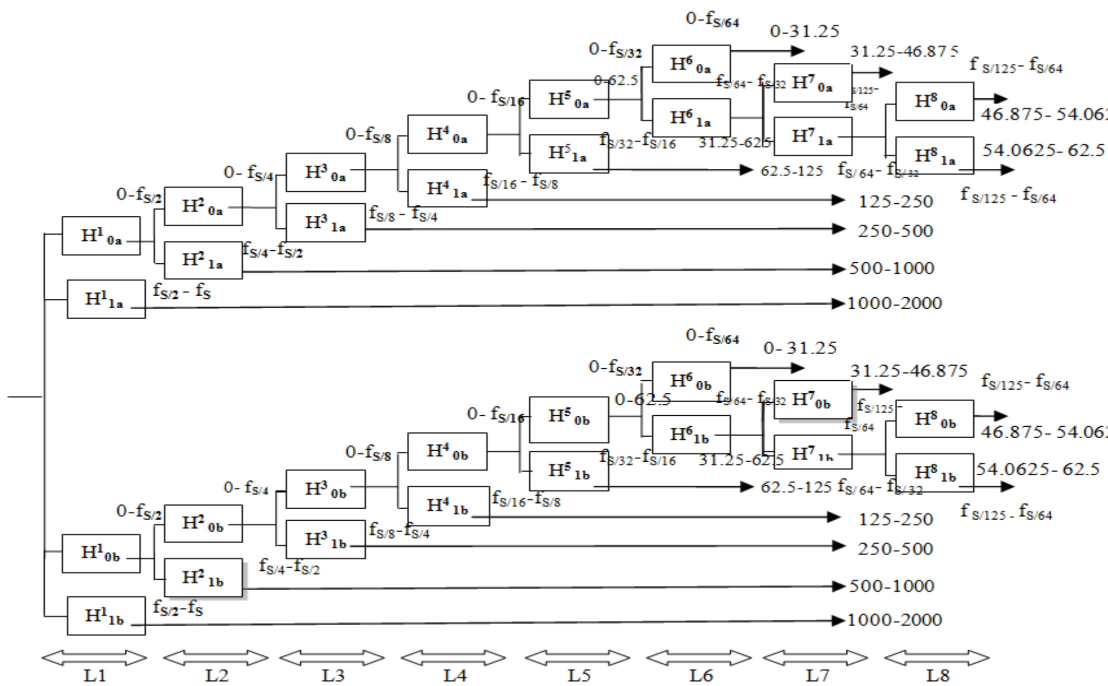

Figure 3 DTCWT Algorithms To Capture PQ Disturbances

8-levels of decomposition are carried assuming the input sampling frequency to be of 2000 Hz. The seventh and eight level decomposition is carried out on high pass coefficients, as the high pass band in level 6 hold the PQ signal of interest. The low pass bands in level 6 are discarded. The low pass band in level 8 is in the frequency range of 46.875 Hz to 54.0625 Hz and captures the undistorted PQ signal. The high pass band in level 8 captures the PQ signal in frequency range of 54.0625 Hz to 61.15 Hz and hence will contain the voltage sag and voltage swell distortions. The low pass band in level 7 is in the frequency range of 31.25 Hz to 46.875 Hz and this band will also hold the voltage sag and swell distortions. From 8-level decomposition the DTCWT sub bands of importance are shown in Table 2 along with the information content. PQ events are captured in $DDC^8_{a/b}$, $DC^7_{a/b}$, $D^5_{a/b}$, $D^4_{a/b}$, $D^2_{a/b}$, $D^1_{a/b}$ sub bands.

Table 2 Selected DTCWT Sub Bands For PQ Classification

Band	Sub bands	Frequency Range (Hz)
1	$DDC^8_{a/b}$	46.875-54.0625
2	$DDD^8_{a/b}$	54.0625-62.5
3	$DC^7_{a/b}$	31.25-46.875
4	$C^6_{a/b}$	0-31.25
5	$D^5_{a/b}$	62.5-125
6	$D^4_{a/b}$	125-250
7	$D^3_{a/b}$	250-500
8	$D^2_{a/b}$	500-1000
9	$D^1_{a/b}$	1000-2000

The events in $C^6_{a/b}$ are noise and are discarded and the event in $D^3_{a/b}$, band is very high harmonics which is also discarded. The data in $DDD^8_{a/b}$ in PQ undistorted signal and is also interest. The process of quantization and thresholding is designed to retain the PQ events in bands 1,3,5,6,8,2,9. All other bands are discarded as the information content is very low. From the real and imaginary sub bands only the real band low pass coefficients are selected. As both of them have similarly energy levels. All the eight high pass bands are selected for encoding. The selected sub bands at level-4 will contain PQ disturbances such as voltage sag and swell. These disturbances may also be present in the low pass bands. The remaining three bands $\{D^3_{a/b}, D^2_{a/b}, D^1_{a/b}\}$ will contain all other disturbances. The $D^1_{a/b}$ sub band will have high frequencies disturbances and is considered with high priority. In addition to 9 energy levels computed from 9 sub bands, an additional energy level E10 representing the energy of undistorted PQ signal is considered which will

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be a non-zero input to the ANN. The advantage of DTCWT is that it supports shift invariant property as it generates both real and imaginary samples denoted by E_R and E_I. The absolute value of DTCWT energy features are computed by $E=(E^2_R+E^2_I)^{1/2}$ from all the nine sub bands that are used as inputs to RANN architecture.

4. DESIGN OF ANN CLASSIFIER

Feed forward neural network (FFNN) architecture with 10 inputs, 16 neurons in the hidden layer and 4 neurons in the output layer is

DTCWT Energy levels	Sine	Swell	Sag	Harmonics
sub1 (R)	1.99E-05	0.000137	0.000371	0.003276
sub2 (R)	5.42E-05	0.000396	0.001101	0.028076
sub3 (R)	0.000398	0.002106	0.005102	2.468314
Sub3 (I)	0.00373	0.030153	0.027624	8.569848
Sub2 (I)	5.74E-06	7.99E-05	0.000308	0.001567
sub6 (R)	3.56E-05	0.000324	0.000806	0.025268
Sub1 (I)	0.00024	0.0017	0.002799	2.485433
Sub9 (R)	0.001534	0.012724	0.020683	8.72095
Sub8 (R)	3.998176	21.92961	14.15104	9.263175
Sub8 (I)	4.000876	21.94859	14.16427	9.102733

designed as shown in Figure 4. The hidden layer outputs are denoted by $\{a_1, a_2, \ldots\ldots\ldots\ldots a_{16}\}$ and the corresponding weights and biases are represented by $W_{n,m}$ and b_n respectively where n represents the neuron and m represents input. The hidden layer neuron output is represented as HE_n. $HE_n = f(a_n)$ and a_n is represented by Eq. 1,

DTCWT Energy levels	Harmonics with swell	Harmonics with sag	Interrupts
sub1 (R)	0.001464	0.001803	2.08E-05
sub2 (R)	0.004626	0.006116	6.17E-05
sub3 (R)	0.466609	0.716754	0.000484
Sub3 (I)	6.23813	9.175324	0.005576
Sub2 (I)	0.000505	0.000847	6.60E-06
sub6 (R)	0.002725	0.004212	3.97E-05
Sub1 (I)	0.452896	0.662299	0.000327
Sub9 (R)	6.446904	9.616177	0.0037
Sub8 (R)	8.34146	12.50206	3.410184
Sub8 (I)	8.175389	12.18538	3.412575

$$a_1= E_1W_{1,1}+ E_2W_{1,2}+\ldots + E_{10}W_{1,10}+ b^1_{1,} \quad (1)$$

The hidden layer network function is tan sigmoid function. In general, the intermediate outputs a_k are represented by Eq. (2)

$$a_k=\sum_{i=1}^{10} (E_i w_{i,k})+ b^1_{k,i}, \quad k=1,2,3,4\ldots\ldots16 \quad (2)$$

Similarly the output layer output is mathematically represented by Eq. (3) and the network function is purelin.

$$O_k= \sum_{i=1}^{16} (HE_i w_{k,i})+ b^2_{k,i}, \quad k=1,2,3,4 \quad (3)$$

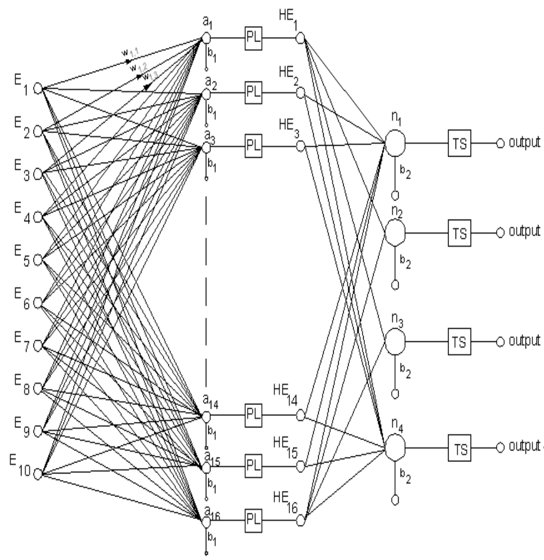

Figure 4 Feed forward neural network architecture

The FFNN architecture is initialized with random weights and biases is trained by setting the targets as T= [0.08, 0.08, 0.08, 0.08] if the input is PQ event and T= [0.02, 0.02, 0.02, 0.02] if the PQ event is undistorted PQ signal. The PQ signals are transformed by performing DTCWT to obtain 9 sub band levels. Each of the sub band levels is quantized and energy levels in each sub band are computed as discussed in previous section and are presented in Table 3(a)-(b).

Table 3 (a) Energy levels of DTCWT sub bands for sine, swell, sag, harmonics PQ events

Table 3 (b) Energy levels of DTCWT sub bands for Harmonics with swell -sag, interrupts PQ events

The frequency bands of PQ events such as swell and sag is captured in 1, 2 and 3 bands and hence overlaps. In order to resolve these issues, the corresponding imaginary bands are also considered. Similarly, the interrupt event is also captured by considering the R and I bands as presented in Table 3(a)-(b).The neural network architecture is designed with 10 inputs representing the energy levels from

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10 DTCWT sub bands. Figure 5(a)-(e) presents the energy levels of all six PQ events compared with undistorted PQ signal. From the energy level diagram it can be implied that the energy levels of PQ events are significant as compared with sine signal energy level. Further, it is also observed that energy levels are very significant only in the last two sub bands for sag, swell and interrupt events. With harmonics the energy levels are distributed significantly in more than two sub bands. it is also observed that the energy levels in all other sub bnnds are less significant but not negligible. Thus the neural network architecture is designed with tansig function and the input levels are normalized to be less than 0.005.

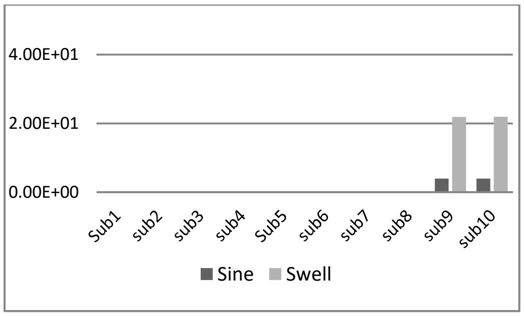

Figure 5(A) Comparison Of Energy Levels Of Sine And Swell PQ Events

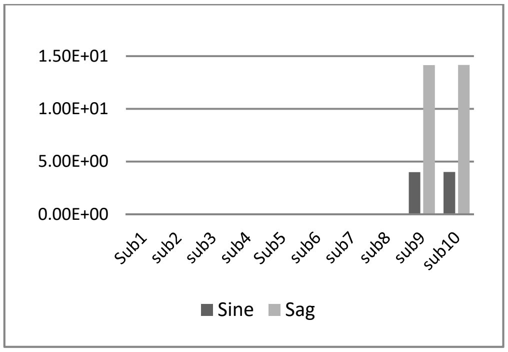

Figure 5(B) Comparison Of Energy Levels Of Sine And Sag PQ Events

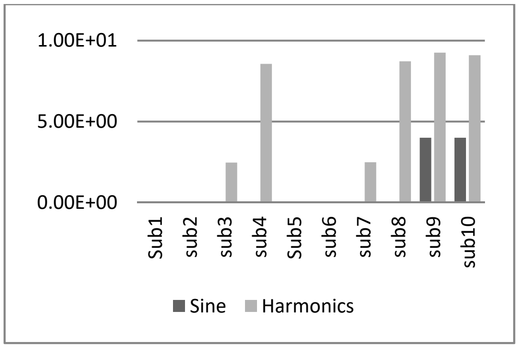

Figure 5(C) Comparison Of Energy Levels Of Sine And Harmonics PQ Events

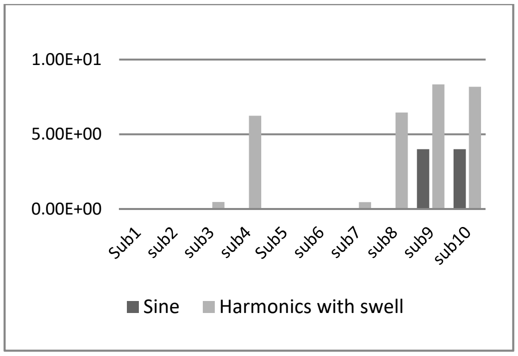

Figure 5(D) Comparison Of Energy Levels Of Sine And Harmonics With Swell PQ Events

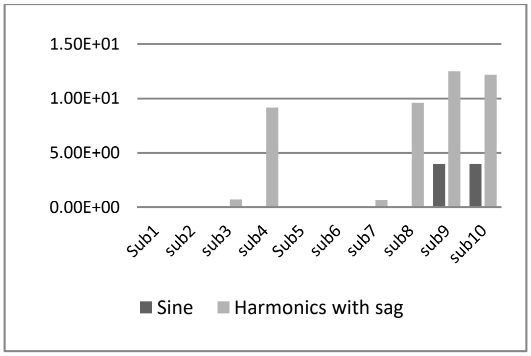

Figure 5(E) Comparison Of Energy Levels Of Sine And Harmonics With Sag PQ Events

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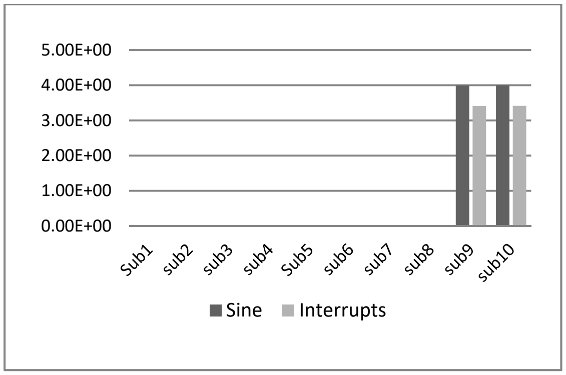

Figure 5(F) Comparison Of Energy Levels Of Sine And Interrupts PQ Events

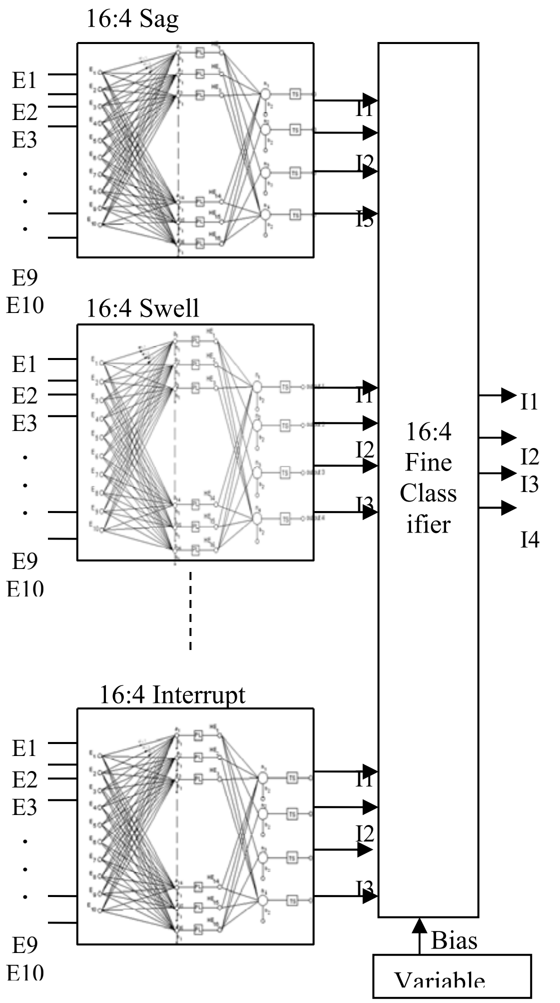

Figure 6 Feed Forward Network Architecture For Real PQ Signal Classification

Figure 6 presents the proposed RANN architecture which consists of six FANN architectures. The energy levels computed by considering 10 bands DTCWT sub bands are processed by all the six FANN architectures. Each of the network architectures classify only the corresponding events that they are trained for. The level -1 FANN output will be either 0.2 or 0.8. If the network in level-1 generates any other output other than these the output is discarded. The level-2 network is trained to classify the inputs to corresponding PQ events. Thus the two level training improves reliability I classification process. The level-1 network is defined as coarse classifier and is responsible for classification of six events, the fine classifier at level-2 is responsible for improving the accuracy in classification as the inputs to this classifier consists of 6 inputs each one selected from the output of coarse classifier.

5. EXPERIMENTAL SETUP

In the proposed PQ detection and classification algorithm the classifier consists of two parallel architectures that process PQ signals generated using parametric models and real time PQ signals that are acquired from solar PV system. The detector and classifier algorithm is modeled in MATLAB with input data being interfaced in Excel format. The real time PQ signal acquired by the DAQ card in the power meter is read into excel format and interfaced to MATLAB. Figure 7 shows the complete set up of solar PV connected to PQ recorder along with net meter.

Figure 7 Internal Connection Of PQ Analyzer Connected To PV System

The data login module is connected to one phase of the grid and the PQ data is recorded continuously for four days. The recorder or data login module captures RMS values, calculated in each half-period (10ms at 50Hz, 8.3ms at 60Hz), which are out of the thresholds set upon configuration by 1% to 30% of a set reference value

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with a 1% step. To validate the proposed algorithm, RMS values of raw voltage data is considered from PQ data recorder instrument.

6. RESULTS AND DISCUSSION

The PQ detector and classifier algorithm proposed is modeled in MATLAB environment and is verified for its functionality. The DTCWT based feature extractor module processes the test signals and the DTCWT sub bands are obtained using 10-tap dual tree filter. The sub bands presented in Table 2 are selected based on information content are quantized and thresholded to retain maximum information for classification process. Figure 8(a)-8(f) presents energy levels of PQ events compared with reference data.

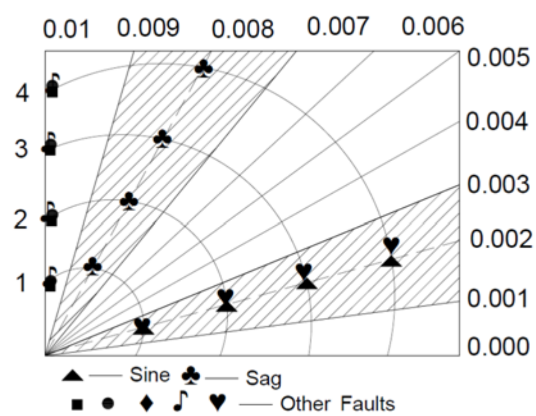

Figure 8(A) Classification Results Of Sag Event

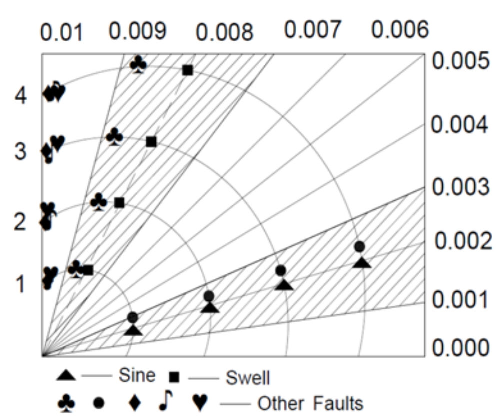

Figure 8(B) Classification Results Of Swell Event

The energy levels of all six events are reordered into column matrix with each column matrix comprising of 10 energy levels. Test data of 3000 test cases are considered for analysis in addition another 3000 test case data is considered for validation. The neural network proposed in Figure 2 is trained to obtain the optimum samples and the results are presented in Figure 8(a)-(f). Figure 8(a) presents the classification results of sag event. The FFNN architecture is trained to classify the sag event and reference or undistorted PQ event into two levels of 0.2 and o.8 respectively. If the FFNN output is 0.2 then the PQ event is said to be undistorted, if FFNN output is 0.8 then the PQ event is said to be sag. In addition to classification of these two events the trained network is also validated with test PQ signals other than sag. The shading region in Figure 8(a) is set as margins for network to classify as sag or sine event. If the classifier produces output other than expected they are mapped on the graph shown. From the results it is observed that interrupt PQ event has energy levels similar to sag event and hence give false results. All other events are accurately classified as they lie in areas away from the region of interest. In order to classify interrupt event it is required to compute entropy as an additional parameter other than energy levels. If the number of DTCWT decomposition levels can be increased from N to N+4 then interrupts can be captured for accurate classification. Similarly figure 8(b) represents classification results of swell event, in which sag faults are come slightly in region of swell and Interrupt in region of sine.

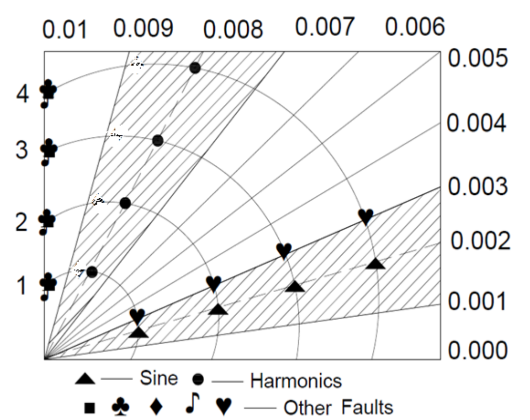

Figure 8(C) Classification Results Of Harmonics Event

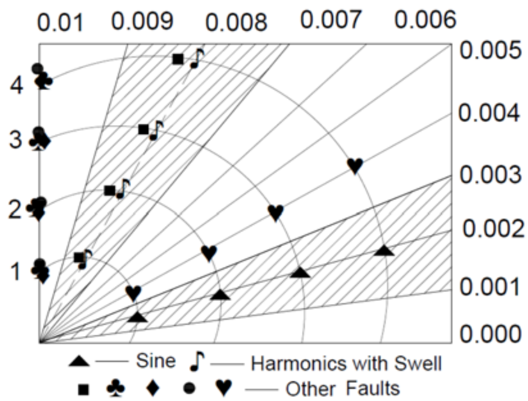

Figure 8(D) Classification Results Of Harmonics With Swell

Figure 8(c) represents classification results of Harmonics event where all other event likes sag, swell, harmonics with swell, harmonics with sag and interrupts are away from this region. This proves that accuracy in classification. Whereas Fig 8(d) shows the classification results of Harmonics with swell. Only harmonics events comes in regions of 'Harmonics with swell' but remaining all other faults like sag, swell, harmonics with sag and interrupts are away from this region that proves accuracy in results.

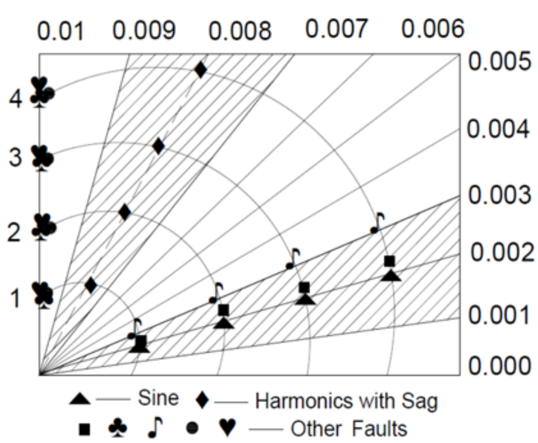

Fig 8(E) Classification Results Of Harmonics With Sag Event

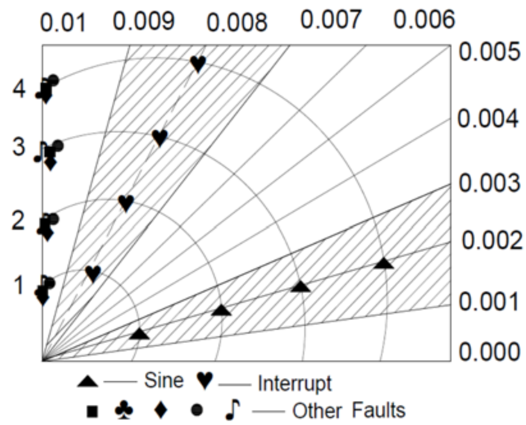

Fig 8(F) Classification Results Of Interrupt Event

Figure 8(e) shows the classification results of harmonics with sag event, where all other event likes swell, harmonics with swell, harmonics with sag and interrupts are away from this region. Only sag comes near the sine event. Figure 8(f) shows the classification results of Interrupt event, where all other events are accurately classified as they lie in areas away from the region of interest. This proves accuracy in classification.

TABLE 4 Comparison With Other Methods

METHOD	MRA-NN [2]	DWT-ANN[4]	EWT [5]	PROPOSED METHOD
ACCURACY	95.5%.	90%.	94%	97.5%

Table 4 shows the comparative results of MRA-NN, DWT-NN and Empirical wavelet transform classifiers along with proposed method DTCWT for feature extraction with design of two stages FFNN for classification. The proposed method achieves good results but still scope for further improvements.

7. CONCLUSION

PQ event detection and classification is carried out using DTCWT for feature extraction and design of two stages FFNN for classification. The DTCWT decomposition gives rise to 10 sub bands that are appropriately quantized and accurate features that indicate presence of PQ event are identified. The two step FFNN architecture is trained to obtain the optimum weights and biases. The trained network consisting of six FFNN architectures perform coarse classification, the second stage classifier performs fine classification. With two stage classifier unit PQ events represented in terms of

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DTCTW features are classified with 97.5% accuracy. Simulation results show that the proposed DTCWT approaches are successfully for the automatic classification of the PQ disturbances. Moreover, two stages FFNN for classification is compared with MRA-NN, DWT -NN, Empirical wavelet transform classifiers, and the best results are observed from DTCWT based technique. Therefore, the proposed approach would be an effective solution for detection and classification of PQ events. And this result still can be improved with modified CTDWT method. The proposed method can be further implemented in FPGA hardware as a future work.

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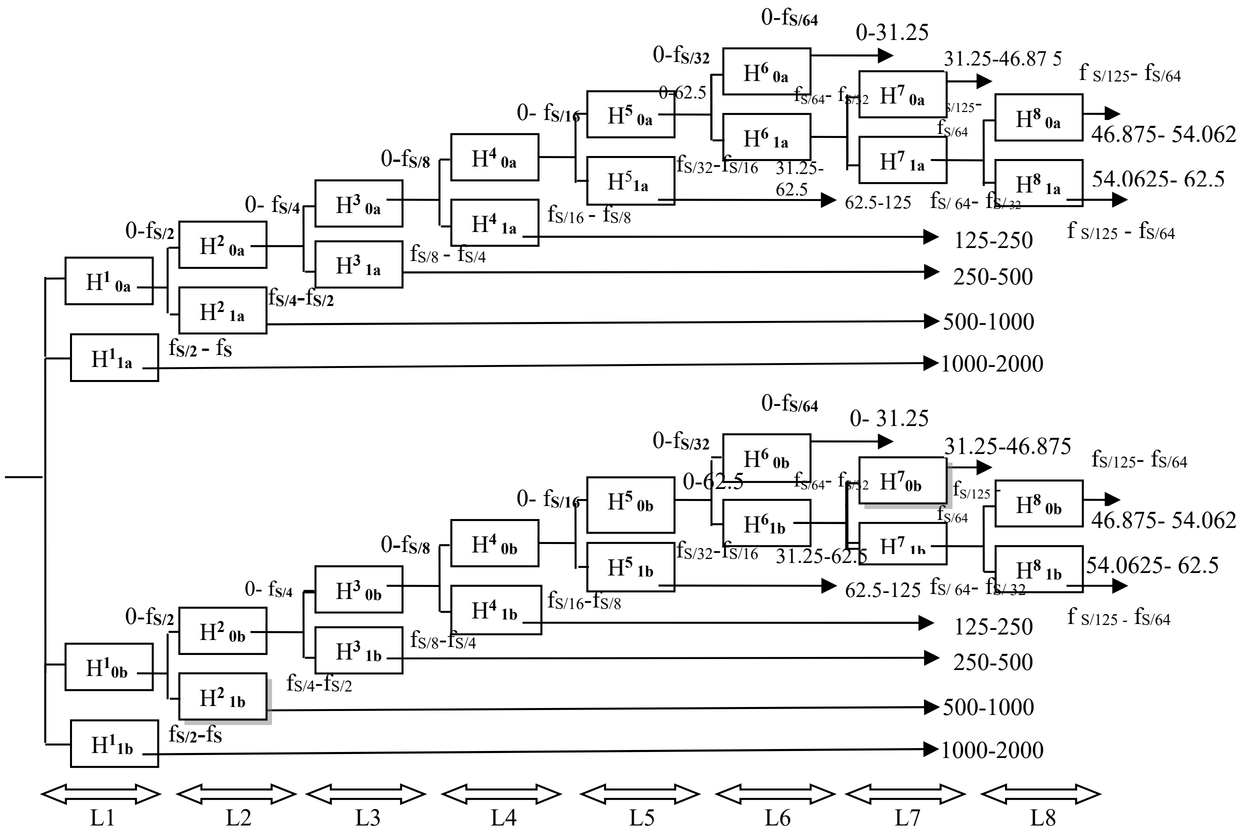

Figure 3 DTCWT algorithms to capture PQ disturbances