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High Impedance Fault Detection using LVQ Neural Networks

Abhishek Bansal and G. N. Pillai

Abstract**—**This paper presents a new method to detect high impedance faults in radial distribution systems. Magnitudes of third and fifth harmonic components of voltages and currents are used as a feature vector for fault discrimination. The proposed methodology uses a learning vector quantization (LVQ) neural network as a classifier for identifying high impedance arc-type faults. The network learns from the data obtained from simulation of a simple radial system under different fault and system conditions**.** Compared to a feed-forward neural network, a properly tuned LVQ network gives quicker response.

Keywords**—**Fault identification, distribution networks, high impedance arc-faults, feature vector, LVQ networks.

I. INTRODUCTION

HIGH impedance faults (HIFs) on distribution systems create unique challenges for the protection engineer. HIFs that occur do not produce enough fault current detectable by conventional overcurrent relays or fuses [1]. A high impedance ground fault results when a primary conductor makes unwanted electrical contact with a road surface, sidewalk, tree limb, or with some other surface, or object which restricts the flow of fault current to a level below that reliably detectable by conventional overcurrent devices [1]. These faults are characterized by intermittent arc-type nature and very low current rich in low harmonic content and high frequency noise spectra. The failure of HIF detection may lead to potential hazards to human beings and potential fire [2]. Therefore, from both public safety and operational reliability viewpoints, detection of HIFs is critically important.

Engineering efforts for the development of a reliable method for the detection of high impedance arc-type faults led during the last two decades to important progress in understanding the electrical characteristics of these faults and in the evaluation of several detection concepts [3]. Various techniques of fault detection encompass fractal techniques [4], expert systems [5], neural networks [6-8] and dominant harmonic vectors [9, 10]. The use of high frequency harmonics is not feasible in practical relay because of the filtering by the substation current transformers. Other methods that try to reduce the limitation of frequency domain methods include Kalman filtering [11] and wavelet transform based methods [2, 12]. Among many techniques proposed by different research groups, use of information contained in the low frequency spectral behavior, in terms of both magnitude and phase, seems to be the most promising approach for the next steps which will bring the industry closer to the realization of a fully operation HIF detector [13].

In [14], a novel time domain HIF detection scheme based on low frequency harmonic excursion patterns and phase portraits is used to detect the high impedance arc-type faults on a radial distribution system. In this paper we propose a novel approach of employing learning vector quantization (LVQ) neural networks to detect HIFs in radial distribution system. In the proposed scheme, the reference vectors are set to the locations mostly matching the probability distributions of training vectors to improve the learning characteristics of LVQ. The improved learning characteristics ensure more accurate classification results. The sample system studied in this paper is a 25 kV power distribution network studied in [14].

The paper is organized as follows. Section 2 deals with a brief review of the system description and fault simulation method. Section 3 provides a basic description of the employed LVQ networks. Section 4 reports the case study and discusses the simulation results. Section 5 concludes the paper with some general remarks on the idea of optimizing neural networks.

II. SYSTEM DESCRIPTION AND FAULT SIMULATION

Single line diagram of the sample radial distribution system [14] is shown in Fig. 1. The distribution line is represented by lumped passive elements without mutual coupling. Constant impedance load is assumed. Fig. 2 represents the equivalent per phase circuit during fault with nonlinear arcing fault resistance R_f. The training data is obtained by applying nonlinear and linear faults to the circuit model at different fault locations x. The system parameters and nonlinear arc model are given in the Appendix.

Using Fig. 2, following nodal equations can be written in s-domain. All variables are in s-domain and (s) is dropped for domain. The variables in s-domain are shown in capital letters. For linear faults, the fault resistance is not varying as shown in Appendix.

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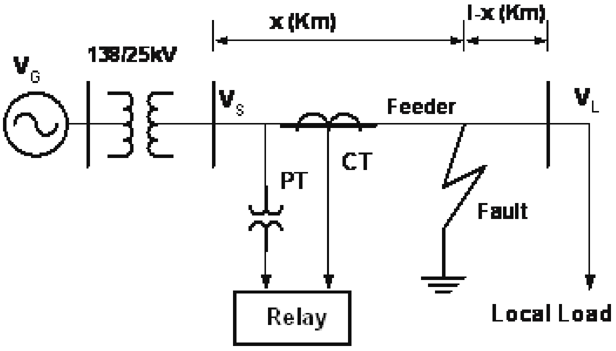

Fig. 1 Single line diagram of a radial distribution line

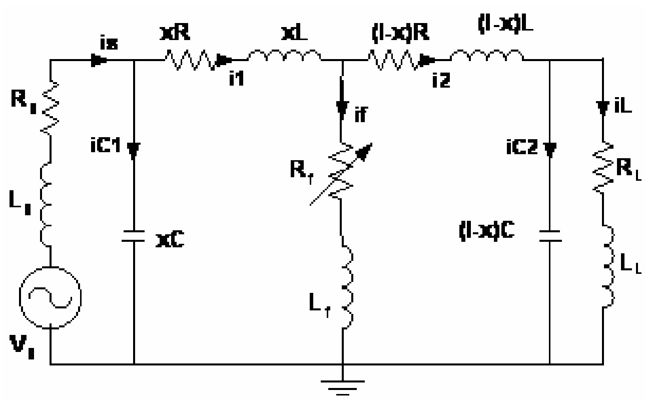

Fig. 2 Per phase equivalent circuit with HIF arc-type fault

$$
\begin{aligned}
I_S &= (V_S - V_1)\frac{1}{L_S s + R_S} \\
I_{C1} &= I_S - I_1 \\
V_1 &= \frac{1}{xCs} I_{C1} \\
I_1 &= (V_1 - V_f)\frac{1}{xLs + xR} \\
I_f &= I_1 - I_2 \\
I_2 &= (V_f - V_2)\frac{1}{(1-x)Ls + (1-x)R} \\
V_f &= (L_f s + R_f) I_f \\
I_{C2} &= I_2 - I_L \\
V_L &= \frac{1}{(1-x)Cs} I_{C2} \\
I_L &= V_L \frac{1}{L_L s + R_L}
\end{aligned}
\tag{1}
$$

Using the above equations, a MATLAB/SIMULINK simulation model is made as shown in Fig. 3. The radial system is subjected to an Arc type fault at different locations from x=0 to full feeder length. For linear and nonlinear HIFs, the value of fault impedance R_f is given in the Appendix.

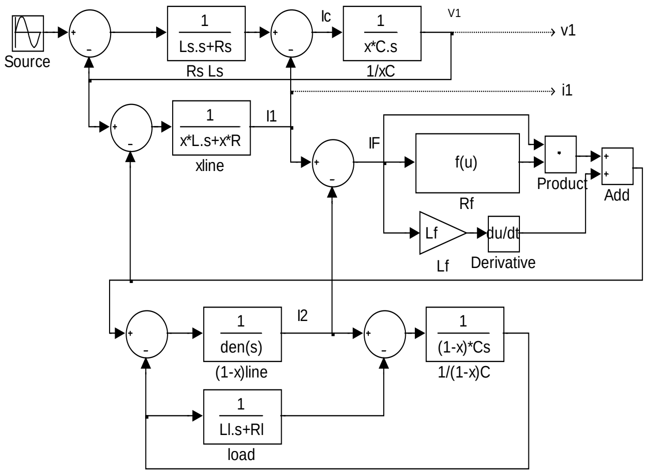

Fig. 3 MATLAB/SIMULINK functional model of radial system

III. Learning Vector Quantization (LVQ) Neural Networks

LVQ networks are supervised versions of vector quantization for adaptive pattern classification [15]. The method illustrates how an unsupervised learning mechanism can be adapted to solve supervised learning tasks in which class membership is known for every training pattern. Vector quantization is a technique whereby the input space is divided into a number of distinct regions, and for each region a reconstruction vector is defined [16]. When presented with a new input x, a vector quantizer first determines the region in which the vector lies. Then the quantizer outputs an encoded version of the reconstruction vector w_i representing that particular region containing x. The set of all possible reconstruction vectors w_i is usually called the codebook of the quantizer. When the Euclidean distance similarity measure is used to decide on the region to which the input x belongs, the quantizer is called a Voronoi quantizer [16].

In LVQ networks, class information is used to fine-tune the reconstruction vectors in a Voronoi quantizer so as to improve the quality of the classifier decision regions [17]. In classification problems, it is the decision surface between classes and not the inside of the class distribution that should be described most accurately. The quantizer process can be easily adapted to optimize placement of decision surface between different classes. The method starts with the calibration of a trained Voronoi quantizer using a set of labeled input samples. Each w_i is then labeled is according to the majority of classes represented among those samples which have been assigned to w_i. Here the distribution of the calibration samples to the various classes, as well as the relative numbers of the w_i assigned to these classes, must comply with the priori probabilities of the classes, if such probabilities are known [15]. The tuning of the decision surfaces is done by rewarding correct classifications and punishing incorrect ones. When training pattern x^k from class c_j is presented to the network, let the closest reconstruction w_i belong to class c_l. Then only vector w_i is updated according to the following supervised rule

$$\Delta w_i = \begin{cases} +\eta^k (x^k - w_i) & if\ c_j = c_l \\ -\eta^k (x^k - w_i) & if\ c_j \neq c_l \end{cases} \quad (2)$$

where the learning rate η^k is assumed to be a monotonically decreasing function of the number of iterations k.The decreasing learning rate allows the network to converge the network to a state in which the weight vectors are stable. The primary effect of equation (2) is to minimize the number of misclassifications. At the same time, the vectors w_i are pulled away from the zones of class overlap where misclassifications persist. The algorithm described here is referred to as LVQ1 learning rule.

A. Feature extraction

The radial distribution system is subjected to an arc type fault at different locations by varying x, measured from the substation bus. The voltage and current signals at feeder terminals v_1 and i_1 are used as detection signals as shown in Fig. 4. The instantaneous values of these detection signals are captured and transformed into frequency domain using one cycle Fast Fourier Transform FFT. The FFT-harmonic vectors v_3, i_3, v_5, and i_5 are processed to obtain feature vectors and are used to train the LVQ network.

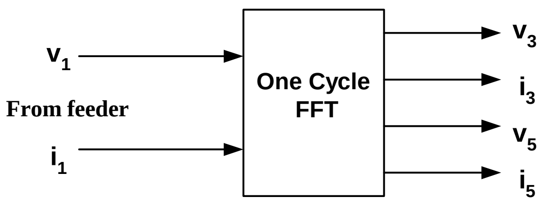

Fig. 4 Feature vector extraction

Many cases of linear and nonlinear faults are simulated by varying the fault locations, source impedances and fault resistance. Equal numbers of linear and nonlinear fault cases are simulated. The obtained data is cast into a classification problem by associating half of the samples into linear and the other half into nonlinear cases.

B. LVQ network Configuration

The input nodes of the LVQ neural network are v_3, i_3, v_5, and i_5. The output layer consists of two linear neurons representing the linear and nonlinear fault cases. This layer represents the target classes. The first layer is a competitive layer representing the prototype weight vectors. The prototype weight vectors classify the input vectors into subclasses. Both the competitive and linear layers have one neuron per (sub or target) class. The structure of the neural network is 4-10-2 assuming 10 subclasses. The LVQ1 learning rule is used for training the network.

IV. SIMULATION RESULTS

A set of 220 patterns obtained by the proposed system using the Matlab toolboxes is used for training the network. 100 additional samples are generated for testing. Initial learning rate of 0.15 is selected for training the LVQ network. Repeated trials of the program show that this choice of learning rate is very helpful for faster convergence. Initially, reference vectors are randomly chosen for training the network. To improve the learning characteristics of the network, the reference vectors are set to the locations matching the probability distribution of training vectors. This is done by dividing the training data into different classes and calculating the mean of the samples in these classes. Network structures with different number of reference vectors (subclasses) are tested.

Fig. 5 shows the training error as a function of no. of epochs with random initial vectors. The initial learning rate is 0.15 and the number of subclasses is 10. It is clearly seen from the figure that substantial training error exists even after 150 epochs and needs to be further minimized.

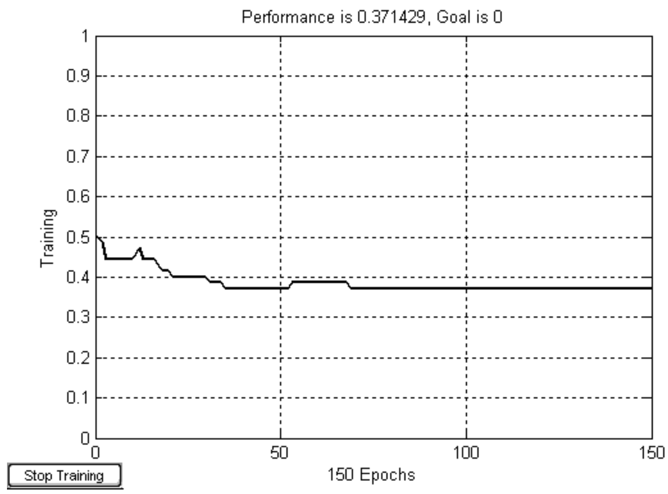

Fig. 5 Training error as a function of no. of epochs in case of LVQ network with random initial vectors.

In Fig. 6, the initial vectors are chosen in consistency with the probability distribution of the input features of the training samples. The initial learning rate and number of subclasses are same as in Fig. 5. Training error reduces to zero after 43 epochs. Thus by properly selecting the initial reference vectors, the training error in an LVQ network can be reduced significantly.

Table 1 shows the training and testing errors when the number of subclasses is changed from 8 to 16. When the number of subclasses is 10, the LVQ network gives better performance with both random and selected subclasses. The

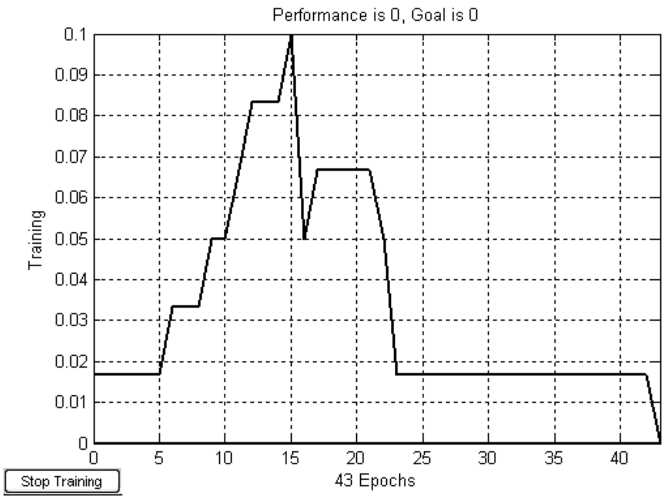

Fig. 6 Training error as a function of no. of epochs in case of LVQ network with selected initial vectors

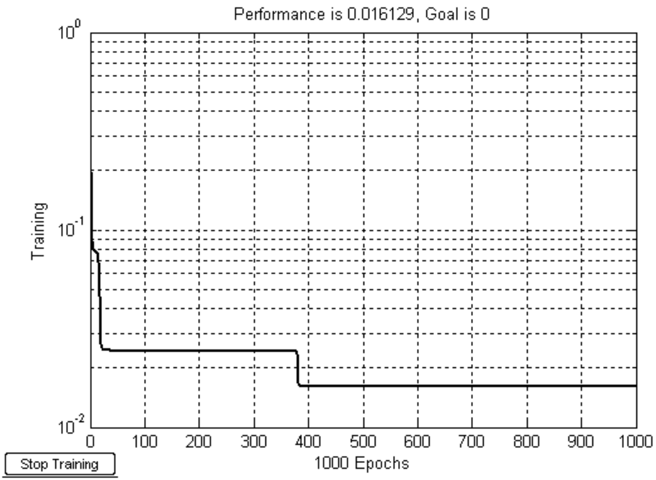

Fig. 7 Training error as a function of no. of epochs in case of MLP with backpropagation algorithm.

ability of the network to classify the samples is improved by the location of the reference vectors, topology of the network and initial learning constant.

The same data set is used to train a multilayer perceptron (MLP) with backpropagation algorithm [7-8]. The architecture used for simulation consists of two hidden layers and one output layer. The output layer consists of one neuron whose output is zero or one for discrimination between linear and nonlinear faults. In the hidden layers, the neurons in the first hidden layer and second hidden layer can be varied to get optimum results. The transfer function in the neurons is log-sigmoid because the output of this function ranges from 0 to 1 which matches the output of the linear fault cases ('0') and nonlinear fault cases ('1'). The training algorithm used is the supervised Levemberg-Marquardt backpropagation implemented in Matlab's ANN toolbox. A training error of 1.67% and testing error of 5.0% was obtained when there were 8 neurons in the first hidden layer and 4 neurons in second hidden layer. But the algorithm took 1000 epochs to reach this training error. The training error can be further reduced by selecting more neurons in the hidden layers.

TABLE I
TRAINING AND TESTING ERROR OF LVQ NETWORKS

No. of subclasses	LVQ with random subclasses		LVQ with selected subclasses	
	Training error %	Testing error %	Training error %	Testing error %
8	38.1	39	6.2	7
10	37.1	38	0	01
12	39.8	40	1.1	02
16	37.6	39	2.2	04

From the results, it can be seen that an LVQ network has an inherent ability to classify more rapidly than the corresponding MLP with backpropagation algorithm. Further, architecture of MLP network with backpropagation algorithm is much more complex than corresponding LVQ network to obtain same rate of accuracy.

One of the most attractive features of LVQ learning is that the parameterization in terms of prototype vectors allows for an immediate interpretation of the classifier. Prototypes are defined in the same space as the data; they are, for instance, images themselves and provide direct information about the achieved classification and the features that it is based on. This is in contrast to feed forward neural networks.

V. Conclusion

A method for detecting the high impedance fault in a radial distribution system using LVQ networks is proposed in this paper. The study involved computer simulation of power systems, frequency analysis and investigation to improve the learning characteristics of LVQ classifier. The proposed method is capable of detecting the arc-type high impedance faults with higher accuracy. The improvement in the performance of LVQ networks is achieved by properly selecting the learning constant, architecture and setting the proper location of initial weight vectors. A properly designed LVQ network for fault detection is simpler in architecture and faster than a feed-forward multilayer perceptron with backpropagation algorithm.

Appendix

(a) AC System

$$V_S = \frac{25}{\sqrt{3}}\sin(314t), \quad R_S = 0.7\Omega, \ ; L_S = 7mH$$

(b) HIF Fault Model

(1) Linear HIF fault

$$R_f = 30 \ to \ 100\Omega$$
$$L_f = 1 \ to \ 5mH$$

(2) Nonlinear (Arc-type) HIF fault

$$R_f = R_{f0} + R_{f1}\alpha(\frac{i_f}{i_{f0}})^{\beta}$$

$$R_{f0} = 20\Omega, \quad R_{f1} = 10 \ to \ 100\Omega$$

$$L_f = 1 \ to \ 5mH$$

$$i_{f0} = 70, \ \alpha = 0.6, \quad \beta = 2$$

(c) Transmission line

Length l = 32 km

$$R = 0.25\Omega/km, \ L = 0.99472mH/km, \ C = 0.01117\mu F/km$$

(d) Load Parameters

$$R_l = 180\,\Omega \quad L_l = 0.2\,H$$

References

[1] "High impedance fault detection technology," Report of PSRC working group D15, Mar. 1996.

[2] A.-R. Sedighi, M.-R. Haghifam, O. P. Malik, and M.-H. Ghassemian, "High impedance fault detection based on wavelet transform and statistical pattern recognition," *IEEE Trans. Power Delivery*, vol. 20, no. 4, pp. 2414-2421, Oct. 2005.

[3] M. Aucoin, "Status of high impedance fault detection," *IEEE Trans. PAS,* vol. 104, no. 3, pp. 638-644, Mar. 1985.

[4] A. V. Mamishev, B. D. Russell, and C. L. Benner, "Analysis of high impedance faults using fractal techniques," in: *IEEE Power Industry Computer Application Conf.*, 1995, pp. 401–406.

[5] C. J. Kim and B. D. Russell, "Classification of faults and switching events by inductive reasoning and expert system methodology," *IEEE Trans. Power Deliv. 4* (July (3)) (1989) pp. 1631–1637.

[6] S. Ebron, D. L. Lubkeman, and M. White, "A neural network approach to the detection of incipient faults on power distribution feeders," *IEEE Trans.Power Deliv. 5* (April (2)) (1990) pp. 905–914.

[7] L. A. Snider and Y. S. Yuen, "The artificial neural networks based relay for the detection of stochastic high impedance faults," Neurocomputing 23 (1998) pp. 243–254.

[8] A. M. Sharaf, L. A. Snider, and K. Debnath, "A neural network based relaying scheme for distribution system high impedance fault detection," in: *Proc. First New Zealand Int. Two-Stream Conf. Artificial Neural Networks and Expert Systems*, 1993, pp. 321–324.

[9] B. M. Aucoin and B. D. Russell, "Detection of distribution high impedance faults using burst noise signals near 60 Hz," *IEEE Trans. Power Deliv. 2* (April (2)) (1987) pp. 342–348.

[10] D. I. Jeerings and J. R. Linders, "A practical protective relay for downconductor faults," *IEEE Trans. Power Deliv. 6* (April (2)) (1991) 565– 574.

[11] A. A. Girgas, W. Chang, and E. B. Makram, "Analysis of high-impedance fault generated signals using a Kalman Filtering Approach," *IEEE Trans. Power Deliv. 5* (October (4)) (1990) pp. 1714–1724.

[12] T. M. Lai, L. A. Snider, and E. Lo, "Wavelet transform based relay algorithm for detection of stochastic high impedance faults," Electrical Power System Research, 76 (2006) pp. 626-633.

[13] A. E. Emanuel, D. Cyganski, J. A. Orr, S. Shiller, and E. M. Gulachenski, "High impedance fault arcing on sandy soil in 15 kV distribution feeders: contributions to the evaluation of the low frequency spectrum," *IEEE Trans. Power Deliv. 5* (April (2)) (1990) pp. 676–686.

[14] A. M. Sharaf and G. Wang, "High impedance fault detection using feature-pattern based relaying," *Transmission and Distribution Conf. and Exposition, 2003 IEEE PES,* vol. 1, 7-12 Sept. 2003, pp. 222 – 226.

[15] M. H. Hassoun, *Fundamentals of Artificial Neural Networks***,** MIT PRESS, 1996.

[16] Gray, R.M., "Vector quantization," *IEEE Acoustic, Speech, and Signal Processing Magazine, 1,* pp. 4-29, 1984.

[17] T. Kohonen, *Self-Organizing Maps*, Springer, Berlin, 1995.

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