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Application of Random Forest and Hidden Markov Models for Automatic and Fast Classification of Power Quality Signals

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Abstract*: *In this paper, wavelet transform, namely the maximal overlap discrete Wavelet Transform (MODWT) and the second generation Wavelet Transform (SGWT) have been implemented. These wavelet transforms are applied to get selected features of the signals. Features are used as inputs to two types of classifiers namely, Hidden Markov Model (HMM) classifiers and the Random Forest (RF) classifier in the both absence and presence of Noise to evaluate the efficiency. The classification accuracy (CA) calculated using these classifiers clearly shows that the RF classifiers is a better classifier then the HMM classifier as it possess higher recognition rate at all levels of noise along with the pure PQ signals. Another important property of RF classifier is the proper classification of large number of class of both slow and the fast disturbances.

***Keywords:* Hidden Markov Model , Maximal Overlap Discrete Wavelet Transform, Power Quality Disturbance, Random Forest, Second Generation Wavelet Transform.**

I. INTRODUCTION

Supply of clean and stable power has become an important issue in the power system. The improvement of the quality of supply power, different disturbances are identified and remedies are taken to eliminate it in the system. The identification of power quality (PQ) signals are the more important aspects in analysis of power quality for the mitigation of the disturbances as soon as possible.

In order to expel the disturbances, the different techniques such as the Fourier transform (FT), the short-time Fourier transform (STFT), wavelet transform (WT), Neural Network, Fuzzy logic, S-transform have been used [1]-[4]. The FT only provides frequency information. So, FT is not convenient technique in the transient signal analysis. Similarly, the time frequency information of the distorted signal (stationary signals) can be easily obtained in STFT introduced by Gaber [5]. But, the most commonly used STFT only characterizes the properties of the signals providing the frequency as well as the time information and is fail to track the transient signals properly [6].

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The wavelet transform affords the time-scale analysis of the non-stationary signal. WT based on Multi-Resolution Analysis (MRA) property [7]-[9].

Moreover, WT is capable for detection and localization of disturbances providing time-frequency information. In this paper, the variants of WT namely the Maximum Overlap Discrete Wavelet Transform (MODWT) [10]-[13] and the Second Generation Wavelet Transform (SGWT) [14], [15] have been deployment. The features dataset extracted from the coefficients are fed for categorization of the distorted signals.

The fast detection of the PQD and the determination of the classification accuracy are the important indicator. However, commonly used automated classification techniques are based on the Artificial Neural Network (ANN) [16]-[18], fuzzy and neuro-fuzzy systems [19]-[21]. But the main drawback of ANN based classifier is retraining requirement. However, the construction of a rule based classifier is tedious job. So the Hidden Markov Model (HMMs) has been introduced to classify the large number of fast transient phenomena, but the HMMs is unsuitable to categorize the slow phenomena [22]-[25].

The Random forest (RF) is selected because it categorize both the fast and slow phenomena unlike the HMM [26].

The paper is organized as follows. Section II explains about MODWT and SGWT and the Section III concern with the feature extraction and two types of classifiers used in computing the classification accuracy. The Section IV has carried out the process of detection using the theory described in the section II. The Section V has used the features extraction theory and the two classification methods described in section III to compute the classification accuracy (CA). Finally, the Section VI has been concluded this paper.

II. APPROACH FOR LOCALIZATION

The MODWT and SGWT have been implemented to decompose the PQ disturbances. These have been explained briefly in this section.

A. Maximum Overlap Discrete Wavelet Transform

Good The main motivation to develop the MODWT is the capability of the free selection of a starting point of signal. The efficiency of DWT degrades due to invariance translation. The MODWT is the brother of the conventional WT.

Signal of any sample size can be analyzed by MODWT whereas DWT can only apply to
the signal length N to be an intermultiple of 2^j where j=1,2 3,….J is the scale number[12],[13]. The MODWT scaling filter $\tilde{h}_l$ and the wavelet filters $\tilde{g}_l$ are related with the DWT filters through $\tilde{h}_l = \frac{h_l}{\sqrt{2}}$ and $\tilde{g}_l = \frac{g_l}{\sqrt{2}}$. The filters of MODWT are quadrature mirrors and are as follows

$$\tilde{g}_l = (-1)^{l+1}\tilde{h}_{L-1-l}$$

$$\tilde{h}_l = (-1)^{l+1}\tilde{g}_{L-1-l}$$

Where l=0,1,2,3,………,L-1. L is the width.

The *n*th element of the first stage scaling coefficients and first-stage MODWT with X (n) can be given as

$$\tilde{W}_{1,n} = \sum_{l=0}^{L_1-1}\tilde{h}_l X_{n-l \bmod N} \quad (1)$$

$$\tilde{V}_{1,n} = \sum_{l=0}^{L_1-1}\tilde{g}_l X_{n-l \bmod N} \quad (2)$$

where n=1,2,3, ………..N-1, N is the length..

The first-stage approximations and details can be calculated by the equations (3) and (4)

$$\tilde{A}_{1,n} = \sum_{l=0}^{L-1}\tilde{g}_l \tilde{V}_{1,n+l \bmod N} \quad (3)$$

$$\tilde{D}_{1,n} = \sum_{l=0}^{L-1}\tilde{h}_l \tilde{W}_{1,n+l \bmod N} \quad (4)$$

The scaling and wavelet coefficients of the *j*th stage (at the *n*th element) can be written by the equations (5) and (6)

$$\tilde{V}_{j,n} = \sum_{l=0}^{L_j-1}\tilde{g}_{j,l} X_{n-l \bmod N} \quad (5)$$

$$\tilde{W}_{j,n} = \sum_{l=0}^{L_j-1}\tilde{h}_{j,l} X_{n-l \bmod N} \quad (6)$$

Similarly, $\tilde{A}_j$ as well as $\tilde{D}_j$ of the *n*th element of the *j*th stage are given by the equations (7) and (8)

$$\tilde{A}_{j,n} = \sum_{l=0}^{L-1}\tilde{g}_{j,l} \tilde{V}_{1,n+l \bmod N} \quad (7)$$

$$\tilde{D}_{j,n} = \sum_{l=0}^{L-1}\tilde{h}_{j,l} \tilde{W}_{1,n+l \bmod N} \quad (8)$$

where { $\tilde{g}_l^{o}$} is periodized { $\tilde{g}_l$} to length *N* and also the { $\tilde{h}_l^{o}$} is periodized { $\tilde{h}_l$} to length *N*.

So the considered original time series signal can be stated as follows

$$X(n) = \sum_{l=0}^{j}\tilde{D}_j + \tilde{A}_j \quad (9)$$

However, the original signal can be retrieve easily from the decomposed signals.

The SGWT is faster than DWT. The memory consumption SGWT is less than the MODWT.

B. Second Generation Wavelet Transform

The Lifting scheme (LS) based SGWT is similar to DWT. The SGWT operation based on iterations of the three stage such as split, predict and update [14], [15], [30] as represented in Fig.3.

Split: In the analysis of SGWT, first the signal S[n] is divided into two disjoint subsets. This local correlation is of the disjoint sunset described below.

$$S[n] = X[n]_{even} + Y[n]_{odd} \quad (10)$$

Predict: The details of the original signal S[n] are determined as given in (11). By applying the predictor operator, Y[n] can be envision from X[n]. P is the predictor operator.

$$d[n] = Y[n] - pX[n] \quad (11)$$

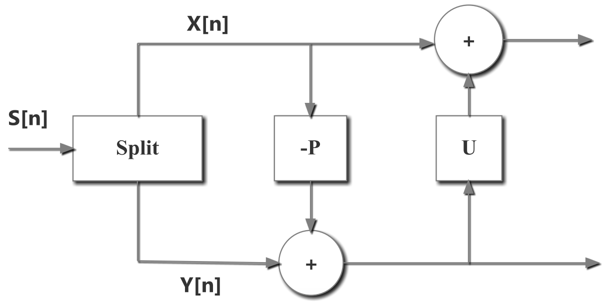

Fig.2 Basic Block diagram for SGWT decomposition

Update: The approximation coefficients of S[n] can be found by using (12). The U is deployed to the details and the output is summed with X[n]. Where U is the update operator.

$$C[n] = X[n] + U(d[n]) \quad (12)$$

The achieved approximation at level one is used to repeat the process.

III. THEORY OF FEATURE EXTRACTION

Feature extraction

After the PQD signals are detected by the MODWT and also the SGWT, the approximate and detailed coefficients are found at every of the decomposition levels using the wavelet. Using these coefficients, four features namely the energy, the mean, the standard deviation and the entropy are extracted. These obtained parameters nourish as input to classifiers to reduce the size of raw data. The equations for the same are given below [27], [28].

$$\text{Energy } ED_i = \frac{1}{N}\sum_{j=1}^{N}\left|D_{ij}\right|^2 \quad (13)$$

$$\text{Mea } \mu_i = \frac{1}{N}\sum_{j=1}^{N}D_{ij} \quad (14)$$

$$\text{Standard deviation } \sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}\left(D_{ij}-\mu_i\right)^2\right)^{1/2} \quad (15)$$

$$\text{Entropy } ENT_i = -\sum_{j=1}^{N}D_{ij}^2\log\left(D_{ij}^2\right) \quad (16)$$

Total energy

$$E_{Total(i)} = \sum_i |C_{ij}|^2 + \sum_{j=1}^{N}\sum_i |D_{ij}|^2 \quad (17)$$

Where i=1, 2, 3…………………..l. (level of decomposition).

Similarly N is the number of samples. Disturbance signals such as like the sag, the swell, the sag with harmonics and the swell with harmonics can be distinguished by the standard deviation curve, the other signals fail. So, the obtained features are fed to the classifiers. These classifiers are discussed below

IV. CLASSIFICATION APPROACH

The parameters collected has been used as inputs to the classifiers. The total 34000 numbers of signals has been simulated. At each level of decomposition data are normalized with the maximum value to formulate the dataset. For each classifier out off 100% data, 70% of the total data are implemented for training of model and 30% are implemented for testing.

Hidden Markov Model: After the disturbances are detected the features vectors are extracted, the HMM is applied to determine the maximum likelihood in the data set. The HMM, being the extension of the Markov model. However, an HMM can be represented as $\lambda = (N, M, \pi, A, B)$ where the parameter N denotes the number of states of the model, M is the number of distinct observation, π is considered as the initial state distribution vector, similarly, A denotes the state transition probability and finally B is observation probability matrices. A discrete HMM is explained in [22] through the model of individual states.

Like the other classifiers, the HMMs operation is partitioned into the training and the testing stage of the dataset. In this study, ten different HMMs are trained for ten disturbance classes. For this classification process, the logarithmic probability is determined for the unknown input signals. In order to develop a proper HMM, the selection of the optimum number of state and the density function are very important but there is no explicit rule for the selection of these factors except the application type and the parameters. In this work, three states are selected to stipulate the output with the Gaussian mixtures function. The prior distribution is used over the state transition to favour the transitions to stay in the same state. The prior is multiplied by the likelihood function and then normalized according to the Bayes theorem. In this work, for each dataset 10 models are constructed for ten disturbance classes with eight-Gaussian mixtures and three-states. The CA [29] depends on the number of matching is given in the equation (18)

Classification Accuracy (%)

$$= \frac{No.of\ samples\ correctly\ classified}{Total\ no.of\ samples\ in\ the\ data\ set} \times 100 \quad (18)$$

But the HMMs fails to analysis the slow disturbance signals. Moreover, these double stochastic HMMs are not suitable for all the disturbance classes with large number of input variable which motivate to introduce RF for the classification of large number of datasets. The over fitting problem has no rule in RF, so it possesses very high classification accuracy, and has the ability to model complex iterations among predictor variables and is the flexible for the statistical data analysis. So these unique virtues make the RF as a novel method for the classification of multiple disturbances simultaneously [26].

Random Forest:

The Random forest is a fast classifier, which fits many classification trees [26], [30]. In RF, the classification trees construct the rule. At each step, an optimization is done to select a node. So, the validation is not required in RF model. The splitting process continues till a constant Gini index is obtained. The final regions are called the leaf node which carries the result. The working process RF is follows the steps as.

- Select many bootstrap samples (i.e 500) from the dataset.
- Consideration of the observation of the out-of-bag.
- Prediction of the out-of-bag observations for each fully grown tree.
- Calculate the predicted class of observation by calculation.
- Calculation and average the accuracies and error rates.

In this paper, Gini Diversity Index optimization is carried out to reduce the node impurity and can be represented as

$$\sum_{m=1}^{M} \hat{P}_{mn}(1-\hat{P}_{mn}) \quad (19)$$

Where, M is the number of classes. $\hat{P}_{mn}$ is the proportion of patterns.

V. RESULTS OF DETECTION

The decomposed wave forms and the corresponding expiations for the pure sine wave with sag, sine wave with swell and swell with harmonic etc are shown below.

- Pure sine wave with sag:

A pure sinusoidal voltage signal with swell has been considered. Signal is decomposed up to 4th levels employing MODWT and SGWT. These decomposed levels are shown in Fig.2 (a) and Fig.2 (b) respectively.

Table.1 Class labels for PQD signals

PQD signals	Class labels
Sag	CL1
Swell	CL2
Interruption	CL3
Oscillatory transient	CL4
Flicker	CL5
Harmonic	CL6
Sag+harmonics	CL7
Swell+harmonics	CL8
Notch	CL9
Spike	CL10

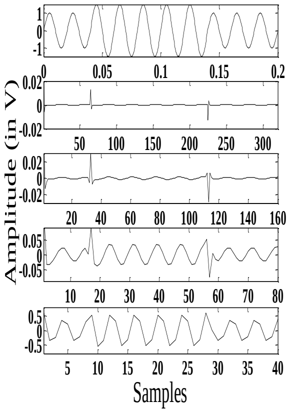

Fig.2 (a) Localization of swell using MODWT

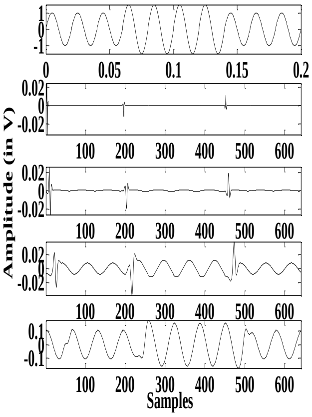

Fig. 2(b) Localization of swell using SGWT

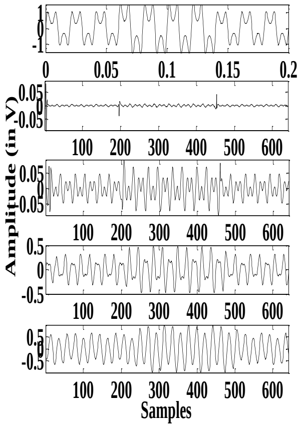

Fig.3(a) swell harmonics Localization using SGWT

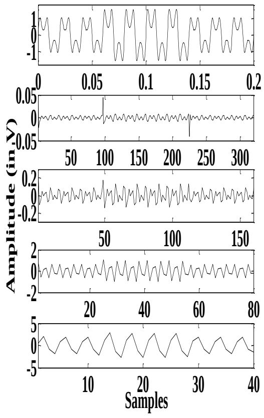

Fig. 3(b) swell harmonic localization using MODWT

The horizontal axis i.e x-axis represents the time in terms of samples and the vertical axis i.e y-axis represents the magnitude. The initial point and the end point of the disturbances of each decomposition levels in SGWT decomposition are at the same alignment with that of the considered signal. In MODWT decomposition, the first level waveform and original siganal are at same the alignment but the other decomposition levels are shifted towards right. This shifting is due to the property of circular shifting. The MODWT decomposition also point out the shifting of the signal initial points.

The decomposition using both SGWT and MODWT of swell with harmonics signal is presented in Fig.3. In Fig 3. (a) MODWT gives the shifting of the initial point of the signal, that's why the initial point of disturbance are also shifted due to property of the circular shifting. But in SGWT all are at same alignment irrespective of level numbering.

Similarly, the rest eight types of PQ disturbances are the processed using the MODWT and the SGWT.

VI. RESULTS OF CLASSIFICATION

The automated classifiers are easy to implement than the traditional ANN based classifier.

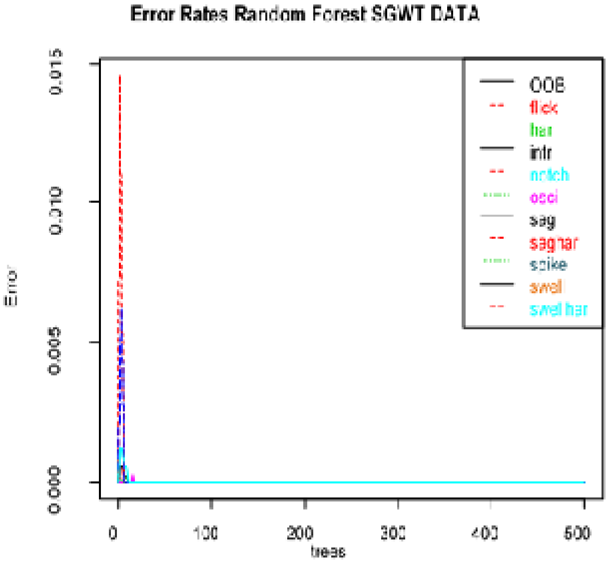

Fig.4 Error of RF using SGWT decomposed data

In the Fig.4, flick: flicker, har: harmonic, intr: interruption, osci: ocsillation

The classification accuracy computed using the automated HMMs and the RF model are presented. The implementation of HMMs and RF first associate with the training phase. During this phase, a model is built for each disturbance.

The input parameters to RF operation are the input data, tree number. The input data set are categorized at each split by 5 variables.

The OOB (out of bag) error of RF model is the proportion of misclassified data. The OOB error rate with 500 tree of RF using SGWT extracted data is 0% and the maximum error rates is 0.004 as shown in Fig. 4. For each of the tree in Fig.4, the error obtained for a constant Gini value is plotted.

With the Gini values shown in Fig.5, the trees are optimized for SGWT based data set. In RF the output patterns are trained till a constant value of Gini Diversity Index is obtained. This constant value provides fully grown tree with higher classification accuracy. The figure shows the results for Tree 1 in the absence of noise, similarly this procedure can be repeated for rest of trees the signal with the different level of SNR or without SNR. When a tree reaches the constant Gini Index, then all the trees has given same CA value. The CA of ideal PQD signals is given in Table.2.

For each dataset classification, 30% of the total input are reserve as the testing sets. These data are applied to compare with the build training model. The Table.2 shows the computed values of the CA by employing the two WT and the two classifiers.

The last row from Table.2 to Table.7 is the average CA of all the ten classes. Similar procedure is carried out to obtain (Table.3 to Table.7) CA when the PQD signals are added with AGWN of different noise levels.

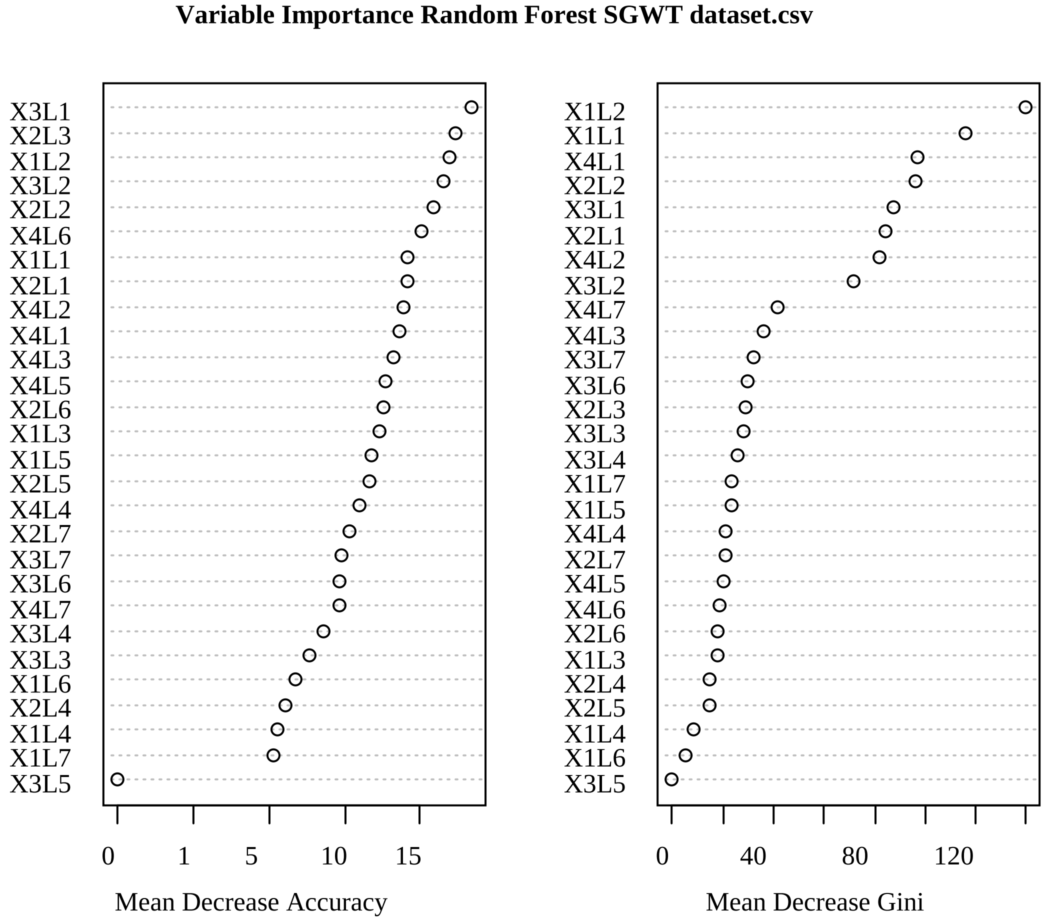

Fig. 5 Mean decrease of Gini and Accuracy

Table.2 CA (%) of pure signals

CLASS	MODWT		SGWT	
	HMM %(CA)	Random Forest %(CA)	HMM %(CA)	Random Forest %(CA)
CL1	75.21	98.64	92.60	99.05
CL2	99.56	98.75	80.82	98.76
CL3	0	100	34.36	100
CL4	98.36	100	99.97	100
CL5	93.3	100	83.43	100
CL6	47.61	100	33.03	100
CL7	43.32	100	73.91	100
CL8	73.60	100	95.94	100
CL9	100	100	96.10	100
CL10	98.33	100	100	100
Total	72.92	99.73	79.01	99.78

Table.3 CA (%) of signals with 40dB noise

CLASS	MODWT		SGWT	
	HMM %(CA)	Random Forest %(CA)	HMM %(CA)	Random Forest %(CA)
CL1	95.21	99.25	92.6	98.59
CL2	84.65	97.57	78.97	94.93
CL3	0	100	29.47	100
CL4	100	100	99.97	100
CL5	81.36	100	100	100
CL6	45.61	100	33.34	100
CL7	51.48	100	55.66	100
CL8	78.65	100	99.04	100
CL9	99.18	100	95.88	100
CL10	83.6	100	100	100
Total	71.97	99.58	78.49	99.35

Table.4 CA (%) of signals with 35dB noise

CLASS	MODWT		SGWT	
	HMM %(CA)	Random Forest %(CA)	HMM %(CA)	Random Forest %(CA)
CL1	94.78	100	92.6	98.13
CL2	98.77	99.69	81.95	94.3
CL3	0	95.90	23.89	100
CL4	100	100	99.95	100
CL5	80.71	100	98.1	100
CL6	4.15	100	34.06	100
CL7	47	100	54.88	100
CL8	46.13	100	94.55	100
CL9	99.18	100	96.92	100
CL10	84.42	100	99.59	100
Total	65.51	99.55	77.64	99.24

Table.5 CA (%) of signals with 30dB noise

CLASS	MODWT		SGWT	
	HMM %(CA)	Random Forest %(CA)	HMM %(CA)	Random Forest %(CA)
CL1	94.78	97.64	92.6	98.13
CL2	84.65	97.29	86.72	94.26
CL3	0	100	0	100
CL4	100	100	99.98	100
CL5	77.63	100	97.82	100
CL6	1.71	100	31.08	100
CL7	47.78	100	46.03	100
CL8	45.64	100	93.94	100
CL9	99.18	100	96.92	100
CL10	92.21	100	98.77	100
Total	64.35	99.48	74.38	99.23

Table.6 CA (%) of signals with 25dB noise

CLASS	MODWT		SGWT	
	HMM %(CA)	Random Forest %(CA)	HMM %(CA)	Random Forest %(CA)
CL1	94.04	97.24	92.57	98.5
CL2	84.65	97.6	92.81	98.12
CL3	0	100	0	100
CL4	100	100	100	100
CL5	72.42	99.93	94.4	95.05
CL	2.56	100	32.02	100
CL7	47.54	100	44.24	100
CL8	41.17	100	94.17	100
CL9	100	100	93.03	100
CL10	98.53	100	98.97	100
Total	64.09	99.41	74.22	99.16

Table.7 CA (%) of signals with 20dB noise

CLASS	MODWT		SGWT	
	HMM %(CA)	Random Forest %(CA)	HMM %(CA)	Random Forest %(CA)
CL1	93.04	97.69	92.16	97.64
CL2	91.03	86.95	87.35	94.64
CL3	0	97.57	0	99.64
CL4	100	100	100	100
CL5	80.74	97.74	82.13	98.91
CL6	1.07	100	29.9	100
CL7	34.40	100	51.57	100
CL8	55.94	100	91.85	100
CL9	93.03	100	100	100
C10	91.07	100	100	100
Total	64.03	97.99	73.49	99.04

These above tables (Table.3-Table.7) provide the classification accuracy computed using the two classifiers absence and presence of the noisy environment. The same data sets are fed to the two classifiers but the CA of HMM is very poor for interruption and harmonics like slow disturbances for both the SGWT and MODWT analysed dataset. The Tables has been demonstrated that the CA values of RF are higher for each signal class in every dataset as compared to HMMs. The RF has the ability to model complex iterations among predictor variables is also flexible for statistical data analysis. RF classifier recognizes all the signals properly for both MODWT and SGWT based data set in noisy as well as noiseless environments.

VII. CONCLUSION

The discrimination of the power quality disturbances is a vital task for smooth monitoring of the deregulated power system. In this paper, the MODWT and the SGWT are used to pin down the disturbances present in sinusoidal signal. Moreover, the useful features of the ten types of PQ disturbances have been extracted using the wavelet based signal processing in noiseless and noisy conditions. The CA of the two automatic classifiers based on maximum likelihood is presented in this paper to manifest the better recognition rate. The recognition rate and performance of the RF classifier is better for slow as well as the transients as compared to HMM classifier. RF successfully classified combined disturbances. Moreover, the simulation outcomes concludes that the RF can discriminates huge figure of classes efficiently.

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