Cross-Correlation and Canonical Correlation Aided Feature Extraction and Classification of Power Signal Disturbance

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Abstract— Electrical energy generally produces from non-renewable energy resources like coal. Its wastage is undesirable. Electrical utility companies try to put restriction on usage of electrical energy. But disturbance in electrical power signal is inevitable. Its mitigation is hectic. Its protection can be taken to prevent electrical hazards. Different electrical disturbance has different protection technique, hence it is vital to identify the type of faults occurring in electrical power signal. Continuous monitoring of electrical power signal is important to keep track on variables of electrical quantities. Here, soft computation technique is employed to classify faults. Multiple electrical disturbances are classified here.

Keywords—*voltage disturbance, correlation, classification*

I. INTRODUCTION

Industrialization indulges use of sophisticated electrical equipments for development of different sectors of a county's economy. The economic development reflects the ranking of a country worldwide in respect to development. Hence, reliable operation of electrical equipments is necessary for the fast growing world. Electrical power signals should have lower disturbances for smooth operation of electrical equipments. Researchers are step ahead to mitigate electrical faults. Detection of faults is a very indispensible task. Engineers are curious about the effects of electrical faults so earlier detection is necessary. Since, different faults have their respective mitigation technique so a smart relay should be used which can detect type of fault and send a trip signal to smart circuit breaker to protect healthy part from faulty part of power system. [1] detects electrical disturbance using time warping classifier. Acceleration of classification is achieved by vector quantization. Walsh transform and fast Fourier transform technique are used for extraction of features. This method has better classification result than traditionally artificial neural network and fuzzy logic controllers though it is less sensitive to noisy electrical disturbance. Subsequent years has proof a method of localization and classification of short duration disturbances in power networks using phase-corrected wavelet transform known as S-transform and extended Kalman filter in [2]. It has time-frequency resolution characteristics and provides detection, localization and visual patterns perceptible for automatic recognition of automatic classification of electrical faults. Ömer Nezih Gerek et. al attempts to detect electrical disturbance having feature vector composed of selected features like, local wavelet transform at various decomposition levels, spectral harmonic ratios local extrema of higher order statistical parameters in [3]. The method shows a lower detection accuracy of approximately 70%. [4] has classification accuracy of 98.5% using the S-transformation technique. Features like No. of main frequency, No. of peak in standard deviation (STD)curve, No. of peaks in high frequency of (STD) curve, mean of power disturbance signal and a composite feature after S-transformation of power disturbance signal. Ameen M. Gargoom et.al.in [5] classifies electrical disturbances using multi-resolution S-transform and Parseval's theorem. Energy of these vectors are used to classify disturbance signal using Parseval's theorem. Fast variant of S-transform algorithm for extraction of relevant features are used to distinguish different electrical signal deviations by a fuzzy decision tree based classifier in [6]. Fast dynamic S-transform is used to for appropriate time-frequency localization, decision tree algorithm finds its use in selection of optimal features and fuzzy decision rules complements overlapping patterns. It has an accuracy rate of 98.6% for classifying electrical distortion with 40 dB noise level.

The coming years have several sophisticated and delicate technique to detect electrical faults. Swati Banerjee *et. al.* in [7] successfully classifies ECG signal based on features extraction from cross-wavelet transformation. Cross-wavelet transformation is used for analysis of different stationary ECG signals. It incurred detection precision of an ECG signal class of 97.6%.

Sovan Dalai *et.al.* in [8] successfully selects the optimal features from cross-correlation sequence between PQ disturbance signal and power signal of fundamental frequency(50Hz). Several signals with single fault and combination between different fault signals are used to generate other different categories of fault signals using simulation software (MATLAB). Their work emphasize on successful extraction of 12 features namely maximum value of correlation sequence, index value of correlation sequence**,** equivalent width**,** centroid**,** absolute centroid**,** root mean square depth**,** mean value of correlation, standard deviation, skewness of correlation sequence, kurtosis of correlation and PQ disturbance signal. Rough set theory is used as it successfully selects optimal features from a situation where knowledge of features is less and also redundant features exist.

Condition attributes is tabulated containing the features from correlation sequence of PQ disturbance signal and power signal of fundamental frequency. Decision attribute is created based on rough set theory concept. Their proposed approach has the classification accuracy of 97.10%.

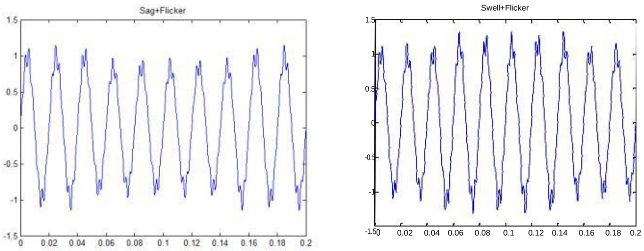
Shufan He *et. al.* in [9] uses hybrid method based on S-transform and dynamics. Hybrid method primarily dynamics to identify the signal components in frequency spectrum of Fourier transform and uses inverse Fourier transform to some signal components. Features are extracted from Fourier transform, S-transform and dynamics and decision tree is used to classify the faults. Reduction of Heisenberg's uncertainty is achieved by windowing signal components by different Gaussian windows, results in better adaption and flexibility. DSP-FPGA hardware platform is used to test run time and justification of the proposed method.

Martin-Valtierra Rodriguez *et. al.* in [10] proposed a new method of classifying single and multiple electrical disturbances using dual neural network. It uses adaptive linear network for estimation of harmonic and inter-harmonic for computation of root mean square voltage and total harmonic indices. These indices are used to classify sag, swell, outages and harmonic and inter-harmonic disturbances whereas feed-forward neural network is used to recognize pattern of identification of spike, flicker, notch and oscillatory transients from vertical and horizontal histograms of specific voltage waveform. It reaches classification of accuracy of 98% for noiseless signal and 90% for contamination of 20dB SNR noise level.

Zhigang Liu *et. al.* in [11] develops a combination method for recognition of complex electrical disturbances based on ensemble empirical mode decomposition and multi-label learning. EEMD is used to extract features suitable for non-stationary disturbance in signals. Rank wavelet support vector machine is finds its application in classification of electrical distortion. Features are extracted from complex disturbance using EEMD by defining standard energy difference of each intrinsic mode function. Optimization of rank based SVM based of wavelet kernel function ranking function and multilabel functions are prepared.

II. GENERATION OF ELECTRICAL DISTURBANCE

Standard of IEEE 1159-1995 is used to generate electrical disturbance. Mitigation methods of composite electrical disturbance are quite difficult hence here classification of composite electrical disturbances presented. MATLAB simulation software is used to generate samples of electrical faults using IEEE 1159-199 standard.



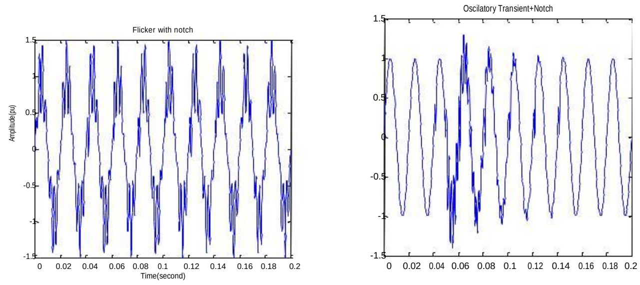


Fig. 1 Generated composite electrical disturbance

Several other composite faults are also generated but their graph is not presented due space scarcity. The table below shows type of electrical disturbance with their associated class used in the method of classification.

TABLE I. LIST OF ELECTRICAL DISTURBANCE WITH CLASS

Sl. No.	DISTURBANCE DESIGNATION	CLASS
1	SAG WITH HARMONICS	1
2	SWELL WITH HARMONIC	2
3	SAG WITH NOTCH	3
4	SWELL WITH NOTCH	4
5	FLICKER WITH NOTCH	5
6	OSCILLATORY TRANSIENT WITH NOTCH	6
7	HARMONIC WITH OSCILLATORY TRANSIENT	7
8	SAG WITH OSCILLATORY TRANSIENT	8
9	SWELL WITH OSCILLATORY TRANSIENT	9

Here only nine composite electrical disturbances have been considered. Other several combination of electrical disturbance can also be used. As this may take more unnecessary computational time for identification of fault, only nine classes of electrical distortions are considered.

III. FEATURE EXTRACTION TECHNIQUE

Several features extraction techniques are used earlier. Cross-correlation and canonical correlation techniques are used to extract total fourteen different features from electrical fault using signal processing technique. Twelve features are extracted from cross-correlogram of normal electrical power signal and disturbance signal whereas two other features are extracted from canonical correlation of two power signal and disturbed signal.

CROSS-CORRELATION

When the two different signals are correlated with provision of arbitrary lag to the sample of disturbance signal, the resulting sequence is called cross-correlation sequence.

$$C_{xy(m)} = \sum_{n=0}^{N-m-1} X_{n+m} X_n,\ m \geq 0$$

$$C_{xy(-m)} = 0,\ m < 0$$

Where m indicated the shift parameter of correlation sequence and $C_{xy(m)}$ indicates the cross-correlation sequence of the signal. If the signal has N no. of samples, then the correlation correlation sequence would have (2N-1) no. of samples.

The table below shows the list of extracted features from cross-correlogram.

CANONICAL CORRELATION

Canonical correlation seeks for linear combination of cross-correlation between two random sets of variable. Here two sets of random values are normal power signal and faulty electrical signal. The method of solution is done y solving Cauchy-Schwarz's inequality. If two set of vectors (here power and disturbed signal respectively) are collinear if two signals are equal. It is known two values of vectors are not equal therefore two relevant features can be extracted from canonical cross-correlogram. Two features are linear combination of values composing of both the signals. The table below shows the extracted features from cross-correlogram and canonical cross-correlogram of normal power signal and disturbed power signal.

TABLE II EXTRATED FEATURES FROM DISTURBED SIGNAL

Sl. No.	Feature Index	Feature Designator
1	F1	Maximum value of correlation sequence
2	F2	Index of the maximum value of correlation sequence
3	F3	Equivalent width of correlation sequence
4	F4	Mean value of correlation sequence
5	F5	Standard deviation of correlation sequence
6	F6	Skewness of correlation sequence
7	F7	Kurtosis of correlation sequence
8	F8	Variance of disturbance signal
9	F9	Kurtosis of disturbance signal
10	F10	Kurtosis of correlation coefficient
11	F11	Variance of disturbance signal
12	F12	Kurtosis of disturbance signal
13	F13	Linear combination of normal power signal
14	F14	Linear combination of disturbance signal

The above listed features are used to form a feature matrix for each class of disturbance signal.

IV. CLASSIFICATION TECHNIQUE

Several classification techniques are used earlier to improve better classification accuracy. Artificial Neural Network (ANN), k Nearest Neighbour (kNN), Support Vector Machine (SVM) etc. are utilized to classify electrical faults. The paper presents Probabilistic Neural Network (PNN) to classify fault. PNN is derived from Bayesian network. It is feedforward neural network. The mechanism is organized in a multilayer feedforward networks with four layers.

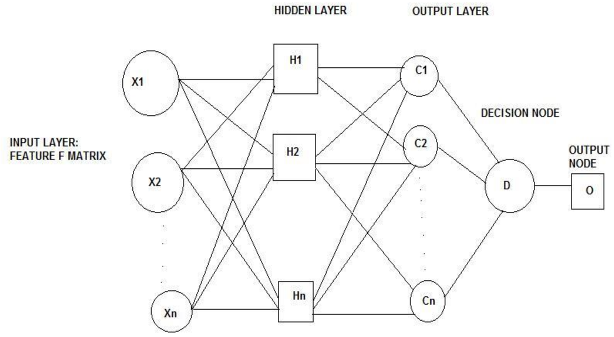


Fig.1 Basic architecture of PNN

The above figure shows fundamental architecture of PNN. The later portion includes discussion about classification accuracy of the disturbance signals by PNN method of classification. PNN takes also less computational time for extraction fo features necessary for classifcation of electrical faults.

V.RESULT

The confusion matrix below shows relative classification accuracy between different class of fault signals.

TABLE III. CONFUSION MATRIX USING PNN METHOD

CLASS	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	6 (%)	7 (%)	8 (%)	9 (%)
1	95	0.9	0	0	3.5	0	0	0.6	0
2	12	80	0	2	0	3	2	1	0
3	0	0	99	0	0	0	1	0	0
4	0	7	0	91	0	0	0	0	2
5	0	0	0	0	100	0	0	0	0
6	8	0	4	0	0	87	0	0.1	0.9
7	0	0	0	0	0	0	100	0	0
8	0	8	2	2.8	1.2	3	0	80	3
9	0	4	3	0	3	2	7	0	81

The above table concludes a average classification accuracy of 99%. 900 samples for each class are used to train the PNN first. Then 600 samples for each class of disturbance are usd to test for validation of classifcation accuracy. PNN shows target of ‘1’ with proper classification whereas ‘0’ for wrong classification. The PNN is also trained with different noise level (dB). The below table shows the classification accuracy corresponding to different noise levels is given below.

TABLE IV. CLASSIFCATION ACCURACY WITH NOISE LEVEL

Sl. No.	NOISE LEVEL (dB)	CLASSIFICATION ACCURACY (%)
1	15	98.6
2	25	98.3
3	35	97.8
4	50	97

VI. CONCLUSION

The result shows that electrical signals without noise have better classification accuracy the noisy electrical signal. This is due the features vary much in values with noise introduction. This effect is dominant with higher noise levels. Feature reduction technique can be used to increase computational time as feature matrix has reduced dimension than earlier. Classification takes lesser time and relay sends the trip signal to circuit breaker faster than earlier. Thus relays become smarter but they become expensive.

VII. REFERENCES

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