A Novel Approach for Fault location and Division Technique using ANN

Aaditya Agarkar[1], Dr.S.B.Mohod[2]
PG Student, Dept of EEE, PRMCEAM-Badnera, Affilated to SGB Amravati University
Assistant Professor, Dept of EEE, PRMCEAM-Badnera,Affilated to SGB Amravati University

ABSTRACT

The work described in this paper addresses the problems encountered by conventional techniques in fault type classification in double- circuit transmission lines; these arise principally due to the mutual coupling between the two circuits under fault conditions, and this mutual coupling is highly variable in nature. A new approach of digital relays for transmission line protection is presented. The proposed technique consists of a preprocessing module based on Discrete Wavelet Transforms (DWTs) in combination with an artificial neural network (ANN) for detecting and classifying fault events. The DWT acts as an extractor of distinctive features in the input signals at the relay location. This information is then fed into an ANN for classifying fault conditions. A DWT with quasi optimal performance for the preprocessing stage is also presented.

Keyword: Vault classification, double circuit transmission lines, combined unsupervised/supervised learning, self-organization mapping, mural networks.

1. INTRODUCTION

Parallel transmission lines which can significantly increase transmission capacity on existing systems are finding morewidespread usage. However, there is difficulty in classifying the fault types on such lines using conventional techniques, Principally because a faulted phase(s) on one circuit has an effect on the phases on the healthy circuit due to mutual Coupling between the two circuits. The problem iscompounded by the fact that this coupling is not constant in nature and is dependent upon a complex interplay amongst a number of variables. As a consequence, the coupled phase(s) on the healthy circuit may sometimes be wrongly diagnosed as being the faulted phase(s) under certain fault conditions. Thus conventional classifiers based on logical comparison techniques or linear algorithms are not well suited for such Circuits. There is thus a need to develop an alternative fault classifier. Very often, fault classification is part of an overall Protection scheme. This is particularly so in techniques based on a modular approach whereby correct fault discrimination (ie whether a fault is within the protected zone) is very muchdependent upon accurate fault type classification in the first place. Since the majority of power system protection techniques are involved in defining the system state through identifying the patterns of the associated voltages and currents, the development of a novel fault classification technique (the subject of this paper) can be essentially treated as a problem of pattern recognition. In this respect, neural computing has the very important attribute to solve non-linear system identification problems through using neurons, links and learning algorithms, and hence neural networks (NNs) are ideally suited to deal with the complex non-hear fault classification problem [l,2,3].

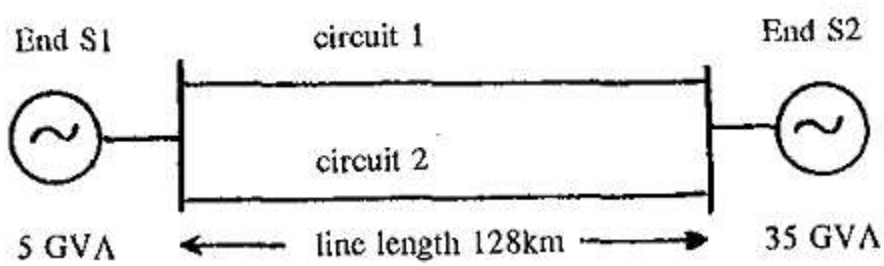

Fig.1.Double circuit lines

SOM Classifiers :

The SOM-based classifier is a technique that separates object recognition into two parts: (i) feature extraction with unsupervised learning in the first stage and (ii) theclassification with supervised learning sitting on the top. An important basic principle is that die features must theindependent of class membership, since the latter is not yet known at the feature extraction stage by definition. Thisimplies that if any learning methods are used for developing the feature extractors, they should he unsupervised in a sense, because the target class for each object is unknown [5,6,7]. Fig.2 typifies a SOM-based network. The unsupervised learning stage is based on the rule that a neuron with the shortest Euclidean distance is fired while the others are inhibited from firing. The range of fired neurons vary as the learning process proceeds. The NN has the competitive relationship in a sense that once a neuron responds to a specific pattern, other neurons never reply to it. In other words, the input patternthat fires a certain neuron makes the neighboring neurons inactive.

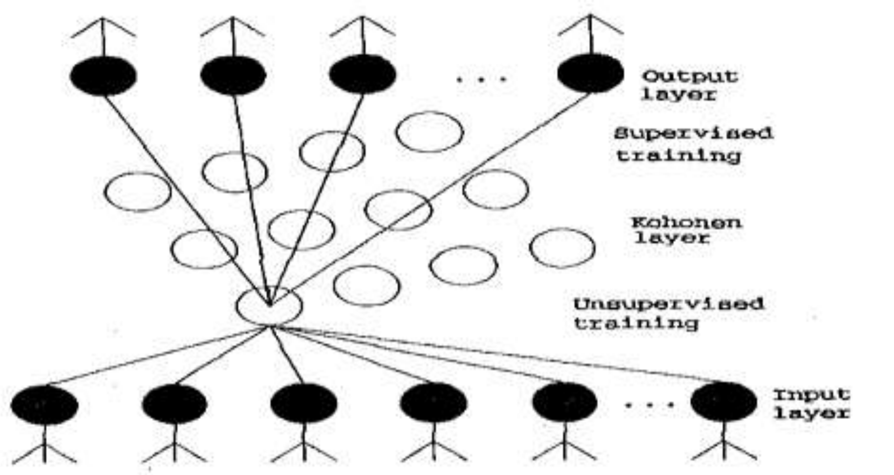

Fig.2. A SOM-based network Structure

A. Input And Output Selection

In order to build up a NN, the inputs and outputs of the network have to be defined for pattern recognition. For these purposes, au accurate knowledge of the three phase voltages and the six phase currents on both the circuits under different system and fault condition is germane to the development of the NN topology. Fig 3 typifies the primary system voltage and current waveforms measured at end S1 (Fig 1) when an 'a'-phase-earth fault occurs (near voltage maximum) on circuit 1 at the midpoint of the line. As expected, there is sane high frequency (HF) distortion on the voltage waveforms, in particular on the faulted 'a'-phase (as shown in Fig 4a) and this so by virtue of the fact that there is a large step change inthe 'a'-phase voltage when the fault occurs. Again as expected, there is a large increase in the magnitude of die measured 'a'-phase current of the faulted circuit I (Fig 3b). However, unlike the voltage waveforms, the current signals are relatively distortion free from a HF point of view and are confined to low frequencies; this is due to the inductive nature of the transmission circuit considered.In practice of course, there are systems in which distortion on current waveforms can he quite significant. However, the technique described herein is based on a relatively low sampling rate (800Hz) and utilises a low-pass, anti-aliasing filter with a cut-off frequency of 250 Hz in order to conform with die Nyquist Rate; this effectively means that even in situations when the waveforms are ridden with HF distortion, the latter would he severely attenuated firstly at the analogue stage and secondly when the signals aredigitised before being processed through the "-based algorithm, thereby having little detrimental effect on theperformance of the fault classifier. More importantly, the currents on the healthy circuit 2 show a significant rise in magnitude from the pre-fault steady state level, from the time of fault inception (Fig 3c) and this arises as a direct consequence of the mutual coupling effect between the two circuits. As mentioned before, it is this coupling which is largely the cause of fault misclassification conventional techniques. In the technique described herein, the digitized three phase voltages and six phase current on both circuitsbecome input signals to NNI (or "2, as the case may he) as shown

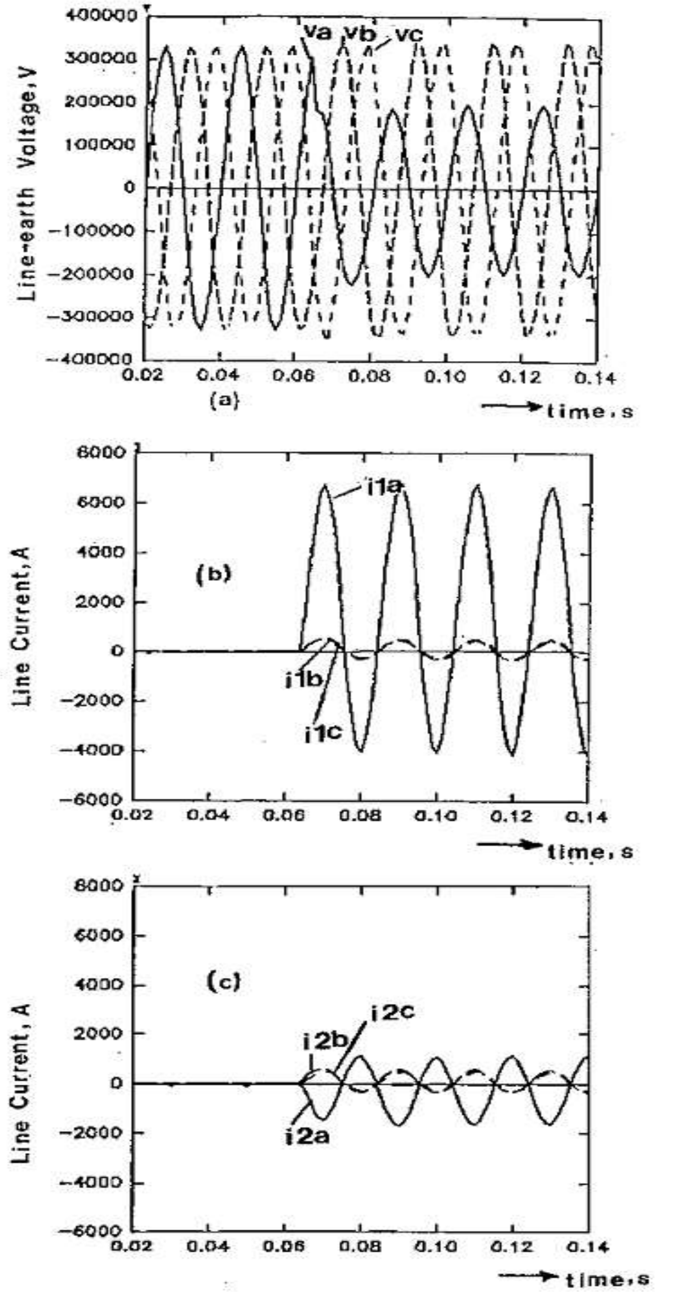

Fig.3.Typical measured voltage and current waveform
(a) voltage waveforms, (b) current on circuit I, (c) currents an circuit 2

2. Artificial neural network

The ANN represents a parallel multi-layer information processing structure. The characteristic feature ofthis network is that it considers the accumulated knowledge acquired during training, and responds to newevents in the most appropriate manner, given the experiences gained during the training process.The model of the ANN is determined according tonetwork architecture, transfer function and the leaning rule. Fig. 1 shows a typical neural network architecture,known as multi-layered perception (MLP), also knownas the error back-propagation network .Here,Xis the ANN input training matrix, W[i] arethe weight matrices, F[i] is the matrix of transferfunctions, b[i] the bias vector for individual neurallayers (i-1, 2), Yis the calculated output vectoraccording to the equation,

Y=F[2](W[2] ·F[1](W[1] ·Xb[1])b[2]) (1)

And **T**is the target output vector in ANN training.The objective of the training process is to adjust allANN weights and biases to obtain minimal deviationsbetween the target and calculated ANN outputs inrelation to the mean value of all input samples.

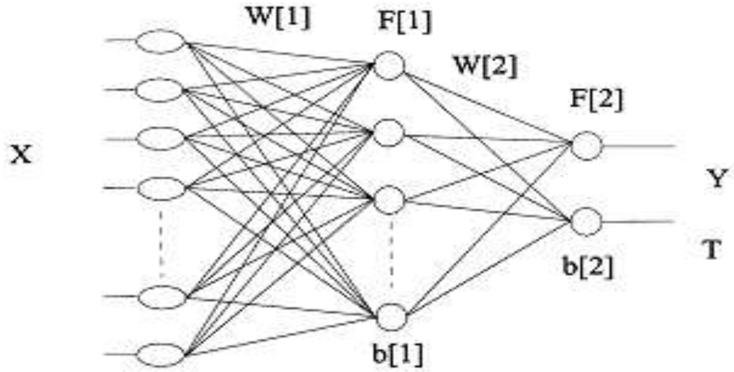

Fig. 4. Multi-layered perception architecture

Once the training process is completed the results oftraining must be checked, first using the samples used intraining and then new samples not used in training. Toimplement a neural network, the following steps mustbe taken,selection of a suitable network architecture;selection of the learning rule best suited to the network established;training of the neural network;checking of network behaviour.3. Fault location approach using ANNThe basic points of the procedure used to implementa neural network in the fault location process in single,two-terminal transmission lines is described below.
3.1. Selecting the right architectureSpecial attention must be paid to accuracy in theobtaining of the fault distance, but it must be remembered that selecting the night size and structure for thenetwork will reduce training time. This is very important, as it simplifies hardware requirements and enablesthe method to be used on a PC.One factor in determining the right size and structurefor the network is the number of inputs and outputsthat it must have. The lower the number of inputs, thesmaller the network can be. However, sufficient inputdata to characterize the problem must be ensured.To enable the method to be implemented in bothfault location devices and centralised systems, only themagnitudes recorded at one end of the line are used There is a drawback in using only voltages recordedat the reference end, they vary according to distance
and fault resistance less than current levels, so trainingconvergence in some short lines is too slow.

6. CONCLUSION

This paper has presented a new approach to faultlocation in two-terminal overhead transmission lines,using ANN's, based on the 50:60 Hz fundamentalcomponents of the fault and pre-fault voltage andcurrent magnitudes measured at each phase at thereference end. The method considers both correctlymeasured magnitudes and readings containing errors.
This paper describes a novel fault classifier for double- circuit lines, utilising a SOM-based network. It is shown that the technique presented correctly identifies the faulted phase(s) in spite of the presence of the highly variable mutual coupling effect between the two circuits.In particular, the performance of the proposed fault classification technique is compared with the one based on a BP network. Generally speaking, a BP network with supervised training has a number of disadvantages. For example, it needs a much larger number of trailing sets to cater for the vast majority of different system faultconditions; this is time consuming and the training is very slow. Moreover, retraining the BP network with new dataassociated with, for example, contingencies may not converge to the desired value.and fault conditions.

REFERENCES

[1]A.O. Ibe, B.J. Cory, A travelling wave-based fault locator fortwo and three terminal networks, IEEE Trans. Power Syst. 1 (1986) 283 – 288
[2]M. Kezunovic, I. Rikalo, D.J. Sobajic, High-speed fault detection and classification with neural nets, Electr. Power Syst. Res.34 (1995) 109 – 116
[3]A.F. Sultan, G.W. Swift, D.J. Fedirchuk, Detection of highimpedance arcing faults using a multi-layered perceptron, IEEE Trans. Power Deliv. 7 (4) (1992) 1871 – 1877.
[4] M., EI-Sharkawi, D., Niebur, Tutorial course on artificial neural networks with applications to power systems. IEEE PowerEng. Soc. 1996.
[5]V.S.Vankayala and N.D.Rao, "Artificial NNs and Their Application to Power Systems -a bibliographical survey", International Journal of Electrical Power System Research, Vo1.28, 1993,pp.67-79.

[6]N.Kandil, K.Kliorasad, R.V.Patel, V.K. Sood,"Fault Identification in AC-DC Transmission System Using Neural Networks", IEEE Trans. on Power System, Vo1.7, No.2, may 1991, pp.812-819.
[7]J.Lampinen and E.Oja, "Distortion Tolerant Pattern Recognitiou Based on Self-Orgatlizing Feature Extraction",Trans on Neural Networks, Vol 6, No 3, May 1995, pp 539-549.
[8] M.Djukanovic, B.Babic, D.J.Sobajic and Y. H. Pao, "UnsupervisedlSupervised Learning Concept for 24-hour Load Forecasting", IEE Proc.- C, Vol.140, No.4, July 1993. pp.311-318.
[9] H.Mori, Y.Tamam, S.TsuzukiaudK.Tama, "An Artificial Neural-Net Based Technique for power System Dynamic Stability with the Kohonen Model", IEEE Trans. on Power System, Vo1.7, No.2, May 1992, pp.856-864.

BIOGRAPHIES

	**Dr.Swapnil B. Mohod** Had completed his PG Degree in Electrical Engineering & Working as a Assistant Professor in EEE Department of PRMCEAM. Having Experience of 14 years .His area of working includes Power System.
	**Aaditya Pradip Agarkar** Is Student of ME 2nd year in Electrical and Electronics Engineering of PRMCEAM Working on High Transient based double circuit transmission line protection and fault classification using line trap .