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A Novel Technique for Ferroresonance Identification in Distribution Networks

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***Abstract*—**Happening of Ferroresonance phenomenon is one of the reasons of consuming and ruining transformers, so recognition of Ferroresonance phenomenon has a special importance. A novel method for classification of Ferroresonance presented in this paper. Using this method Ferroresonance can be discriminate from other transients such as capacitor switching, load switching, transformer switching. Wavelet transform is used for decomposition of signals and Competitive Neural Network used for classification. Ferroresonance data and other transients was obtained by simulation using EMTP program. Using Daubechies wavelet transform signals has been decomposed till six levels. The energy of six detailed signals that obtained by wavelet transform are used for training and trailing Competitive Neural Network. Results show that the proposed procedure is efficient in identifying Ferroresonance from other events.

***Keywords*—**Competitive Neural Network, Ferroresonance, EMTP program, Wavelet transform.

I. Introduction

WAVELET Transform (WT) has been introduced rather recently in mathematics. It is linear transformation much like the Fourier transform, however it allows time localization of differences frequency components of a given signals; Short Time Fourier Transform(STFT) also partially achieves the same goal, but the fixed width windowing function is a limitation. In the case of wavelet transform, the analyzing functions called wavelets, will adjust the time width to the frequency in such a way that high frequency wavelets will be very narrow and lower frequency ones will be broader. In order to detection of accidental events in Power Systems, different signals are noticed. On of signals is Power Quality signals in witch different ways of classification about this matter in articles are published. For example Kalman Filter System[1], Short time-filter Fourier Transform[2], Fuzzy Expert Systems for classification of Power Quality Signals[3], automatic classification based on extraction of characteristics of wavelets[4], Bayesian classification[5], Neural Networks[6] and Hidden Markov Model[7]. The other group that many articles are published about them, are High Impedance Fault.

In time-domain, ratio group relay ways and proportional relay algorithm[8,9] were performed. In frequency-domain with the use of Fourier Transform methods based on harmonic components[10] and interharmonic components[11] are performed. In high frequencies, wavelet transform has a good time resolution and a weak frequency resolution. on the contrary, in low frequencies, it has a good frequency resolution and a weak time resolution. This property is useful about signals with high frequencies in short-time domains and low frequencies in long-time domains. In this paper a new Ferroresonance detection method that uses wavelet transform and competitive neural network is presented. Ferroresonance data was gathered from a 20kV radial distribution feeder in a real network. Transient state data was produced by simulation using EMTP program. A case study and data collection are explained in Section III. The wavelet transform and competitive neural network is introduced in Sections IV,V respectively and simulation results are shown in Section VI.

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II. Ferroresonance Phenomenon

Ferroresonance is a term in witch for description of resonance in a circuit with at least one non-linear inductive element. A Ferroresonance circuit includes series combination of saturable inductor, capacitor and linear resistor. The resonance in witch happens in circuits with saturable reactors is called Ferroresonance. In fact Ferroresonance is a non-linear event, so many ways used to analysis this event are based on time-domain analysis and using EMTP program. Ferroresonance has decaying effects on transformers and other equipments. Some of those effects are as follow: creating high voltages and currents, and disfigurement in voltage and current waveforms. For this reasons, the detection of Ferroresonance from other transients is very important. In this paper a new algorithm is used for detection of this event. By this algorithm we can predict some possibilities in happening Ferroresonance and so we can face it with making some relays that shown in Fig. 1.

III. Obtaining the Signals

In order to obtain the signals, a part of a 20kV feeder has been selected in Qeshm island which is illustrated in Fig. 2 [12]. These signals include: Ferroresonance, capacitor switching, load switching, and transformer switching signals. The models determined to be simulated by the EMTP software are, π and load frequency model (CIGRE), for line and load respectively, saturable model is used for all transformers. The inductor with hystersis loop of TYPE 96 was used for modeling hystersis loop in EMTP, which was connected to the

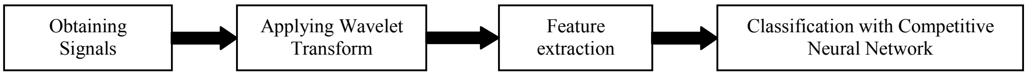

Fig. 1 Proposed algorithm

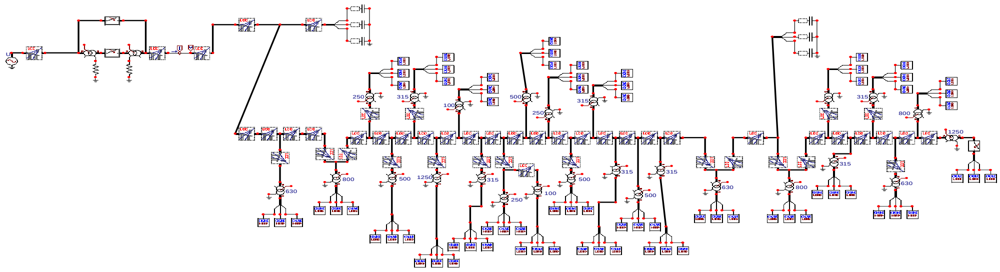

Fig. 2 20kV Feeder

outlet magnetizing branch of the transformer. The magnetization curve of the transformers is illustrated in Fig. 3. Feeder information is provided in the appendix. All kind of Ferroresonance that different parameters such as switching types, transformer connection type, hystersis phenomenon, line capacitance feature, line length and load impact which can be influential in the occurance of this phenomenon have been simulated. Fig. 4 illustrates a type of Ferroresonance which has been simulated by the EMTP. Different types of capacitor switching have been obtained through the switching of the two capacitor banks of the feeder in various forms. For example first capacitor bank was firstly switched, then the second one, next both at a time, and other forms can be achieved through the switching of one of the capacitor bank and then by switching a part of the feeder; an example is provided in Fig. 5. For simulating different types of load switching, we switch the loads in different arrangements. For example, we firstly switch them one at a time, then two at a time, and other arrangements can be achieved by switching one or two of the loads with a part of the feeder. Thus, different signals are obtained. An example of which is provided in Fig. 6. For simulating the transformer switching signals, we switch the transformers in different orders. For example, we switch the transformers one at a time, then two at a time, and different types can be achieved by switching one or two of the transformers with a part of the feeder. Thus, different signals are obtained. An example of which is provided in Fig. 7. This way, for each group of signals, 20 types can be obtained. Then we normalize (scale) them in the max-min range (0 to 1). This is very influential in the exact determination of the features and every pattern.

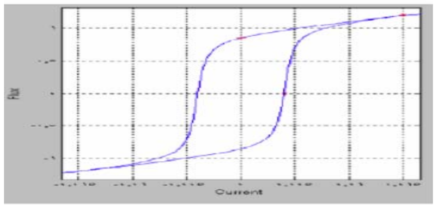

Fig. 3 Magnetizing curve

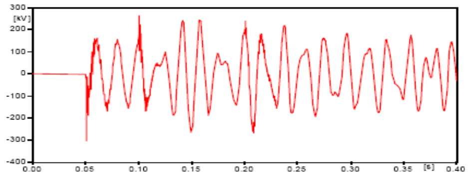

Fig. 4 An example of Ferroresonance

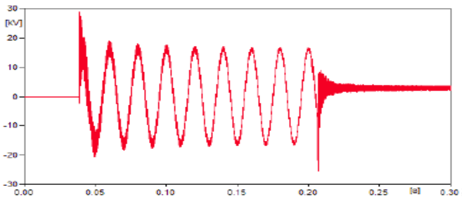

Fig. 5 An example of Capacitor switching

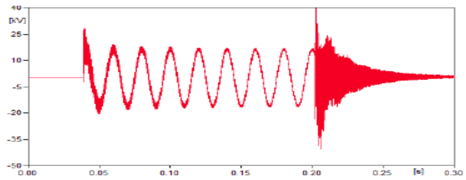

Fig. 6 An example of Load switching

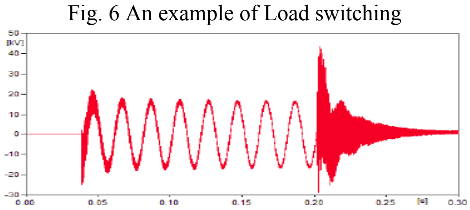

Fig. 7 An example of Transformer switching

IV. Wavelet Transform

The wavelet transform is a powerful tool in the analysis of transient phenomena because of its ability to extract time and frequency information from the transient signal. The theory behind wavelet analysis and the comparison with Fourier analysis has been documented in [13]. This section provides a brief explanation of wavelet analysis, and highlights important considerations. Wavelet analysis is a method of signal processing so that, after a series of decompositions, the signal is represented at different frequency ranges. This is achieved by dilation and translation of a mother wavelet over the signal. To process the data in a digital sense the discrete wavelet transform (DWT) is used which is given by:

$$DWT(m,n) = \frac{1}{\sqrt{a_0^m}} \sum_k x(k) g(a_0^{-m} n - b_0 k) \qquad (1)$$

The signal is decomposed into two other signals which represent a smooth and detailed version of the original signal, termed the approximation and detail respectively. This process is repeated with the approximation being decomposed further to generate the next approximation and detail. This operation is termed multiresolution signal decomposition (MSD). The frequency range of each detail (D) of the DWT is directly related to the sampling rate of the original signal [14]. These frequency ranges are referred to as scales of the wavelet transform due to their special logarithmic structure [15]. The number of decomposition levels (J) can be determined by:

$$J = \log_2 N \qquad (2)$$

where N is the number of samples.

By selecting $a_0 = 2$ or (a_0^{-m} =1, 1/2, 1/4, 1/8, …) and $b_0 = 1$ in eq.(1), the DWT can be implemented by using a multistage filter with the mother wavelet as the lowpass filter $l(n)$ and its dual as the highpass filter $h(n)$. Also, downsampling the output of the lowpass filter $l(n)$ by a factor of 2 (↓2) effectively scales the wavelet by a factor of 2 for the next stage, thereby simplifying the process of dilation. The implementation of the DWT with a filter bank is computationally efficient. The output of the high pass filter gives the detailed version of the high-frequency component of the signal. Also, the low-frequency component is further split to get the other details of the input signal. By using this technique, any wavelet can be implemented. The coefficients of the filters are associated with the selected mother wavelet. There are many types of mother wavelets, such as Harr, Daubichies (db), Coiflet (coif) and Symmlet (sym) wavelets. The choice of mother wavelet plays a significant role in detecting and localizing different types of fault transients. A variety of different wavelet families have been proposed in the literature. The choice of mother wavelet plays a significant role in time frequency analysis. It also depends on a particular application. In this work all wavelets available in the Wavelet Toolbox of MATLAB program [16] were used for the decomposition of the signals and the best answer was obtained with Daubechies mother wavelet. It was found to have the most correlation with the decomposed signals and was selected for this procedure.

A. Applying Wavelet Transform and Feature Extraction

The decomposition is done by modifying the wavelet transform through passing the signal via a digital half band low pass filter. This digital half band low pass filter excludes all the signals which are higher than the half of the value of the largest signal frequency. If a signal having nyquist rate(which is twice the largest frequency in the signal) was taken as a sample, the largest frequency present in the signal would be π radian. That is, nyquist frequency in the range of discrete frequency corresponds π (rad/s). After a signal passes through a digital half band low pass filter, according to the theory of nyquist, half of the signals can be excluded, for now the signal has the maximum frequency of π/2 (rad/s). Thus the obtained signal has a length half of that of the original one. This procedure is repeated for 6 times and the signals omitted by the low pass filter at each time, are considered as detail signals. The energies of these detail signals, are the features extracted from the patterns to feed into the neural network. In Fig. 8 a pattern of 4 signals with 6 detail signals and an approximation signal obtained by applying the Db wavelet transform up to six levels is illustrated. According to the definition, the energy of every discreet signal such as x (n) is defined as follows: (N equals the length of the signal).

$$E(x) = \sum_{n=<N>} |x(n)|^2 \qquad (3)$$

V. Competitive Neural Network

In order to classify two classes (Ferroresonance and other transients) this paper uses a classifier that the competitive neural network plays the role of a classifier. In this part, the competitive neural network is introduced. The self-organization of networks is one of the most interesting subjects of the neural networks. These networks can recognize the organization and connectivity present at the input and respond to the other inputs according to that organization. The neurons of competitive neural networks learn the way of recognizing the similar groups of input vectors. The self-organizing mappings learn how to recognize the similar groups of input vectors by having the adjacent neurons in one neuron layer respond to similar input vectors. The neurons in a competitive vector are distributed in a way that they can recognize the input vectors. The construction of a competitive network is shown in Fig. 9. The **dist** box receives the P input vector and the weight matrix IW as its input and produces a vector having s^1 elements. These elements excluding the distance between the input vector and IW vectors are made up of the input weight matrix row. The net weight of a competitive layer is calculated by adding the bias to the distance of input vector from the weight matrix rows. If the biases equal zero the maximum net weight will be zero. This will happen if the P input vector equals one of the neural network weight vectors. The competitive transfer function receives a net weight vector and produces zero output for all the neurons except the winner neuron (the neuron having the smallest distance) which is the

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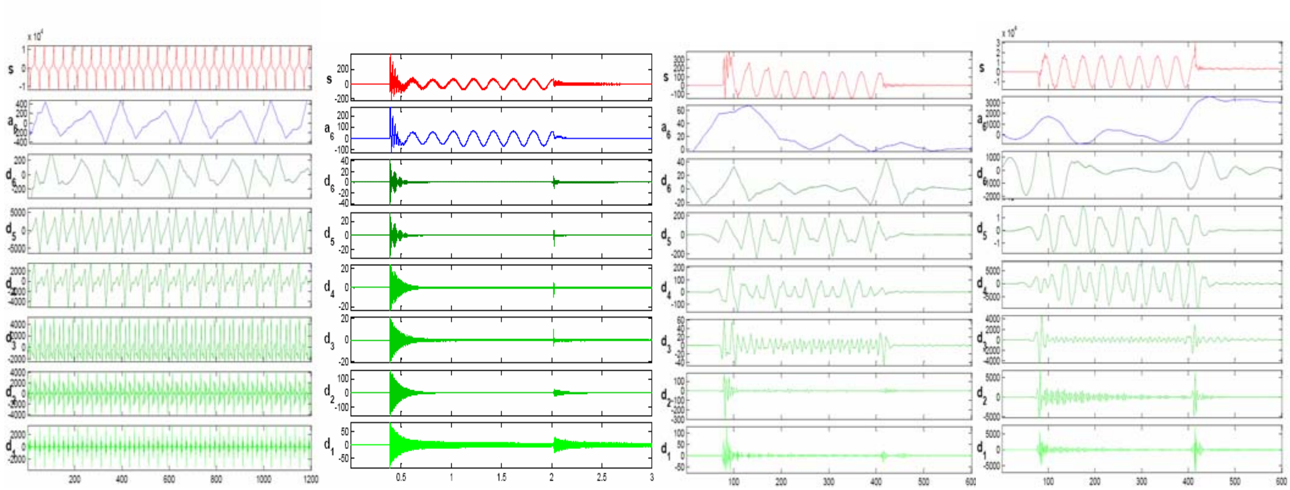


Fig. 8 Decomposition of Signals by Daubechies mother wavelet(F=Ferroresonance,C=CapacitorSwitching,L=Load switching,T=Transformer switching)

same neuron related to the largest net weight element, and the winner neuron's output is 1. The learning process of the competitive network is without supervisor.

While learning, the weights of the winner neuron (a row in the input weight matrix) are adjusted by Cohonen method. Imagine that the "i" th neuron is the winner then the elements of the "i"th row of the input weight matrix will be thus:

$$ {}_{i}IW^{1,1}(q) = {}_{i}IW^{1,1}(q-1) + \alpha\left(p(q) - {}_{i}IW^{1,1}(q-1)\right) \tag{4} $$

Cohonen learning method makes them learn the weights of an input vector neurons, that's why it is important in pattern recognition procedures. In order to prevent a dead neuron, some biases are enforced so that the neurons which are seldom the winner will have the chance to win in the next competitions.

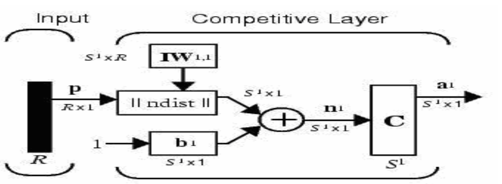


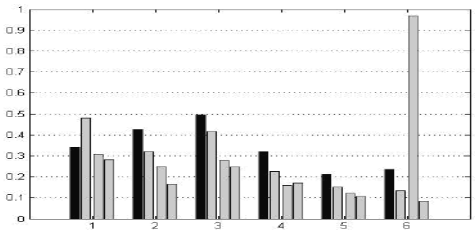
Fig. 9 Competitive neural network

VI. Simulation Results

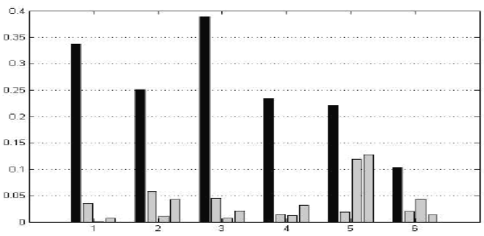
The obtained signals were analyzed by the Daubechies mother wavelet and the energies of the detail signals obtained through the applying wavelet transform up to six levels have been used as the features fed into the neural network. For the competitive neural network, six neurons are determined in the hidden layer, two of which are allocated to Ferroresonance signals and the rest to capacitor switching, load switching, and transformer switching signals. For training the network all four types of signals are used; 15 signals for learning and 10 for testing. Also the learning rate of the neural network is 0.001 and the number of epochs is selected 600. The Daubechies wavelet transform is enforced in all the three phases of current and voltage signals and the competitive neural network. The results are provided in Table I. It should be noted that the currents and the voltages are the primary currents and voltages of the feeder shown in Fig. 1. By applying the Db1 in the second phase current of the signals, the neural network has the least precisian of 58.33% and by applying the Db2 in the third phase voltage of the signals, neural network shows the most precisian of 93.33%. The above results can be justified using Fig. 10. This Figure compares the average of the components correspondent to the feature vectors extracted by applying Db1 and Db2 in the second phase current and the third phase voltage of signals, respectively.(the rectangles corresponding the Ferroresonance signals are darker.) According to the Figure, the features extracted by applying Db1 in the second phase current are much similar. Thus the precision of algorithm is less in this case. But the features exacted by the applying Db2 in the third phase voltage are least similar. Thus the precision of algorithm is more in this case. The above results can be justified using Fig. 11, too. The instantaneous energy of second phase current of signals is much similar. Thus the precision of algorithm is less in this case and the instantaneous energy of third phase voltage of signals is less similar. Thus the precision of algorithm is more in this case.

TABLE I
PERCENTAGE OF NN IDENTIFICATION

Signal	WT	Percentage of NN identification
First phase current	Db1	75%
First phase current	Db2	78.33%
Third phase current	Db3	80%
Third phase current	Db2	80%
Second phase current	Db1	58.33%
Second phase current	Db2	83.3%
Second phase voltage	Db4	83.33%
Second phase current	Db6	83.33%
Third phase current	Db4	81.65%
Third phase voltage	Db2	93.33%
Third phase voltage	Db3	87.48%

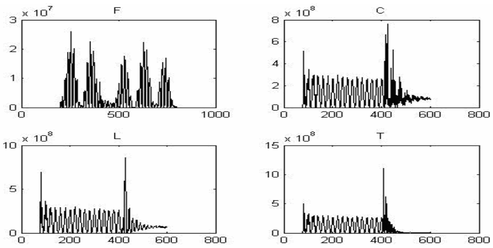


(a) Second phase current

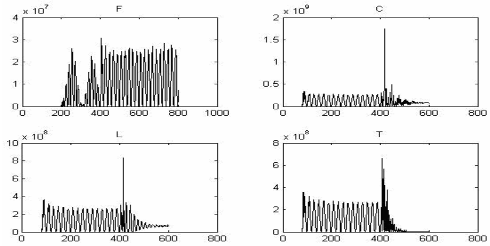


(b) Third phase voltage

Fig. 10 Comparision of the average of the components correspondent to the feature-vectors extracted by applying Db wavelet in second phase current and third phase current of the four groups of the signals when normalized. The four-membered groups from left to right are related to the first to sixth features. In each group, the rectangle respectively refers to Ferroresonance, capacitor switching, load switching and transformer switching



(a) Second phase current



(b)Third phase voltage

Fig. 11 The instantaneous energy of signals (F=Ferroresonance, C=Capacitor switching, L=Load switching, T=Transformer switching)

VII. CONCLUSION

In this paper, the competitive neural network and the wavelet transform have been used to distinguish Ferroresonance from other transients. This algorithm is most precise in 3rd-phase voltage and least precise in the second phase current of signals. In this algorithm, we can readily change the number of the feature extracted from the patterns by changing the level of wavelet according to the number of classes. The network has shown an acceptable precision in recognizing the patterns not used in learning. This shows the practical importance of the algorithm.

APPENDIX

TABLE II
LOAD DATA

No.	I_a(A)	I_b(A)	I_c(A)	I_n(A)	Capacity of connected transformers(KVA)
1	115	78	110	90	630
2	295	200	220	165	800
3	40	60	55	0	500
4	200	250	220	0	1250
5	40	40	40	8	315
6	20	25	25	10	250
7	80	50	40	0	100
8	85	40	70	40	500
9	145	130	120	40	315
10	205	180	205	65	500
11	125	100	105	25	630
12	30	60	50	20	800
13	65	55	55	25	315
14	155	140	105	99	630
15	60	55	55	17	250
16	33	57	45	32	315
17	5	20	20	15	100
18	60	65	75	25	500
19	25	65	60	35	250
20	80	85	75	28	315
21	15	15	15	5	100
22	175	130	145	45	315
23	165	175	150	55	800
24	125	150	150	45	1250

TABLE III
TRANSFORMER DATA

No	S(KVA)	Connection	N_1/N_2	UK%	P_{oc}(W)	In1%	P_{sc}(W)
1	3000	Yd1	63/20kv	14	22410	2.83	151247
2	1250	Dy5	20/0.4kv	6	2100	1.4	16400
3	1000	Dy5	20/0.4kv	6	1750	1.4	13500
4	800	Dy5	20/0.4kv	6	1450	1.5	11000
5	630	Dy5	20/0.4kv	6	1200	1.6	9300
6	500	Dy5	20/0.4kv	6	1000	1.7	7800
7	400	Dy5	20/0.4kv	6	850	1.8	6450
8	315	Dy5	20/0.4kv	6	720	2	5400
9	250	Dy5	20/0.4kv	6	650	2.3	4450
10	100	Dy5	20/0.4kv	6	340	2.6	2150
11	50	Dy5	20/0.4kv	6	210	2.8	1250

A. The Data of Feeder

R = 0.509 Ω/km, X = 0.3561 Ω/km
Outside Radius of conductor = 0.549 cm

B. Configuration of Phases and Mechanical Data

Height of pole = 12 m
Sag in mid span = 2.32 m

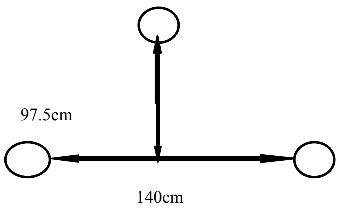


Fig. 12 ConFiguration of phases and mechanical data

C. Constant Parameters of the CIGRE Load Model Usually Considered in the EMTP Program are the Following:

A = 0.073, B = 6.7, C = 0.74

REFERENCES

[1] Haili Ma and Adly Girgis, "Identification and tracking of Harmonics Source in a Power System using Kalman filter" IEEE trans.on power Delivery vol. 11, No. 3, July 1996.

[2] Irene Gu, math Bollen, "Time frequency and Timescale domain analysis of voltage Disturbances" IEEE trans.on power Delivery vol. 15, No. 4, October 2000.

[3] Surya Santoso, Jeff Lamoree, Mack Grady,Edward powers and Siddharth.Bhatt." A Scalable PQ Event Identification System" IEEE trans.on power Delivery vol. 15, No. 2, April 2000.

[4] A.Gaouda M.salama, M.Sultan and A.Chikhani, "Power Quality Detection and Classification using Wavelet Multuresolution Signal Decomposition", IEEE trans.on power Delivery vol.14,No.4, October 1999 [5] Masoud karami, hossein Mokhtari and Reza Irvani ,"Wavelet Based On Line Disturbance Detection for Power Quality Application ", IEEE trans.on power Delivery vol.15,No.4, October 2000.

[5] J.Chung, E.J. Powers, W.M.G rady, and S.C.Bhatt," Electric Power Transient Disturbance Classification Using wavelet Based Hidden Markov Models", Proceeding of 2000 IEEE International Conference on Acoustics, Speech and Signal Processing, vol.6, 2000.

[6] B. Perunicic, M. Mallini, Z. Wang, Y. Liu, and G. T. Heydt," Power Quality Disturbance Detection and Classification Using Wavelets and Artificial Neural Networks", The 8th International Conference on Harmonics and Quality of Power,1998.

[7] C. L. Huang, H. Y. Chu and M. T. Chen, "Algorithm comparison for High Impedance fault based on Staged Fault Test", IEEE trans.on power Delivery vol.3, October 1988.

[8] H. Calhoun, M. T. Bishop, C.h.Eiceler and R. E. Lee, "Development and Testing of an Electro-mechanical Relay to detect Fallen Distribution Conductors", IEEE trans.on power apparatus and systems vol.PAS-100(4), April 1998.

[9] Y. Sheng and S. M. Rovnyak, "Decision Tree- Based Methodology for High Impedance Fault Detection", IEEE trans.on power Delivery vol.19, April 2004.

[10] B. D. Russell, and R. P. Chinchali, "A Digital Signal processing Algorithm for Detecting ASrcing Fault on Power Distribution Feeders ", IEEE trans.on power Delivery, vol 4, January 1989.

[11] A. R. Sedighi, M. R. Haghifam, O. P. Malik, M. H. Ghassemian, "High Impedance Fault Detection Based on Wavelet Transform and Statistical pattern Recognition", IEEE trans. on power Delivery, 2005,pp. 2414 – 2421.

[12] D. C. Robertson, O. I. Camps, J. S.Mayer, and W. B. Gish,"Wavelets and Electromagnetic Power System Transients", *IEEE Trans. Power Delivery,* Vol. 11, pp.1050-1058, April-1996.

[13] P. L. Mao and R. K. Aggarwal, "A novel approach to the classification of the transient phenomena in power transformers using combined wavelet.

[14] Transform and neural network," *IEEE Trans. Power Delivery*, vol. 16, pp. 654-660, Oct. 2001.

[15] S. G. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation," *IEEE Trans. Pattern Anal. Machine Intel.,* vol. 11, pp. 674-693, Apr. 1989.

[16] Wavelet toolbox for Matlab, User manual, MathWorks, Natick, USA.

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