A NEURAL NETWORK BASED APPROACH FOR TRANSMISSION LINE FAULTS

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ABSTRACT

In this study, a neural network based methodology is proposed for power transmission line faults. The proposed method uses Probabilistic Neural Network (PNN) for classifying fault types and Resilient Propagation algorithm (RPROP) for detecting fault locations. Wavelet Transform is also proposed for feature selection and analysis. The hybrid system proposed in this study is tested using a simulation and a prototype power system.

I. INTRODUCTION

A fault occurs when two or more conductors come in contact with each other or ground [1]. Ground faults are considered as one of the main problems in power systems and account for more than % 80 of all faults [2]. In three phase systems, faults are classified as; single line to ground faults, line-to-line faults, double line-to-ground faults, three phase symmetrical faults. These faults give rise to serious damage on power system equipments. So, it is necessary to determine the fault location on the line and clear the fault as soon as possible in order not to cause such damages. Flashover, lightning strikes, birds, wind, snow and ice load lead to short circuits. Deformation of insulator materials also leads to short circuit faults.

There are several methods such as using the variation of line impedance, measuring of faulted current and voltage signals and a lot of study has been continued with advance in computer technology. When fault location is estimated by using current and voltage wave information, methods based on traveling waves, faulty line impedance calculations, Artificial Neural Network (ANN) and Wavelet Transform (WT) are used widely [3]. In traveling wave method, fault location is determined by using time difference between incidents and reflecting waves [2, 4, and 5]. This method has been restricted because of the difficulty in analyzing. Calculating characteristic reactance is another method which is used for estimating fault distance [6]. One of the other techniques is fourier transform which obtains line impedance in the frequency domain [7]. In spite of fourier transform, WT has been used to obtain the best information of current and voltage signals. The main advantage of WT is that the band of analysis can be fine adjusted and the results obtained from WT are shown on both the time and frequency domain. Application of digital technology allows modifications to be made on line to improve the network protection and control in the presence of the controllable and non-controllable devices [8]. Artificial intelligence (AI) techniques naturally become the best choice to improve the performance of the present system used. AI possesses powerful characteristics such as fast learning, fault tolerance and ability to produce correct output when fed with partial input. It can adapt to recognize learned patterns of behavior in electric power systems where exact functional relationships are neither well defined nor easily computable [9].

This paper presents a hybrid method for the transmission line fault analysis. The method consists of three stages. In the first stage, distinctive features of faulty signals are extracted by using WT. In the second stage, the transmission line faults are classified by PNN that has high performance level especially in classification problems than conventional backpropagation algorithm (BPA) [10]. In the third stage, RPROP training algorithm is employed to determine fault locations [11]. Different types of faults (single-line to ground, line to line, double-line to ground and three-phase symmetrical) which are occurred at different locations and inception angles are simulated by ATP [12]. An experimental study is also performed to obtain real data.

II. EXPERIMENTAL STUDY AND SIMULATION

To obtain the necessary information about the fault cases, a 380 kV-360 km long transmission line model is experimented as shown in Figure 1. The system parameters are chosen with 1:1000 scale factors. Line resistance, line inductance, mutual capacitance, earth resistance and earth capacitance are 13 *ohm*, 290 *mH*, 1 μF, 5 *ohm* and 2 μF respectively. For all fault types occurred at 50 different locations, the faulty voltage and current signals are saved by a data acquisition card. Figure 2 denotes a three-phase symmetrical fault voltage curve obtained from sending end of the prototype power transmission line. The prototype power system is simulated by using ATP. The one-line diagram of the studied system is shown in Figure 3. The simulation time is 500 *ms* with 20 μs time step. Fault type, fault location and fault inception time are changed to obtain training patterns covering a wide range of different power system conditions. In Figure 4, the fault voltage of three-phase symmetrical fault occurred at sending end of the line is shown.

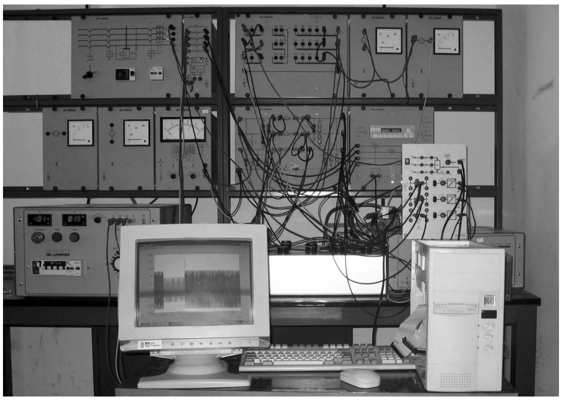

Figure 1. Prototype power system.

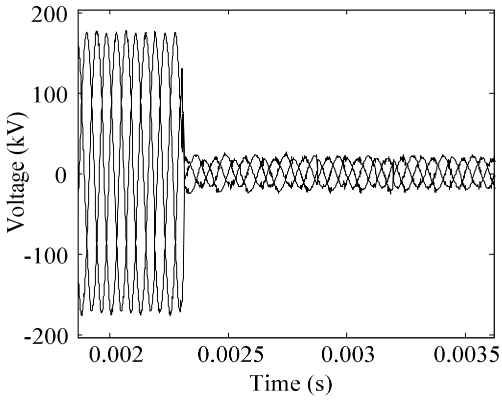

Figure 2. Voltage of three-phase symmetrical fault measured at sending end of the prototype power system.

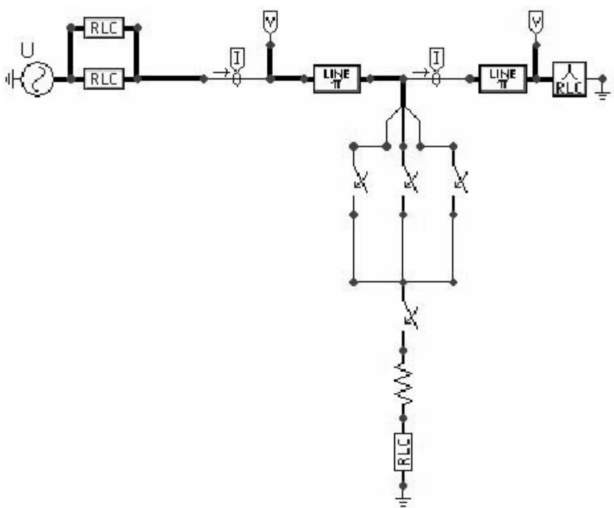

Figure 3. ATP model of power system.

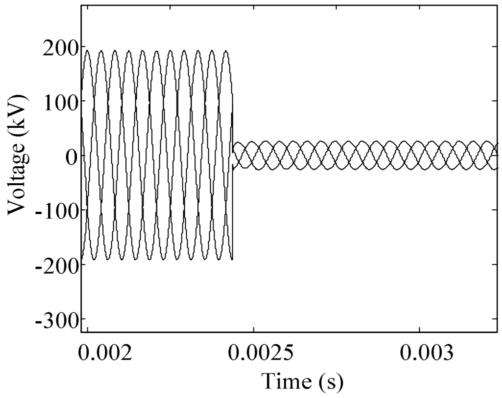

Fig. 4. Voltage of three-phase symmetrical fault measured at sending end of the line simulated by ATP.

III. FEATURE EXTRACTION

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, Wavelet transform (WT) is used to obtain distinctive features of faulty signals. WT is a mathematical technique used for many application of signal processing [13]. Wavelet is much more powerful than conventional methods in processing the stochastic signals because of analyzing the waveform time-scale region. In wavelet transform, the band of analysis can be adjusted so that low frequency and high frequency components can be windowing by different scale factor. Recently WT is widely used in signal processing applications, such as de-noising, filtering, and image compression [1]. Many pattern recognition algorithms have been developed based on the wavelet transforms. It has been also used widely by the power system researchers. According to scale factor, wavelet categorized different section. In this paper the wavelet which is named Discrete Wavelet Transform (DWT) has been used for feature extraction. The wavelet transform of $f(t)$ is defined as;

$$\mathrm{DWT}(m,n)=\frac{1}{\sqrt{2^m}}\sum_k f(k)\psi\left(\frac{n-k2^m}{2^m}\right) \qquad (1)$$

where, ψ is mother wavelet [1]. The decomposition for three-level is shown Figure 5.

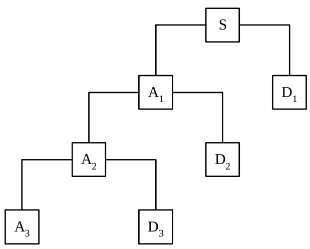

Figure 5. Three-level signal decomposition diagram, S: signal, A_i: approximation, D_i: details,

Half cycle of pre-fault and half cycle of post-fault are considered to reduce the data set in size. Therefore 1000 samples are obtained for each faulty voltage or current signal. Then, DWT has been employed for obtaining high frequency detail component which gives distinctive features about the curves. Daubechies-4 (db4) was selected as a mother wavelet [14]. Wavelet coefficients are shown in Figure 6, for three-level decomposition of voltage signals belonging to a SLG fault at 10th km.

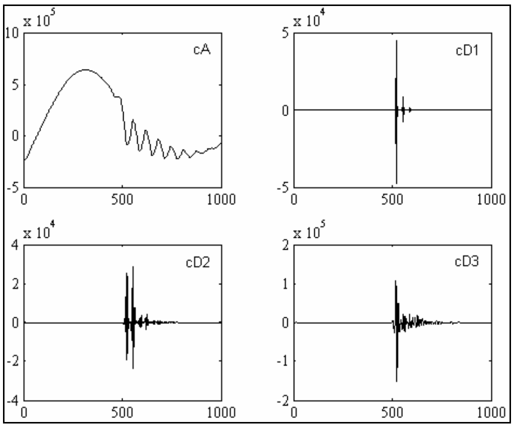

Figure 6. Voltage coefficients of DWT, cA: approximation, cD: details.

IV. CLASSIFICATION OF FAULT TYPES

PNN is employed to classify fault types after feature selection stage. PNN is a kind of radial basis function (RBF) neural networks which are suitable for many classification problems [15]. The most distinctive feature of PNN which differentiates from RBF is that PNN works on estimation of probability density function while RBF works on iterative function approximation. The training of RBF is noticeably faster than BPA feed forward neural networks. In 1990, D. Specht proposed a four-layered feed-forward network topology that implements Bayes' decision criterion and Parzen's method for density estimation. The PNN network described in consists of an input layer, two hidden layers (one each for exemplar/pattern and a class/summation layers) and an output/decision layer as shown in Figure 7. This model can compute nonlinear decision boundaries that asymptotically approach the Bayes' optimal. Bayesian strategies are decision strategies that minimize the expected risk of a classification [16]. In order to classify a feature vector which belongs to different predefined classes, the conditional probability of each class is estimated. Then these estimates are combined by the rule of Bayes to yield a-posteriori class probabilities that allow in making optimal decisions [17].

In order to train PNN, 160 neurons with 18 features belonging to each fault case are introduced to network as inputs. For testing of PNN, a data set which contains current and voltage information of 40 faults occurred at different location and inception angle is used. The application of WT combining PNN to determine fault type is a novel technique with a very high accuracy of 100%. BPA is also tested to evaluate the performance of proposed method and it is shown that the training of PNN is noticeably faster and gives better results than BPA.

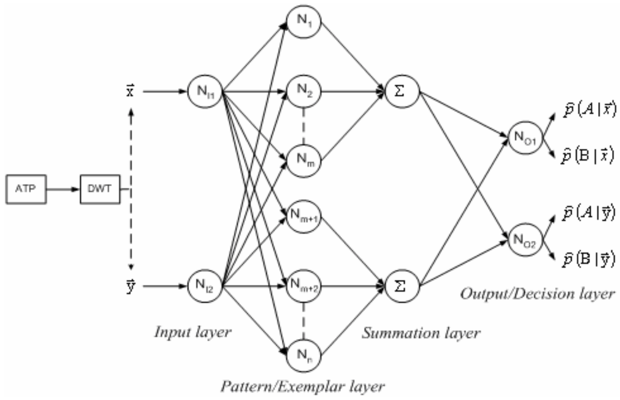

Figure 7. Architecture of probabilistic neural network for two classes.

V. PREDICTION OF FAULT LOCATIONS

In order to predict fault location on transmission line, a multilayer feed-forward network which is used in many non-linear application problems is proposed. Because of the fact that we have a large data set containing features of faulty signals as inputs, we need a network that uses a fast training algorithm and requires less memory. There are several BPAs based on gradient descent such as conjugate gradient, quasi-Newton and Levenberg-Marquardt (LM). In this study, we propose a heuristic BPA called RPROP which is developed from an analysis of the performance of the standard steepest descent algorithm [15].

RPROP bases on the traditional backpropagation method with only one difference: weights are updated by evaluating the behavior of the error function [18]. Multilayer networks typically sigmoid transfer functions in the hidden layers. This causes small changes in the weights and biases even though the weights and biases are far from their optimal values; since the gradient can have a very small magnitude. This problem is eliminated by making use of the derivative sign and not of its value. As a result, RPROP learns faster and uses fewer memory compared to traditional BPAs as depicted in the reference [15, 18]. Figure 8 illustrates a comparison between training curves of RPROP and Levenberg-Marquardt BPA only for the first 100 epochs of both algorithms. Note that within 100 epochs of the training curve, RPROP's mean-squared error is approximately 10^{-4} whereas Levenberg-Marquardt's is still 10^{-2}. The test results of RPROP including 50 different fault locations for each fault type are shown in Table 1.

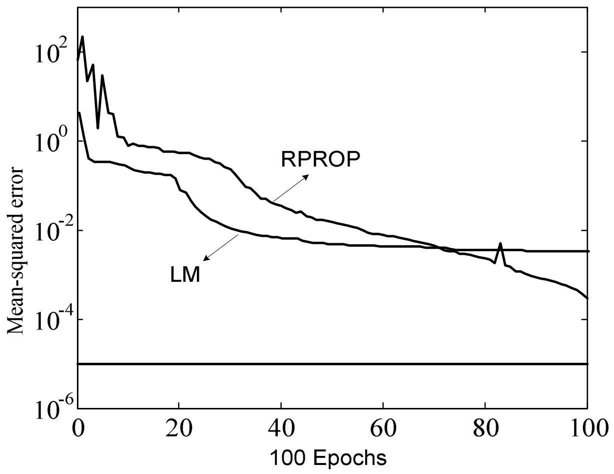

Figure 8. Mean squared-error curves, RPROP: resilient propagation, LM: Levenberg-Marquardt backpropagation

Table 1. Actual and estimated fault locations, SLG: sigle line to ground fault, LL: line to line fault, LLG: double-line to ground fault, LLLG: three-phase to ground fault.

Actual (km)	SLG	LL	LLG	LLLG
48.00	27.62	61.73	66.218	25.93
84.70	89.11	82.369	80.701	89.832
113.68	113.38	114.43	114.78	112.43
137.14	136.62	137.50	137.06	137.14
156.52	156.97	155.75	155.24	157.48
180.00	180.39	179.85	179.30	180.07
192.85	192.69	193.25	192.78	192.51
204.00	203.61	204.41	204.34	203.66
214.00	213.63	213.84	214.18	213.62
222.35	222.45	222.16	222.67	222.44
230.00	230.19	229.63	230.19	231.94
240.00	240.14	239.71	239.98	240.23
256.00	255.83	256.14	255.82	256.08
271.69	271.60	272.11	271.49	271.52
279.31	279.34	279.62	279.18	279.15
288.00	288.15	288.04	288.08	287.64
294.00	294.22	294.19	294.22	293.91
303.61	303.57	303.66	303.67	306.59
309.67	309.46	309.57	311.05	311.99
313.66	313.32	313.40	313.81	313.76
318.58	318.38	318.67	318.84	317.54
322.00	321.99	322.22	321.88	322.36
329.41	330.04	329.75	329.21	329.42
338.00	339.02	338.92	338.07	337.89
342.20	341.66	341.75	341.77	341.44

VI. CONCLUSION

In this paper, a hybrid method based on WT, PNN and RPROP is presented for determining fault types and location on a three-phase system. WT is used for analyzing of faulty signal and selecting distinctive features which are necessary for constructing an effective neural network. Because of its excellent classification performance and training speed, PNN is proposed to identify the fault types. The testing of PNN verifies all fault types with %100 performance while BPA classifies only %89 of faults correctly. Multilayer feed-forward neural networks are used for determining fault locations. A type of BPAs called RPROP is selected as training algorithm to decrease learning time. The proposed algorithm for the estimation of fault location gives very satisfactory results except for the first fault point which is the closest point to source.

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