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Performance of Transient Based System in Different Methodologies for Fault Detection and Classification in Transmission Line Network: An Overview

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Abstract**-The transmission line network plays an important in transmission line system. Fault classification and detection are the two main factors for prevention of transmission line system. To maintain continuity and stability in transmission line we have to detect and classify the fault as early as possible. Different types of faults arise in transmission line system and challenge is to detect and classify the fault more efficiently. So many techniques can be involved to improve the reliability of transmission line system. In this paper we are going to present different comparative methods for fault detection and classification on their transient's basis and also show the difference about its hardware implementation.**

Key words- transmission line, fault classification, fault detection, wavelet transformation, hidden markov model (HMM)

I. INTRODUCTION

Transmission line system can be divided into transmission line and distributed line. Generally fault occurs on transmission line which delivers the power approximately above 24 KV. Faults may occur in high frequency transients current signals. The traditional algorithms was employed from many researchers which is based on steady-state components, have some problems in accelerating protection speed and it has some impact on fault type, fault inception time, fault resistance. [1]-[5]. Based on fault transients, several algorithms have been reported for fault detection and classification. For all of the pro-posed algorithms, how to extract the transients' features from the original fault signal is the most important issue. Wavelet transform (WT), which is the perfect time-frequency localization ability, has been chosen as an effective tool for analyzing the fault transients [2]–[6].Since the transmission line high frequency current signals are non-stationary and random in nature so that it is very difficult to extract the information on it. The Fourier transformation method was employed to extract the information from high frequency signals, but they won't be able to find the exact time instant where the high frequency transients arises. Therefore Fourier Transform is best suited technique for frequency analysis but it can't be claim on time analysis. So this is to be overcome by wavelet transformation technique. It has moving window analysis technique to give the statement regarding to its frequency as well as time. The continues wavelet transform (CWT) and discrete wavelet transform (DWT) are the two forms of wavelet transform, we can choose any one of it but its depending upon the way the dilation and translation functions are used. The DWT is more advantageous then CWT, because DWT decomposes the signal into discrete family of frequency band that do not overlap each other, while in CWT decomposes the signal into its continues family that could overlap each other.

Wavelet modulus maxima (WMM) have been used in [7] and [8]. To analyzed initial modal current travelling waves and an effective approach to fast and accurate fault detection and fault phase selection has been achieved. Wavelet transform can be a best suitable tool for extracting information from high frequency current signals but there are several problems to be solved, In many application [4]-[8]. WT is limited to show some picture and its transformation results contain large number of data which need further processing, and hence several techniques uses the combination of WT with ANN, WT with fuzzy logic. But still these techniques required large number of calculations and its techniques are system dependent, and they cannot manage uncertain factors in transmission system which will influence the reliability of fault detection and classification.

In this paper we are going to discussed and compare the two techniques for fault detection and classification which is based on transients fault classification processes. These techniques are wavelet transformation with singular entropy and HMM (hidden Markov model) classifier and we also discussed about its hardware platform for real time implementation.

II. WAVELET SINGULAR ENTROPY

When we used plane wavelet transform techniques there is some sort of problems arises because there is large number of which required further processing, So that if we combine WT with singular entropy we will get the more efficient results. WSE can be used to extract features from fault transients quantitatively and automatically. It is immune to the noises and many other uncertain factors in the system. Further, it is independent on the magnitude and energy of the transients. The implementation of fault detection and classification based on WSE is put forward and its efficiency is verified by virtue of the simulation tests. This proposed methodology combines the techniques of WT like-

1) Singular value decomposition (SVD) [9].
2) Shannon entropy together; therefore, it is called wavelet singular entropy (WSE) for the acronyms.

Generally, WT consists of successive pairs of low- and high-pass filters. For each pair, the high-scale and low-frequency components are called approximations, while the low-scale and high-frequency components are called details. According to the definition, WSE is used to map the correlative wavelet space into independent linearity space, and to indicate the uncertainty of the energy distribution in the time–frequency domain with a high immunity to noise. Due to its way of implementation, WSE is sensitive to the transients produced by the faults, and the fewer modes the transients meet, the smaller the WSE is.

A) Definitions of wavelet singular entropy

The contribution of singular value decomposition (SVD) and Shannon's information entropy for fault classification and detection as follows-

The coefficient of wavelet transform can be defined as [10]-

$$C(m,\iota)= \int_{0}^{+\infty} s(t).W'_{\iota,m}(t)\, dt \qquad (1)$$

Where 'm' is the scale factor and 'ι' is translation factor depending on this factor we may select mother wavelet. s(t)-discrete sequence with 'n' samples. So that from the knowledge of above equation we first analyze s(t) by WT, where the "db4" mother wavelet and 4-scaled WT are chosen in the transformation.

Then, a 4 by n WT-coefficient matrix can be obtained by means of (1).

Then by using Shannon's entropy we measure uncertainty for evaluating structures and patterns of analyzed data . Let $X=\{x_1, x_2,......x_n\}$ be a discrete random variable with 'n' possible states. Let $P= \{p_1, p_2,....p_n\}$ whose values satisfy the terms of $0<p_i<1$ and $\sum p_i=1$ (i=1,2......n) as the probabilities associated with those n states. The uncertainty information of each possible state x_i is [10]-

$$I(x_i)= \log_a p_i \qquad i=1,2.......n. \qquad (2)$$

Secondly we decomposed the matrix with SVD in (2) then singular value array will obtain and tiny singular values can be neglected. It can be obtained by diagonal matrix whose rank may be very large and the value of diagonal elements. This value decomposition technique is much faster and more effective.

B) *Comparison of WSE with WMM*

The comparison with WMM and a couple of comparisons with other methodologies, such as WT-ANN [1], [11], [12] or WT fuzzy [13], reveal that:

1. The threshold of WSE is higher than that of WMM, in which case the error of the detection result can be reduced and the adaptability of methodology can be Improved;
2. In most conditions, faults can be detected more rapidly by WSE than by other algorithms due to the intuitive, non-training, and non-fuzzy characteristics of WSE.
3. WSE is more effective than others in the case of low-energy fault transients, and this is because WSE takes all WT-scaled features into account and considers their relative, instead of absolute, values as well;
4. Failure in choosing the suitable scale of W. Other WT-involved methodologies tend to be affected by the
5. Signal magnitude while WSE is not. Therefore, WSE is better and more applicable than most of the other previous methodologies in terms of fault detection.

The following table–I shows the comparison in between WSE, WE, and WMM, about its fault angle and fault resistance. 'ta' fault angle and 'R' fault resistance.

Table –I comparison between WE, WSE and WMM [10]

Fault Condition	No. Of Tests	Compared Methods	Failed Fault Classification	Test Accuracy
$t_a=0^0$,d=k50 km R if from 50Ω to 1000Ω step by 50 Ω	20	WE	18	10%
		WMM	9	55%
		WSE	0	100%

III. FAULT CLASSIFICATION BY HMM CLASSIFIER

It is another protection scheme for power system. But one of the concern that discourage the application transients based protection scheme is possibilities of malfunction due to non fault related transients. These transients can be originated from various normal events such as-

1) Switching of lines
2) Capacitor banks
3) Large loads etc.

The difference between previous researches from this is they distinguish faults from other types of transients [14]-[21]. Hidden Markov model (HMM) classifier have been successfully used for classifying disturbances into different categories such as-

1) Voltage sags
2) Swells
3) Flicker capacitor switching

In this technique we may used wavelet transform for feature extraction from high frequency current signals and HMM is to distinguished transients originating fault from other transients. The probabilistic neural network (PNN), HMM and decision tree (DT) can be used for classification purpose. They investigated and compared in [22], [23].

But there are some disadvantages when we implement for real time implementation, PNN technique gives best classification accuracy but difficult due to

- Large amount of computation involved in classification
- Depends on processing time on the size of training data set.

A) *HMM Operation of fault classifier*

In the following equation let X be the HMM classifier decisive factor [24]-

$$X = f\,(E|\lambda_f)\,/f\,(E|\lambda_{nf}) \qquad (1)$$

Where E is input feature set (i.e. wavelet energies) and λ_f and λ_{nf} are the HMMs of faulty and non faulty classes. If X is grater then 1, then probability of event being a fault is grater then that of non fault event.

B) *Effect of measurement noise*

The use of high-frequency sampling, such as 20 kHz, can introduce noise into the measurements. In order to investigate the effect of noise, some noisy waveforms were played back using the RTP. The signal-to-noise ratios (SNRs) ranging from 30 to 60 dB were used [24]. The faults simulated close to the classifier may select for study. In order to make the recognition more robust under noisy conditions, the classifier was retrained using the wavelet energies determined under different noise levels.

C) *Effect of lightning strokes*

The lightning transients were simulated assuming a standard characteristic waveform [24]. The classifier was retrained using a new training database that includes lightening transients. The lightning transients were categorized as non faults. Offline testing showed that the trained classification system is capable of recognizing lightning strikes as non faulty situations.

It should be noted that due to bandwidth limitations in Real time play back system (RTP), lightning transients cannot be played back with their entire frequency spectrum. However, since the input Analog filters have a bandwidth of 0–10 kHz, the absence of these high-frequency components in the played-back signal would not make a significant effect on the classification performance. Also, further investigations showed that any fault followed by a lightning stroke can be recognized as a fault using this system.

In order to make the recognition more robust under noisy conditions, the classifier was retrained using the wavelet energies determined under different noise levels.

D) *Comparison of HMM with PNN-*

The DSP board can be used to implement its prototype for HMM classifier technique. The floating point operation was used for HMM and hence it can be best compatible with DSP. The feature for DSP is having less power consumes capability then FPGA. So here we compared the HNN with PNN about its accuracy for fault classification and easier method for fault classification. The following table –II shows the comparison in between HMM and PNN-

Table –II comparison of HMM with PNN on various cases [24]

Class	Training cases	Test cases	HMM Predicted class NF	HMM Predicted class F	HMM % corr	PNN Predicted class NF	PNN Predicted class F	PNN % corr
NF	220	30	30	0	100	30	0	100
F	105	35	2	33	94	0	35	100

IV. SUMMERIZATION OF ABOVE DISSCUSED METHODS

We have shown the study and analysis of different fault classification and detection techniques, based on their transient's algorithms. The two techniques we have shown above so called Wavelet singular entropy and Hidden Markov model based. Ultimately the aim of both techniques was same but their classification and detection techniques for faults are different. In wavelet singular entropy was used wavelet transformation with singular value decomposition. This method is more advantageous from ANN with WT and Fuzzy logic with WT because it has less computational complexity and system independency then ANN and Fuzzy while combining with WT. The methods like wavelet modulus method and wavelet transformation without SVD give the statement only about its high frequency transients, but can't show the output of low transients signals. Hence some of worst case happened when fault inception angle is 0. So due to very low transient magnitude, the accuracies of the classification based on WT and WMM are only 10% and 15% [10].resp. How-ever, benefiting from its great anti noise property and low dependence on transient absolute magnitude, the WSE-based classification possesses the accuracy of 100% [10]. This is the greatest superiority and improvement of the proposed WSE-based methodology compared to the other algorithms.

In another way of classification of faults so called Hidden Markov model (HMM) gives the fast response about fault detection in terms of only, fault and no fault cases. In this technique they do not use the direct transients signals associated with faults instead of this they also takes the non fault transient's signals. So that it is easier to distinguished transients originating from faults from the other transients. The transient energies determined using the wavelet coefficients were used as the inputs for the classification system. A Gaussian mixer HMM was used for the classification. When we compared the HMM with

Probabilistic neural network (PNN) it shows that neural network involves in large computational complexity and required expert knowledge.

There are some areas which need to be improved from its temporary faults like arcing fault it is one of the temporary fault. Similarly the response to a sequence of transients generating events such as fault combined with auto reclosure operation needs further investigation. In case of its hardware implementation, it is implemented on DSP based platform, when we compared with field programmable gate array (FPGA). We can comment on some parameters like, FPGA is more power consumes then DSP, on other hand largest sampling rate can be achievable then DSP, FPGA is more preferable where high frequency are introduced then DSP, as silicon technology is used in FPGA so that it will more portable then DSP, FPGA does not support for floating point operation while DSP can do this. In some areas FPGA can be advantageous over the DSP and vice versa.

V. DISCUSSION

By going through these two WSE and HMM classifier methods for fault detection and classification it is concluded that, if we consider the WSE for fault detection and classification it gives best results over the WT and WMM, in case of its 1) fault resistances 2) inception angles 3) various fault types 4) fault location. WSE is sensitive to sudden changes in transient's signals and immune to noise.

While in case of second approach called Hidden Markov model for fault detection and classification, which was successfully used for classify disturbances such as 1) Voltage sags 2) Swells 3) Flicker capacitor switching. One of the advantages of this method is that it uses floating point operation which will best compatible with DSP hardware platform to meet specific requirement such as a) high frequency sampling b) high precision calculation c) less distressed to noise, Hence HMM is advantageous over the probabilistic neural network (PNN).

REFERENCES

[1] K. M. Silva, B. A. Souza, and N. S. D. Brito, "Fault detection and classification in transmission lines based on wavelet transform and ANN," IEEE Trans. Power Del., vol. 21, no. 4, pp. 2058–2063, Oct. 2006.

[2] T. B. Littler and D. J. Morrow, "Wavelets for the analysis and compression of power system disturbances, IEEE Trans. Power Del., vol. 14, no. 2, pp. 358–364, Apr. 1999.

[3] A. Gaouda, M. M. A. Salama, M. R. Sultan, and A. Y. Chikhani, "Power quality detection and classification using wavelet multiresolu-tion signal decomposition," IEEE Trans. Power Del., vol. 14, no. 4, pp. 1469–1476, Oct. 1999.

[4] X. Xu and M. Kezunovic, "Automated feature extraction from power system transients using wavelet transform," in Proc. Int. Conf. Power System Technology, 2002, vol. 4, pp. 1994–1998.

[5] Tu, W. L. Hwang, and J. Ho, "Analysis of singularities from modulus maxima of complex wavelets,"IEEE Trans. Inf. Theory, vol. 51, no. 3, pp. 1049–1062, Mar. 2005.

[6] T. Le-Tien, H. Talhami, and D. T. Nguyen, "Simple algorithm forwavelet maxima modulus extraction in time-scale representations," IEEE Electron. Lett., vol. 33, no. 5, pp. 370–371, Feb. 1997.

[7] J. D. Duan, B. H. Zhang, and H. X. Ha, "A novel approach to faulted-phase selection using current traveling waves and wavelet analysis," in Proc. Int. Conf. Power System Technology, 2002, vol. 2, pp. 1146–1150.

[8] Q. L. Su, X. Z. Dong, Z. Q. Bo, and F. Jiang, "New approach of fault detection and fault phase selection based on initia current travelling waves," inProc. IEEE Power Eng. Soc. Summer Meeting, 2002, vol. 1, pp. 393–397.

[9] V. C. Klema and A. J. Laub, "The singular value decomposition: Its computation and some applications, "IEEE Trans. Autom. Control, vol. AC-25, no. 2, pp. 164–176, Apr. 1980.

[10] Zhengyou He, Ling Fu, Sheng Lin, and Zhiqian Bo, "fault detection and classification of faults in T.L. based on wavelet singular entropy" IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 25, NO. 4, OCTOBER 2010

[11] Z. Q. Bo, R. K. Aggarwal, A. T. Johns, H. Y. Li, Y. H. Song, R. L. King, D. Novosel, and M. Kezunovic, "A new approach to phase selection using fault generated high frequency noise and neural networks,"IEEE Trans. Power Del., vol. 12, no. 1, pp. 106–115, Jan. 1997.

[12] N. Zhang and M. Kezunovic, "Transmission line boundary protection using wavelet transform and neural network,"IEEE Trans. Power Del., vol. 22, no. 2, pp. 859–869, Apr. 2007.

[13] V. C. Klema and A. J. Laub, "The singular value decomposition: Its computation and some applications, "IEEE Trans. Autom. Control, vol. AC-25, no. 2, pp. 164–176, Apr. 1980.

[14] Y. Sheng and S. M. Rovnyak, "Decision tree-based methodology for high impedance fault detection, "IEEE Trans. Power Del., vol. 19, no. 2, pp. 533–536, Apr. 2004.

[15] J. Upendar, C. P. Gupta, G. K. Singh, and G. Ramakrishna, "PSO and ANN-based fault classification for protective relaying, "Inst. Eng. Technol. Gen., Transm. Distrib., vol. 4, no. 10, pp. 1197–1212, 2010.

[16] K. M. Silva, B. A. Souza, and N. S. D. Brito, "Fault detection and clas-sification in transmission lines based on wavelet transform and ANN," IEEE Trans. Power Del., vol. 21, no. 4, pp. 2058–2063, Oct. 2006.

[17] M. Oleskovicz, D. V. Coury, and R. K. Aggarwal, "A complete scheme for fault detection, classification and location in transmission lines using neural networks," in Proc. Inst. Elect. Eng., 7th Int. Conf. Developments in Power System Protection, Amsterdam, The Nether-lands, Apr. 2001, pp. 335–338.

[18] T. Dausten and B. Kulieke, "Neural network approach to fault classi-fication for high speed protective relaying,"IEEE Trans. Power Del., vol. 10, no. 2, pp. 1002–1009, Apr. 1995.

[19] M. Kezunovic and I. Rikalo, "Detect and classify transmission line faults using neural nets,"IEEE Comput. Appl. Power, vol. 9, no. 4, pp. 42–47, Oct. 1996.

[20] T. K. Abdel-Galil, E. F. El-Saadany, A. M. Youssef, and M. M. A. Salama, "Disturbance classification using hidden Markov models and vector quantization,"IEEE Trans. Power Del., vol. 20, no. 3, pp. 2129–2135, Jul. 2005.

[21] J. Chung, E. J. Powers, W. M. Grady, and S. C. Bhatt, "Power distur-bance classifier using a rule-based method and wavelet packet-based hidden Markov model,"IEEE Trans. Power Del., vol. 17, no. 1, pp.233–241, Jan. 2002.

[22] N. Perera, A. D. Rajapakse, D. Muthumuni, and R. Jayasinghe, "Devel-opment of an on-line transient classification system," presented at the Int. Conf. Power Systems Transients, Kyoto, Japan, Jun. 2–6, 2009.

[23] N. Perera and A. D. Rajapakse, "Recognition of fault transients using a probabilistic neural network classifier,"IEEE Trans. Power Del., vol. 26, no. 1, pp. 410–419, Jan. 2011.

[24] Nuwan Perera and Athula D. Rajapakse,senior member IEEE," Development and Hardware implementation of a fault transients recognition system",IEEE transaction on power delivery,Vol,27,NO.1, January 2012.