IDENTIFICATION AND CLASSIFICATION OF DISTURBANCES ON HV TRANSMISSION SYSTEMS

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Abstract: Availability of electrical power has much more importance than before and there is no tolerance to power interrupts in today's power networks. There are many different types of transient disturbances and short duration variations affecting the safe operation of sub-components such as high voltage transmission lines, underground power cables, switching equipment, etc. It is necessary to identify and classify those in a very short time in order to provide high speed clearance of the disturbance by taking necessary action such as isolating the faulty line section to enable fast restoration. Therefore, it is needed to develop an algorithm and analyzing scheme that can be used on-line monitoring serving for identification of transient events and their classification by defining the possible underlying root cause. In this paper, a new scheme has been developed for identification and classification of disturbances on transmission lines by utilizing a scheme that is based on wavelet based sub-band energy distribution for feature extraction and artificial neural network (ANN) for classification of disturbances. After defining wavelet related parameters which reveal better classification scheme, energy distribution of wavelet coefficients at each decomposition level was determined and used as transient feature identifier presented to a neural network classifier. Different training algorithms have been tried in ANN and useful ones for this purpose have been identified. Simulation studies have been carried out in order to confirm the effectiveness of the proposed scheme by using common disturbance types on a transmission line. The results indicate that the proposed scheme is effective and able to identify and classify common disturbances with enough accuracy and can be adopted as a line protection algorithm.

1 INTRODUCTION

The importance of power system reliability and availability has been increasing day by day due to the complex structure of a power system. Power system network mainly consists of generation, transmission and distribution sub-systems. There are many different types of disturbances affecting the safe operation of sub-components such as transmission lines, underground power cables, switching equipment, etc. The most common disturbances in power systems are internal disturbances such as switching phenomena, faults or external disturbances like lightning strikes. Depending on the type of disturbances, different voltage, current or frequency characteristics can be seen in power systems. IEEE classified those depending on the duration and magnitude of disturbances. In this context, it is necessary to identify and classify those in a very short time in order to provide high speed clearance of the disturbance by taking necessary action such as isolating the faulty line section to enable fast restoration. Therefore, it is necessary to have an algorithm and analyzing scheme that can be used for on-line monitoring. Cause of disturbance has to be identified in a short time and necessary actions such as isolation of faulty section have to be taken immediately. This is an indispensable issue in enhancement of power system availability.

In general, the techniques used to identify the disturbances are composed of frequency-domain analysis and time-frequency domain analysis. Fourier Transform (FT) is the most popular technique for frequency-domain analysis. However, the sensitivity of FT methods may not be enough to identify the transient overvoltages. Therefore, time-frequency domain analysis can be preferred to determine those. Wavelet Transform (WT) is the best-known technique in terms time-frequency domain analysis. FT and WT were employed in the literature for detection of power quality problems [1-6]. In study [1], WT was used not only to detect the power quality disturbances but also to classify them. In [6], WT was handled to detect voltage sag, voltage swell, flicker and harmonics. The authors obtained better identification rate by using WT.

Several algorithms are employed for classifying power system disturbances. The most popular ones are artificial neural network (ANN), Fuzzy Logic (FL), Support Vector Machine (SVM), and Bayesian Classifiers [7-11]. In [8], ANN was proposed for the classification of power system disturbances. Impulse, voltage sag, harmonics, and interruption were studied to test ANN technique. In [9], Minimum Euclidean distance, k-nearest neighbor and neural network were used as classifiers for different power quality problems. Study given in [10] compares ANN and SVM to classify the different disturbances. It was revealed that ANN took more time than SVM. In [11], the authors used SVM as a classification technique together with wavelet based feature extraction technique and only short duration voltage variations, voltage sag and swell were considered. Study [12] utilized an extended fuzzy reasoning approach for identifying power-quality disturbance waveforms by using energy distribution patterns in the wavelet domain to form linguistic rules.

In this study, disturbances such as short duration variations and transients taken place on HV transmission systems are considered. Those disturbances are voltage sag, voltage swell due to faults, low and medium frequency oscillatory transients due to switching events and impulsive transients due to lightning. In this context, a method has been proposed for identification and classification of disturbances on transmission lines by utilizing a scheme that is based on the wavelet based sub-band energy distribution for feature extraction and artificial neural network (ANN) for classification of disturbances.

2 MULTI-RESOLUTION WAVELET ANALYSIS

Wavelet analysis is an effective time-frequency signal processing tool and is a good candidate for transient signal feature extraction because of its ability to extract non-stationary signals. Similar to Fourier Transform that produces the projection of signal in frequency domain, wavelet analysis is the projection in time-frequency domain. Continuous Wavelet Transform (CWT) of $x(t)$ is given by equation (1), where the transform breaks up the signal into shifted and scaled versions of a mother wavelet $\psi(t)$ [13].

$$CWT(\tau, a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^{*}(\frac{t-\tau}{a}) dt \tag{1}$$

Where τ and a are translation and scaling parameters, respectively. The discrete form of the CWT is obtained by sampling the time-scale plane. Discrete Wavelet Transform (DWT) is expressed by equation (2) where n, b and a are the discrete versions of t, τ and a, respectively [14].

$$DWT(a,b) = \frac{1}{\sqrt{a}} \sum_{n} x(n) \psi^{*}(\frac{n-b}{a}) \tag{2}$$

The general form of discrete wavelet transform the approximation and detail sequences at level $j+1$ are related to earlier sequence that is level j. Equations (3) and (4) give approximation and detail coefficients at higher level, where $h_0(k)$ and $h_1(k)$ are wavelet and scaling filters, respectively.

$$c_{j+1}(k) = \sum_{m} h_0(m-2k) c_j(m) \tag{3}$$

$$d_{j+1}(k) = \sum_{m} h_1(m-2k) c_j(m) \tag{4}$$

Figure 1 represents two level signal decomposition in multi-resolution wavelet analysis. A_0 is the original signal where A_1 and A_2 are approximations; D_1 and D_2 are details after decomposition of the main signal. On the other hand, g and h are high pass, low pass decomposition filters, respectively. Figure 1 only shows until decomposition level of two.

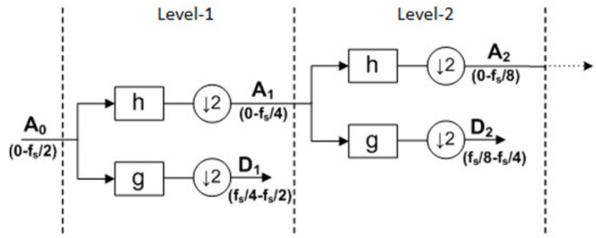

Figure 1: Two level signal decomposition.

Discrete Wavelet Analysis (DWT) was utilized to process voltage data that retains transient event information.

3 PROPOSED SCHEME FOR FEATURE EXTRACTION

Transient disturbances can be seen on transmission lines originated from different sources such as lightning, faults, switching. It is necessary to identify and classify those in a very short time in order to provide high speed clearance of the disturbance by taking necessary action such as isolating the faulty line section to enable fast restoration. Therefore, it is needed to develop an algorithm and analyzing scheme that can be used on-line monitoring serving for the identification of transient events and their classification by defining the possible underlying root cause. This is an indispensable issue in enhancement of power system reliability.

Identification of those disturbances is possible with wavelet analysis based signal detection methods, but for classification another tool is necessary such as neural networks, support vector machines etc. In order to have a good accuracy in classification, reliable and efficient features have to be extracted from the disturbance signals by revealing classified outputs for different disturbance signals. For this purpose, in this study, wavelet analysis has been used for feature extraction from the transient disturbances on transmission lines based on frequency based behavior in wavelet domain. The wavelet transform provides decomposition of a signal into a hierarchical set of details and approximations. In this study, it is realized that energy distribution patterns of different transient disturbances on transmission lines give characteristic properties which are very useful to be utilized in a classification tool.

Selection of mother wavelet is the first step for wavelet based decomposition of a signal. The right mother wavelet enables better reconstruction and enables more accuracy. If selected wavelet matches well with the shape of the signal of interest, larger wavelet coefficients associated with signals are obtained. In this study, db4 has been used as the mother wavelet, which is widely used for power quality studies [15-16].

Signal energy based approach has been used to define classification feature. Amount of energy contained in a sub-band is given in equation (5).

$$E(a) = \sum_{i=1}^{N} \left| W(a,i) \right|^2 \tag{5}$$

Where, a indicates decomposition level, N is the number of wavelet coefficients, $W(a, i)$ is the wavelet coefficients at that level. Depending on the frequency content of the disturbance signal, energy distribution of sub-bands provides information about disturbance type. By using selected db4 wavelet, energy distribution of signal to the decomposition level of 7 was enough. There might be more than one appropriate solution. However, unnecessarily higher decomposition levels are not advised.

4 SHORT DURATION VARIATIONS AND TRANSIENT DISTURBANCE SIGNALS

In order to check the effectiveness of the proposed method five different disturbances have been simulated, which are common on a HV transmission line network. These disturbances are sag and swell as short duration variations, low and medium frequency oscillatory transients, and impulsive transient types.

An oscillatory transient with a primary frequency element less than 5 kHz, and having duration from 0.3 ms to 50 ms, is called a low frequency transient as defined in IEEE Standard 1159-1995 [17]. Switching events and transformer energization fall into this category. An oscillatory transient with a main frequency component between 5 and 500 kHz and having duration of tens of microseconds is identified as medium frequency transient. An example would be the transients generated by back-to-back capacitor energization and switching cables. Lightning disturbances are impulsive disturbance type.

Figure 2 indicates original normalized voltage waveform and five different typical disturbances that are used. For feature extraction, the scheme explained in section 3 has been applied and obtained decomposition level based energy distribution samples are given below. Figure 3 indicates original waveform energy distribution, Figure 4 and 5 show sag and low frequency oscillatory transient, respectively.

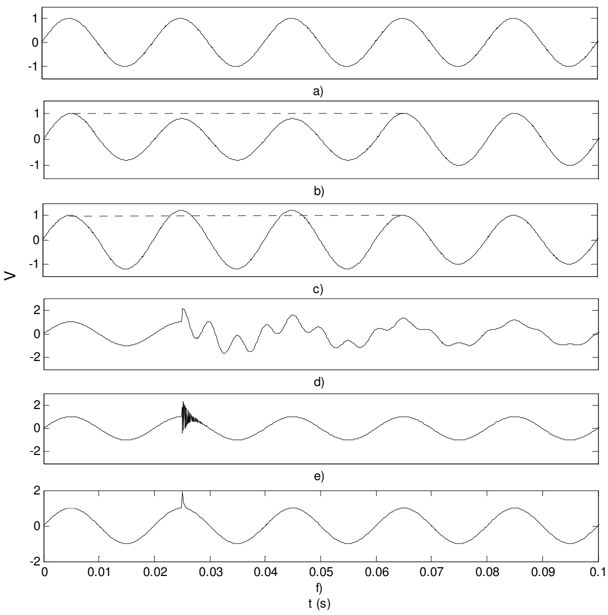

Figure 2: Transmission line typical disturbances: a) original waveform, b) voltage sag, c) voltage swell, d) low frequency oscillatory transients e) medium frequency oscillatory transients, f) impulsive transient.

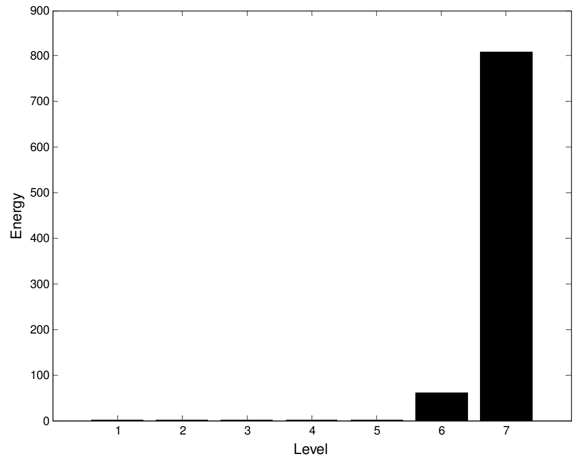

Figure 3: Original waveform energy distribution.

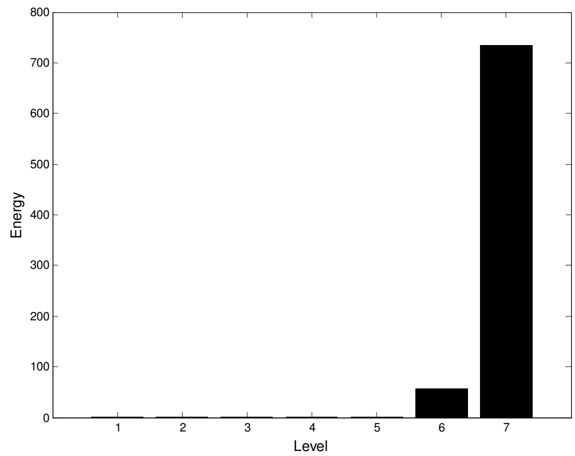

Figure 4: Sag detail energy level distribution.

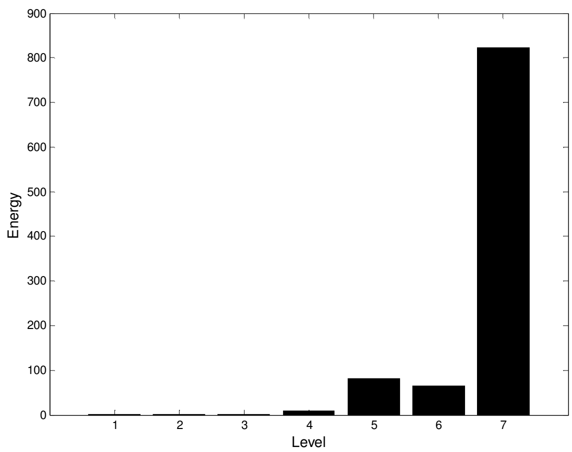

Figure 5: Low frequency oscillatory transient detail energy level distribution.

When three figures are compared, it is easy to see that energy distribution patterns of decomposition level detailed coefficients indicate different characteristics. As an example Figure 3 and 4 comparison reveal that sub-band coefficient energy values are reduced in sag in the same ratio that of original waveform. On the other hand, low frequency oscillatory transient shows different dispersion among sub-band energy levels. These features are used for disturbance classification means.

To be used in training algorithms and finally classification purpose, variety of disturbance data were generated with different parameters representing transient disturbances on transmission lines.

5 ANN-BASED PATTERN RECOGNITION FOR CLASSIFICATION

Pattern recognition is widely used for classification problems. Decision Trees, Bayes Classifier, Genetic Algorithms, Support Vector Machines are some of the methods used for pattern recognition. Artificial neural network (ANN) is one of the popular one among these methods. It is fast reliable and suitable for classification problems and clustering.

A classification problem has inputs and each input belong a class according to defined features. In this study, classification problem includes six classes. Each class denotes a different transients caused by some transmission line disturbances. No disturbance, voltage sag, voltage swell, low and medium frequency oscillatory transients, and impulsive transients are the main power system transients that were chosen as classes. Problem features were obtained using discrete wavelet analysis (DWT) with seven levels. That means each transient waveform or input was represented by seven coefficients.

Computations were done by using Matlab codes obtained from pattern recognition toolbox. Classification problems are multi-input and one output problems, so the structure of the network becomes one input layer with seven input neurons, one hidden layer and one output layer with seven output neurons.

Three different training algorithms were used during the training process of the network. For this study; Levenberg Marquardt (LM), Gradient Descent (GD) and Scaled Conjugate Gradient (SCG) methods were applied in order to train the system respectively. However, the results of GD weren't given in this paper due to the insufficient performance of the algorithm.

In order to assess the proposed scheme 147 different data set were prepared for the problem. Each data were represented with seven features. So the input matrix was formed as 7×147 matrix. Each class was represented with a 6×1 vector and total of 6×147 matrix was formed as targets. All the data divided into three parts as training, validation, and test. Data partition is very important for neural network performance. In this context, 70%-15%-15% are the percentages of training, validation, and test data used in the study, respectively. This is the default partition for the neural networks. During the calculation, some other combinations of partitions like 65%-15%-20% were also used.

Training and validation data were used in training and calculation of the weights of the network. After the weight calculation network was checked with the test data and the system performance was defined. Tree growing method was applied to the network to find the best configuration. One hidden layer was chosen and hidden neuron number was changed from 1 to 10. For each hidden layer size, classification success values indicated as percent were calculated for both test data and rest of it.

Figure 6 indicates one of the confusion matrixes obtained from the test data. Numbers of 1 to 6 indicates the classes as “no disturbance”, “voltage sag”, “voltage swell”, “low” and “medium frequency oscillatory transients” and “impulsive transients”, respectively. This matrix shows how many data classified correctly. Also the matrix gives the wrong classification data. Diagonal elements indicate that data were classified. Similarly, off-diagonal elements represent misclassified data. According to the figure, 96.6% of the 28 data were correctly classified. One of the data belongs the class 5 classified in class 4.

For each hidden layer size and training algorithm, network was run for 50 times. Iteration number was fixed at 2000 epoch during the calculations.

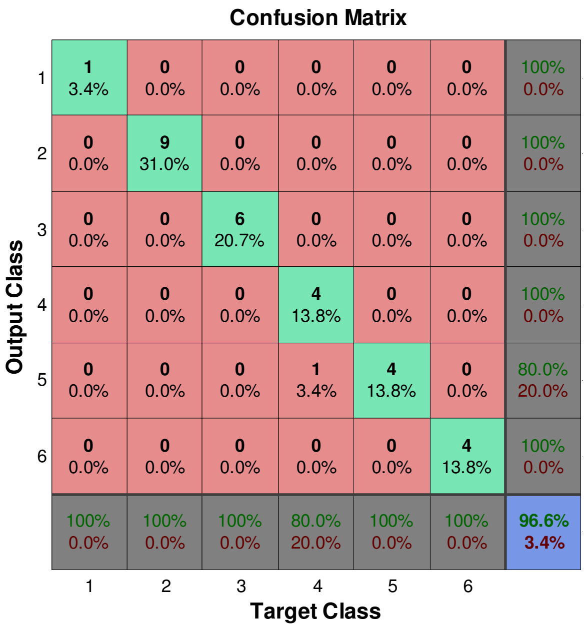

Figure 6: Confusion matrix for test data.

In each run, % of success classification of both tests and all data were calculated from confusion matrices. The mean value of the 50 trails was represented as the classification success of the related network.

Table 1 shows the classification success results of the network for two different learning algorithms. The results state that LM algorithm classifies more inputs than the SCG. This table also indicates that optimum hidden layer size is different for each algorithm. LM algorithm with eight hidden neuron configuration reached the maximum test data success. However the highest success of the SCG algorithm with hidden layer size of 10 is only 91.28%. Besides, LM converges with less epoch number that means less computational burden and faster than SCG.

Table 1: Classification results.

Hidden layer size	LM		SCG	
	Test	All	Test	All
1	43.32	48.73	25.19	26.09
2	81.19	88.67	64.57	70.18
3	89.58	94.34	81.76	86.14
4	88.14	92.81	86.29	89.37
5	91.43	95.96	89.43	90.85
6	91.00	95.39	90.13	93.76
7	91.71	95.03	89.27	92.43
8	**94.13**	**96.61**	85.15	89.08
9	88.84	93.22	90.14	93.79
10	91.00	95.09	**91.28**	**95.50**

All the simulations indicated that detection of transmission line network transients can easily be solved by converting the system into a classification problem. Figure 7 shows the regression curves for a given neural network.

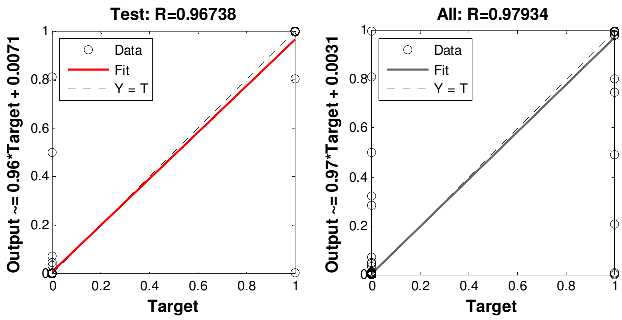

Figure 7: Regression curves for ANN with 8 hidden neurons and LM training algorithm.

ANN has very good regression both for test and all data. So, it can be seen that ANN provides very high accuracy for pattern recognition. Success of the both training algorithms is also very high. Computation times of LM and SCG are admissible for online detection and monitoring.

6 CONCLUSION

In this paper, a new scheme has been developed for identification and classification of disturbances on transmission lines by utilizing a method that is based on the wavelet based sub-band energy distribution for feature extraction and artificial neural network (ANN) for classification of disturbances. Variety of different scenarios with different parameters have been studied in order to assess the effectiveness of the proposed method by using common disturbance types on a transmission line. Different training algorithms have been tried in ANN and useful ones for this purpose have been identified. The results reveal that the propounded scheme based on the wavelet feature extraction and neural network based classification for transient disturbances produces adequately accurate results in terms of both identification and classification, and can be adopted as a line protection algorithm.

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