TRANSMISSION LINE FAULT CLASSIFICATION BASED ON WAVELET ENTROPY AND NEURAL NETWORK

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ABSTRACT

Classification of faults in power system has been a major challenge for power system engineers. In this paper, a technique for fault classification in transmission lines has been developed. EMTP software has been used to simulate the transmission line model. The simulation is followed by analysis of the voltage waveforms for classification of faults system using wavelet transform and artificial neural network in the MATLAB environment. The entropy values of the voltage signal obtained from wavelet transform have been fed into the neural network for automatic fault type classification. It has been found that only three level of decomposition of the voltage signal is sufficient for classification of faults. The proposed scheme is tested under different types of faults, such as single line to ground faults, line-to-line faults, double line to ground faults and three phase symmetrical faults for different varying fault locations and fault resistances.

Index terms: Entropy, Faults, Probabilistic neural network, Wavelet transform

1. INTRODUCTION

Transmission and distribution networks are the important components of power system network. Electric power systems are constantly affected with faults which disturb the system’s reliability, security and delivered energy quality. For the economic operation and stability of
the power network, it is of vital importance to detect, classify and clear the transmission line faults as quickly as possible. The importance of protection of power system network plays a great role in the successful operation of power system. In power system protection schemes classification of fault types in a radial and non radial system are the important issues. This can be done by detecting, localizing and classifying different fault types.

Safty and Zonkoly [1] presented a paper where EMTDC/PSCAD software has been used to detect fault types and wavelet entropy principle is implemented to analyze the current signals. Routray et al. [2] proposed a real time wavelet-fuzzy combined approach for digital relaying. Jung et al. [3] used a MATLAB based simulation tool to calculate the short circuit faults in power system transmission lines. The discrete wavelet transform has been used along with the fuzzy logic system to detect the fault classification of a transmission line. Kim et al. [4] presented a fault location algorithm using the Neuro-fuzzy systems in a combined transmission lines along with underground power cables. A fault location method employing wavelet fuzzy neural network has been proposed by Chunju et al. [5]. A new one-end fault location method for overhead transmission lines embedded in a general n-bus interconnected system has been discussed by Eisa et al. [6]. Jain et al. [7] proposed the problems encountered by conventional distance relays when protecting double-circuit transmission lines. Salim et al. [8] presented a paper in which fault location on transmission lines has been detected by impedance calculation method. A novel approach for robust fault detection and identification has been proposed by Zan et al. [9]. Borghetti et al. [10] presented a paper based on a continuous wavelet transform for the analysis of voltage transients due to line faults, and discussed its application to fault location in power distribution systems. Magnago et al. [11] identified the fault location on the parallel transmission lines using wavelet. Saleh et al. [12] proposed a differential equation to obtain the transient and steady state condition analysis. Fault location in transmission line is presented by Ekici et al. [13]. Chanda et al. [14] presented a multi resolution analysis (MRA) for locating the point of strike of lightning in transmission lines.

In this paper, half cycle of the pre fault and half cycle of the post fault voltage signal has been considered and decomposed by wavelet transform up to level 3. It has been found that the entropy values of detail coefficients of level 1 and level 3 only are sufficient for the detection and classification of faults in both a radial and non radial power system network. The entropy values have been fed into the neural network for automatic fault classification. The proposed protection scheme is tested under different fault types, varying fault location and varying fault resistances.

2. POWER SYSTEM MODEL

Two types of power system network have been considered here. In the first case a single transmission line has been considered and in the second case a six bus eight line non radial power system network has been considered. The simulation has been done in Electro Magnetic Transient Program. This program allows us to simulate the faults of any types at any location along the transmission line. In the first case a 400KV, 150Km long, three phase transmission line as shown in Fig. 1 has been considered. The voltage waveforms are monitored from the sending end of the transmission line. The circuit consists of an ac voltage source of 400KV, 50Hz which is supplying power to the network throughout the entire period. 15 LCC 3 phase blocks of 10km are taken for simulating 150km long overhead transmission
The line resistance is taken 0.031 ohm per km. The faults have occurred at 15 different locations.

Fig 1: Simulated radial power system network

In the second case, 400V, 15Km six bus eight line non radial power system network as shown in figure 2 is considered. The length of each line is 15km. The transmission lines are constructed with 15 identical 3 phase LCC blocks of 1km each. The voltage for the two generators is assumed to be 11KV and the MVA rating is 10MVA. The rating of the power transformers are 11KV/440V and 10MVA, each having delta-star connection. The three phase balanced load are connected at the four load buses. All types of faults are simulated at 1km intervals in all the eight lines. The voltage signals are monitored from bus 1 only. The line resistance is taken 0.0585 ohm per km.

The fault resistance considered for both the cases is 10 ohms and the total simulation time in 80 milliseconds. The sampling frequency is 2000 samples per cycle. All the different types of faults are generated after 40 milliseconds i.e. after two cycles. The technique developed in this paper mainly detects the type of faults in the transmission line.

Fig 2: Simulated 6bus-8line non radial power system network

3. FEATURE EXTRACTION USING WAVELET TRANSFORM

Feature extraction can be defined as a unique process that transforms the raw signals from its original form to a new form to extract suitable information from them. The feature extraction step is crucial in an automatic classification system. This is because a classifier can operate reliably only if the features of each event are selected properly. During fault, the amplitude and frequency of the test signal will change significantly as the system change from normal state to faulty state. The Shannon entropy will change accordingly. Wavelet transformation has the ability to analyze different transmission line faults simultaneously in both time and frequency domains. The wavelet transform is useful in detecting and extracting faulty features of various types transmission line faults both in radial and non radial network because it is sensitive to signal irregularities but insensitive to the regular-like signal behavior. The wavelet
The transform can be interpreted as the inner product of the complex conjugate of wavelet function $h^*_{a,\tau(t)}$ and the input signal $s(t)$:

$$\text{WT}_{(a,\tau)} = \int h^*_{a,\tau(t)} \cdot s(t) \, dt$$

(1)

Where the wavelet function $h^*_{a,\tau(t)}$ is defined as:

$$h^*_{a,\tau(t)} = a^{-1/2} h(t-\tau/a)$$

(2)

The variable $a$ is the scale parameter of the wavelet function and is proportional to the reciprocal of the frequency, $\tau$ is the translation parameter and $h$ is called the mother wavelet. Wavelet analysis deals with unsteady signals while entropy expresses information of the signal. Hence Wavelet entropy can analyze fault signals more efficiently. The feature extraction is very important in signal processing operations because the rough and large data sets cause difficulties, when a network is trained. In this study half cycle of pre fault and half cycle of post fault of the faulty voltage signals of all the three phases are considered to reduce the data set in size.

Wavelet Packet is employed on all the voltage signals which are originated from EMTP simulation for obtaining high frequency detail component which gives distinctive features about the signals. A mother wavelet is a function that oscillates, has finite energy and zero mean value. Normally, the mother wavelet that resembles the analyzed signal is the best choice, as this would reduce the number of non-zero Wavelet coefficients. For our project purpose $DB_4$ is selected as the mother wavelet. $DB_4$ owns a good time resolution providing an accurate detection of the fast transients induced by faults.

In this paper wavelet coefficients of voltage signals are decomposed at level 1 for classification of fault types. Entropy values are considered as the input features for classification of different types of faults (SLG, LL, DLG and LLL) at different locations. Entropy is a common method in many fields, especially in signal processing applications. Entropy indicates the amount of information which is stored in observed signal. Wavelet packet is applied to find the entropy values of different voltage signals at different levels.

4. CLASSIFICATION OF FAULTS USING ARTIFICIAL NEURAL NETWORK

An artificial neural network can be defined as a data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the human brain. ANN is powerful in pattern recognition, classification and generalization. Neural networks are useful for power system applications because they can be trained with off line data.

Probabilistic neural networks (PNN) are a kind of radial basis network suitable for classification problems. The architecture is feed forward in nature which is similar to back propagation, but differs in the way that learning occurs. PNN is supervised learning algorithm but includes no weights in its hidden layer. Instead each hidden node represents an example vector, with the example acting as the weights to that hidden node. These are not adjusted at all. Figure 3 illustrates a sample PNN structure.
Basically, PNN consists of an input layer, which represents the input pattern or feature vector. The input layer is fully interconnected with the hidden layer, which consists of the example vectors (the training set for the PNN). The actual example vector serves as the weights as applied to the input layer. Finally, an output layer represents each of the possible classes for which the input data can be classified. However, the hidden layer is not fully interconnected to the output layer. The example nodes for a given class connect only to that class’s output node and none other. The other important element of the PNN is the output layer and the determination of the class for which the input layer fits. This is done through a winner-takes-all approach. The output class node with the largest activation represents the winning class. While the class nodes are connected only to the example hidden nodes for their class, the input feature vector connects to all examples, and therefore influences their activations. Therefore the sum of the example vector activations determines the class of the input feature vector.

In PNN algorithm, calculating the class-node activations is a simple process. For each class node, the example vector activations are summed, which are the sum of the products of the example vector and the input vector. The hidden node activation, shown in the following equation, is simply the product of the two vectors (E is the example vector, and F is the input feature vector).

$$ h_i = E_i F $$  \hspace{1cm} (3)

The class output activations are then defined as:

$$ C_j = \sum_{i=1}^{N} \frac{h_i - 1}{\gamma} $$  \hspace{1cm} (4)

Where $N$ is the total number of example vectors for this class $h_i$ is the hidden-node activation, and $\gamma$ is a smoothing factor. The smoothing factor is chosen through experimentation. If the smoothing factor is too large, details can be lost; again if the smoothing factor is too small, the classifier may not generalize well.

Total 15 sets of data, each set containing entropy values of the pure and ten types of faulty signals are created for the training and testing of the neural network for the radial and non radial power system network to identify the fault types. Out of these 15 sets, 7 sets are used for the training purpose and remaining 8 sets of data are used for the testing purpose for radial network. Similarly 9 sets are used in the training purpose and remaining 6 sets of data are used for the testing purpose for non radial network.
4.1 Training of PNN

The designed PNN model is trained by 77 signals. The size of the input vector for type identification in single transmission line is 6×77, where 6 are approximation and detail values of level 1 for all the three phases and 77 comes from 11 types of signals multiplied by 7 different locations. The size of the input vector for type identification in non radial power system network is 6×792, where 792 comes from 11 types of signals multiplied by 9 different locations in eight different lines. Target of PNN for fault classification are 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11 for Pure, SLG-R, SLG-Y, SLG-B, LL-R-Y, LL-Y-B, LL-B-R, LLG-R-Y, LLG-Y-B, LLG-B-R, LLL faults respectively.

4.2 Testing of PNN

Pure signal along with ten different types of faults are considered in each set. In radial network all the 11 signals in eight different locations are used for the testing purpose. Hence 88 different signals are created for radial network to classify the types of faults. In non radial network similar 11 types of waveforms are considered. These signals are taken in 6 different locations in 8 lines. Hence 48 different locations are made. 11 types of signals multiplied by 48 different locations give 528 different signals for non radial network for the testing of the PNN model for classification of faults.

5. RESULTS

After training, the neural network based fault detector and classifier is extensively tested using independent data sets consisting of fault scenarios not used previously for training the network. Fault type, fault location and fault resistances are changed for different faults in the validation/test data set to investigate the effects of these factors on the performance of the proposed method.

In the case of single transmission line ten different types of faults along with the pure signal are classified very accurately at eight different locations. Table 1 gives the classifier performance for each type of fault. The classifier gives 100% accurate results for LLG and LLL type of faults. In the case of SLG and LL there are some misclassifications. Hence, the overall accuracy of the classifier is 93.18%.

The results of classification for non radial system are shown in table 2. To investigate the accuracy of the proposed method in these cases, 100% accurate results are found for SLG and LLG type of faults. The accuracy rate is slightly decreased for some misclassifications in LL and LLL faults. In some cases three phase symmetrical faults are classified as line to line faults. Hence PNN model based fault identifier identifies the fault types with an accuracy of 93.94% in a very fast and effective manner. Fault resistances are varied to identify the fault types at different lines in non radial power system network. Fault resistances are varied from 0 to 30ohms.
Table 1: ANN result for fault classification in single transmission line

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Overall accuracy 93.18%

Table 2: ANN result for fault classification in non radial system

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Overall accuracy 93.94%

6. CONCLUSIONS

The purpose of this paper is to find an effective technique suitable for the fault classification of power system transmission lines. The proposed method uses wavelet packet decomposition which provides more features about the signal than classical wavelet. After wavelet packet decomposition of voltage signals up to three decomposition levels, the entropy values are calculated only for detail level 1 and 3 for each faulty voltage waveforms. Therefore the size of the feature vectors is reduced considerably. The features obtained by this way are used as the inputs of ANN for determination of all types of faults along with affected phases within half cycle after the occurrence of the faults. The results presented in this paper confirm the possibility of developing an accurate fault classification scheme that may aid the development of reliable transient-based protection schemes. Further investigations are being carried out to confirm the robustness of the performance under changes in the network configuration. The proposed scheme is easily comprehensible, deterministic and is feasible for practical implementation.
ACKNOWLEDGEMENT

The authors acknowledge the financial support given by Department of Science and Technology (DST), Govt. of India for sponsoring this research to Dr. Sudipta Nath.

REFERENCES

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