

MLP for Defect Detection from Power Plants Flow Pipelines Equipped by Principal Component Analysis

Saeedreza Ehteram (Corresponding author)

Engineering & Research and Development Department

MAPNA Electrical and Control Engineering & Manufacturing Co. (MECO)

MAPNA Blvd, 6th Km of Malard Road, Fardis, PO box 31585-1551, Karaj 31176, Iran

E-mail: ehteram@mapnaec.com

Borzoo Afkham

Engineering & Research and Development Department

MAPNA Electrical and Control Engineering & Manufacturing Co. (MECO)

MAPNA Blvd, 6th Km of Malard Road, Fardis, Karaj 31176, Iran, P.O. Box 31585-1551

E-mail: afkham@mapnaec.com

Y. Rezazadeh Sereshkeh

Electrical and Computer Engineering Faculty, Shahid Rajaei Teacher Training University, Lavizan, Tehran, Iran

E-mail: rezazadeh@srttu.edu

Received: August 29, 2011

Accepted: October 9, 2011

Published: December 1, 2011

doi:10.5539/mas.v5n6p165

URL: <http://dx.doi.org/10.5539/mas.v5n6p165>

Abstract

This research effort proposes an intelligent control approach for Defect detection of flow pipelines in power plants by applying Multilayer Perceptron (MLP) for classification by which equipped with Principal Component Analysis (PCA). This fusion has been applied to have an intelligent defect detection algorithm of power plants flow pipelines. Among various methods of Non Destructive Testing (NDT), Magnetic Flux Leakage (MFL) technique is the most useful method due to its efficiency and low cost. For this reason models were developed to determine more accurate surface-breaking defects along the applied field when using the magnetic flux leakage technique. The theoretical model fits the experimental MFL results from simulated defects. For MFL sensors, the normal magnetic leakage field is subsequently used for evaluation of defects. Three different defects are analytically performed for this research. These are named Data type1 up to 3. In our previous works, we applied linear discriminate analysis (LDA) and observed that the results were more accurate in some cases but this algorithm is simpler and so fast rather than previous one, also mentioned method in this paper is so useful and could be simply simulate.

Keywords: Magnetic Flux Leakage(MFL), Non Destructive Testing(NDT), Principal Component Analysis (PCA), Multilayer Perceptron (MLP)

1. Introduction

Flow pipeline transportation is one of the fundamental modes in power plants. It is necessary for pipeline's security evaluation and maintenance to detect defects of the pipeline regularly using pipeline detector and obtain the precise information of the defect (Saeedreza Ehteram, Alborz Rezazadeh Sereshkeh, Seyed Zeinolabedin Moussavi, Ali Sadr & Ali Akbar Jalali, 2009; A. Bergamini, 2001; A. Bergamini, 2002). Among various pipeline inspection technologies, MFL inspection is the most widespread and perfect one. Indeed it needs long time for human to analyze a long flow pipeline data. So finding the intellectual algorithm to recognize pipeline defect quantitatively is urgent (A. Bergamini, 2002). For this reason we applied a mathematical relation between the magnetic field applied on the surface and the defect properties. In this way an approach is to find exactly samples from a defect which is sorted in the surface by its various radial and depth and the pipeline MFL signal

is recognized in an artificial algorithm to be used for training neural networks (P. Ramuhalli, L. Udpa & S.S. Udpa, 2002). In follow, database preparation, feature extraction and classification of database is presented.

2. Database of defects from MFL testing

The database of the experimental MFL signals that is employed in this project is from Applied Magnetics group (AMG) in the department of physics from Queens in Canada. This database concludes signals of MFL that measured from outside and Inside of a power plant flow pipeline. Details of this database will lead to both un annealed and annealed data plots of increasing dent depths from 3mm to 7mm, resulting in a total of 10 plots for each one.

3. Formulation of an analytical model from MFL defect measurements

If a material is magnetized near saturation, the MFL field generated by a subsurface flaw can be described as follows:

$$H_y(x, y) = \frac{2xy(m - 2H_a a^2)}{(x^2 + y^2)^2} \quad (1)$$

Where m is the dipole moment per unit length this is measured as follows:

$$h = 1.05 \times 10^{-34} \quad m = \frac{\sqrt{3}}{2} h \quad (2)$$

Where h bar is the plank coefficient, H_a is the applied magnetic field that is 1 Tesla (R.R. da Silva, S.D. Soares, L.P. Caloba, M.H.S. Siqueira & J.M.A. Rebello, 2006) and a is the radius of the defect (C Mandache, B Shiari & L, 2005; D.E. Bray, 1997). If the MFL on the surface of a sample is calculated, the variable y is constant and is equal to the depth h of the defect So the magnitude of h could specify the depth of defect. As mentioned above, it is not necessary to get physical information, like size or position of the defect. If the unknown system and material properties are defined in $p=2h(m-2H_a a^2)$ and $q=h^2$ parameters we obtain so the following simple fit function for the MFL on the surface of a sample could be illustrated as below:

$$f(x) = \frac{px}{(q + x^2)^2} \quad (3)$$

In the developed device the signal is measured by induction coils and for this reasons the measured signal is the derivative in x direction times the velocity of $f(x)$ of measuring device. With regards to the previous equation, the MFL signal becomes as below. In this relation we try to calculate the rate of measured signal in time. So with acknowledge of velocity, that is rate of measuring device distance in time, and by timing this term to deviation of $f(x)$, we could reach to rate of delta f to delta t that is rate of depth in time.

$$F(x) = v \cdot f'(x) = v \left(\frac{p}{(q + x^2)^2} - \frac{4px^2}{(q + x^2)^3} \right) \quad (4)$$

On the assumption that the velocity is constant, a new parameter P can be defined as:

$$P = v \cdot p = 2hv(m - 2H_a a^2) \quad (5)$$

4. Feature extraction for recognition

PCA is a well-known statistical technique for feature extraction. Each $M \times N$ MFL signal in the training set was row concatenated to form $MN \times 1$ vector x_k . Given a set of training signals $\{x_k\}$, $k=0, 1, \dots, N_T$ the mean vector of the training set was obtained as (Philip J, Rao C B, Jayakumar T & Raj B, 2000).

$$\bar{x} = \frac{1}{N_T} \sum_{k=1}^{N_T} x_k \quad (6)$$

A $N_T \times MN$ training set matrix $X = \{x_k - \bar{x}\}$ can now be built. The basis vectors are obtained by solving the Eigen value problem:

$$\lambda = V^T \sum_x V \quad (7)$$

Where $\sum_x XX^T$ is the covariance matrix, V is the eigenvector matrix of $\sum_x$ and λ is the corresponding diagonal matrix of Eigen values. As the PCA has the property of packing the greatest energy into the least number of principal components, eigenvectors corresponding to the m largest Eigen values in the PCA are selected to form a lower-dimensional subspace. It is proven that the residual reconstruction error generated by discarding the $N_r - m$ components is low even for small m (M.Turk, A.Pentland, 1991).

As has been said, PCA computes are the basis of a space which is represented by its training vectors. The basis vectors computed by PCA are in the direction of the largest variance of the training vectors. These basis vectors are computed by solution of an Eigen problem, and as such the basis vectors are eigenvectors. These eigenvectors are defined in the signal space. They can be viewed as signals and indeed look like its inherent shape. Hence they are usually referred to as Eigens.

4.1 Recognition of defects

The recognition of power plants flow pipeline corrosion defects in this paper includes preprocessing and classification analysis. The former can be accomplished by recognizing and classifying typical features of signals from magnetic flux signals in types of mathematical forms. An approach is to classifying and performing a liable decision. For this reason, these are a both Multilayer Perceptron (MLP) neural networks however other procedures like Learning Vector Quantization (LVQ) (R. Christen, A. Bergamini & M. Motavalli, 2004; Self Organized Machine (SOM) (Martin Golz, David Sommer, 2006) are approaches for classification. In this work multilayer perceptrons are applied with sigmoid transfer function and back propagation algorithm.

4.2 Classification for recognition

According to construction of combiners, they are all made of learning process. Therefore to have different combiners different ways of training is essential. The process of learning is based on many ways such as: different ways to show inputs, samples for learning, training process, differ consulting technologies although in this task many theories are offered but each of them should due to some results:

1. The first requirement is that each expert has high level of performance and independently in deciding feature.
2. Expert has an arithmetic mathematics Table to refer this point as strong point of each expert.

Classifying is done by many ways such as: multilayer perceptron, (MLP), radial basis function (RBF), k-mean etc.

This paper presents MLP for classifying. MLP means multi layer perceptron. Classifying is done by neural networks such as MLP. Fundamental work of MLP is to changing weights between layers and each layer has (m) nodes. Number of input nodes is depended on dimension the database. Amount of nodes located in hidden layer are subject to change by complicated rate of the expert. In this paper an approach is shown in follows that specifies the number of each layer this equations for this reason is earned experimentally but the result of this employment is satisfied. In training situation the weights are subject to change until reaching the best weights. The number of training situations is determined by the number of epochs that is kept done until less mistakes appears in output.

In this algorithm two Networks with the names of MLP1 and MLP2 are employed. Both experts are learned by a same set of database and the result of classification is disposed in a Table .

5. Employed algorithm

We have applied similar algorithm to SSCE (Hiroshi Wakuya, Hiroyuki Harada, Katsunori Shida, 2007) to database of MFL signals. In this map we apply preprocessing to the crude data. this section is discussed and as a brief it contains extracting different kinds of defects from physical formulation and normalization then two classes perform a decision on the their inputs, the rate of each of which is composed by a voter to achieve a well decision. See Figure 1.

6. Results and discussion

In order to investigate the statistical distribution of the error rate, two neural networks with the same structure and transfer functions (but with different number of neurons that are referred to initial state) were trained with the same data set (Saeedreza Ehteram, Seyed Z. Moussavi, 2007; Saeedreza Ehteram, Ali Sadr, Seyed zeinolabedin Mousavi, 2007; R. Ebrahimpour, S. R. Ehteram, E. Kabir, 2005). In this approach each expert is trained to recognize a sort of defect so that each of which experts in final are tried to find three common sort of defects. Then the accuracy rate of each network is calculated. To calculate different numbers of input parameters were

trained and compared to the network described in the above sections. The following experimental rule was used to define the structure of the network:

$$\begin{aligned} N_{input} &= 2 \times P \\ N_{hidden} &= \text{approx}(N_{in} + N_{out}) \\ N_{out} &= 2 \times P \end{aligned} \quad (16)$$

Where N is the number of neurons in the corresponding layer and P is the number of input parameters that could be even or odd. In this project first we try to test a simple network by different characteristics and then we design two experts. In some information about the set of trained networks is given by accuracy rate as well as the worst and the best network, respectively. Furthermore, maximum or minimum of the average of output of each network in ten times training is mentioned. Summary of the network performance for different input parameters is as follows: P1, P2, q1, q2, and q3.

As is demonstrated in the Table below there is q1, q2, q3, P1, P2 parameters. These parameters are described as follows in (17):

$$\begin{aligned} P &= \nu \cdot p = 2h\nu(m - 2H_a a^2) \\ q &= h^2 \end{aligned} \quad (17)$$

P1= P for h=0.002 & a=0.001 [m]

P2= P for h=0.003 & a=0.0015 [m]

q1=q for h=0.002 [m]

q2=q for h=0.003 [m]

q3=q for h=0.004 [m]

6.1 Historical discussion

If we have a discussion to what is done before in this way, we would observed some of published researches that are based on the analytical model of MFL signals from magnetic charge (Qi Jiang, Qingmei Sui ; Dobmann G & H"oller P, 1980; Shcherbinin V E & Pashagin A I, 1972; Forster F, 1986; Edwards C & Palmer S B, 1986). But for an exception, reference (Mandal K & Atherton D L, 1998) is just discussed a single defect. , The often encountered practical situation of two adjacent defects is also discussed only by Uetake and Saito (Mandal K & Atherton D L, 1998), but their study is limited to slots with parallel walls, of a maximum of 4mm in length. With regards to this effort that considered a multiple defect case. The proceeding numerical modeling of MFL phenomena is exposed by Lord and co-workers (Uetake I & Saito T, 1997; Hwang J H & Lord W, 1975; LordW & Hwang J H, 1977). In oppose of the significant progress made in this area to include non-linear material properties (Lord W, Bridges J M, Yen W & Palanisamy R, 1978; Atherton D L & Daly M G, 1987; Patel U & Rodger D, 1995), a quantitative relationship between magnetic leakage field and defect length has not been clearly specified. Furthermore, numerical modeling involves a direct MFL approach, since it includes predefined defect geometries and material characteristics. Calibration of the MFL signals in terms of defect depth has been studied both through finite element modeling (Hwang J H & Lord W, 1975; LordW & Hwang J H, 1977; Lord W, Bridges J M, Yen W & Palanisamy R, 1978; Patel U & Rodger D, 1995) and through analytical methods based on dipolar magnetic charge (LordW & Hwang J H, 1977; Altschuler E and Pignotti A, 1995). Two of the numerical analysis studies (Hwang J H & Lord W, 1975; Patel U & Rodger D, 1995) correctly predicted that the amplitude of the normal MFL signal Component increases with defect depth, and that the separation between the extreme MFL values is directly proportional to the Defect length.

In this paper, with regards to previous works, a new simple algorithm is applied that could determine defects with various shapes. For problem of encountering different kinds of defects we initializes deferent defects with two classes which each of them tries to learn a defect with determined characteristics. These features are an estimate of two large groups of defects.

7. Conclusion

In this study, we have discussed intelligent defect detection directly from MFL signals. An analytical model is employed to account defects of power plants flow pipelines. That was to have an appropriate MFL profile with the defect dimension along an impregnating magnetic field. The efficiency of the model was confirmed through experimental results in MFL defect detection that is discussed in historical discussion. A clear advantage of the

method presented here is the low number of parameters that have to be considered. For a satisfactory estimation we classify all the defects in three groups with different shapes in this case all the defects ranged to depth of 2 till 4 millimeter and radius of 1 up to 1.5 millimeters all three groups are called data type1 up to 3. These later are subject to recognize. For the reason of fast and facility of simulation, two expert systems were learned to recognize the request. PCA is used to compress the database and provide classification on low and efficient dimensional database. The result of all are shown and discussed in Table 1. The accuracy rate of 95 percent foe data type1 shows the efficiency of the mentioned algorithm.

References

- Altschuler, E. & Pignotti, A. (1995). *NDT & E Int*, 28, 35–40. [http://dx.doi.org/10.1016/0963-8695\(94\)00003-3](http://dx.doi.org/10.1016/0963-8695(94)00003-3)
- Afzal, M., & Upda, S. (2002). Advanced signal processing of magnetic flux leakage data obtained from seamless steel pipeline. *NDT&E Int*, 7, 449–457. [http://dx.doi.org/10.1016/S0963-8695\(02\)00024-5](http://dx.doi.org/10.1016/S0963-8695(02)00024-5)
- Atherton, D. L., & Daly, M. G. (1987). *NDT Int*. 20, 235–8. [http://dx.doi.org/10.1016/0308-9126\(87\)90247-1](http://dx.doi.org/10.1016/0308-9126(87)90247-1)
- Bergamini, A. (2001). Nondestructive testing of stay cables. *IABSE conference on cable-supported bridges*, pp. 312–313.
- Bergamini, A. (2002). Nondestructive testing of stay cables field experience in South East Asia. *Third World conference on structural control*, 2, 1057–1064.
- Bray, D. E. (1997). *Nondestructive evaluation* (revised ed.). Boca Raton, FL: CRC Press.
- Christen, R., Bergamini, A., & Motavalli, M. (2004). Three-dimensional localization of defects in stay cables using magnetic flux leakage methods. *J Non Destructive Eval*, 22 (3), 93–101. <http://dx.doi.org/10.1023/B:JONE.0000010736.74285.b6>
- Chandrasekaran, S., Manjunath, B. S., Wang, Y. F., Winkeler, J., & Zhang, H. (1997). An Eigensapce update algorithm for image analysis to appear. *journal Graphical Model and Image Processing*.
- Chung, Y., Bang, L. Won, J, Dong, K. J., & Won, M. K. (2003). Damage estimation method using committee of neural networks. *Proceedings of the SPIE—the international society for optical engineering*, 5047, 263–274.
- Dobmann, G., & H'oller, P. (1980). *Research Techniques in Nondestructive testing R. S. Sharp* (New York: Academic). IV, 39–69.
- Duda, R. O. & Hart, P. E. (1973). *Pattern Classification and Scene Analysis*, John Wiley & Sons.
- Ebrahimpour, R., Ehteram, S. R., & Kabir, E. (2005). Face Recognition by Multiple Classifiers, a Divide-and-Conquer Approach. *Lecture Note in Computer Science (LNCS)*, 3686, 225-232. http://dx.doi.org/10.1007/11553939_33
- Ebrahimpour, R., Zeinolabedin, M. S., & Ehteram, S. (2006). Multiple Binary Classifier Fusion (MBCF) in Application of Satimage Database. *IATED from proceeding (522) Applied Simulation and Modeling*. Greece.
- Edwards, C., & Palmer, S. B. (1986). *J. Phys. D: Appl. Phys*, 196, 57–73.
- Forster, F. (1986). *NDT Int*. 19, 3–13. [http://dx.doi.org/10.1016/0308-9126\(86\)90134-3](http://dx.doi.org/10.1016/0308-9126(86)90134-3)
- Hiroshi, W, Hiroyuki, H., & Katsunori, S. (2007). An architecture of self-organizing map for temporal signal processing and its application to a Braille recognition task. Wiley Periodicals, Inc. *Syst Comp Jpn*. 38(3): 62-71. <http://dx.doi.org/10.1002/scj.20260>
- Hwang, J. H., & Lord, W. (1975). *J. Testing Eval*. 3, 21–5. <http://dx.doi.org/10.1520/JTE10129J>
- Jamali, M. R., Arami, A., Dehyadegari, M., Lucas, C., & Navabi, Z. (2008). “Emotion on FPGA: Model driven approach”. *ESWA 3156*(PP 10-20).
- Ken, C., & Gent, P. Image compression and the discrete cosine transform. *math45 collage of Redwoods*(pp1, 2).
- Lord, W., Bridges, J. M., Yen, W., & Palanisamy, R. (1978). *Mater. Eval*. 36, 46–54.
- Lord, W., & Hwang, J. H. (1977). *Br. J. Non-dest. Testing*, 19, 14–18.
- Mandache, C., Shiari, B., & Clapham, L. (2005). Defect separation considerations in magnetic flux leakage inspection. *Insight*. 47(5), 271. <http://dx.doi.org/10.1784/insi.47.5.269.65050>
- Mandal, K., & Atherton, D. L. (1998). *J. Phys. D: Appl. Phys*, 31, 3211–17. <http://dx.doi.org/10.1088/0022-3727/31/22/006>

- Martin, G., & David, S. (2006). "The Performance of LVQ Based Automatic Relevance Determination Applied to Spontaneous Biosignals, KES. Bournemouth, UK. October 9-11. Proceedings, Part III, Lecture Notes in Computer Science, Springer Berlin / Heidelberg, 1256-1263.
- Patel, U., & Rodger, D. (1995). *IEEE Trans. Magn.* 31, 2170–3. <http://dx.doi.org/10.1109/20.376477>
- Philip, J., Rao, C. B., Jayakumar, T., & Raj, B. (2000). *NDT & E Int.* 33, 289–95. [http://dx.doi.org/10.1016/S0963-8695\(99\)00052-3](http://dx.doi.org/10.1016/S0963-8695(99)00052-3)
- Ramuhalli, P., Udpa, L., & Udpa, S. S. (2002). Electromagnetic NDE signal inversion by function-approximation neural networks. *IEEE Trans Magnetics*, (6), 3633–364.
- Sui, J. Q., Lu, Q. M., Zachariades, N. P., & Wang, J. H. Detection and estimation of oil gas pipeline Corrosion defects. [Online] Available: <http://corporate.coventry.ac.uk/conten>.
- Silva da, R. R., Soares, S. D., Caloba, L. P., Siqueira, M. H. S., & Rebello, J. M. A. (2006). Detection of the propagation of defects in 170ressurized pipes by means of the acoustic emission technique using artificial neural networks. *Insight*, 48 (1), 45–51. <http://dx.doi.org/10.1784/insi.2006.48.1.45>
- Saeedreza, E., Sereshkeh, A.S., Moussavi, S. Z., Sadr, A., & Jalali, A. A. (2009). Utilizing a Pattern Recognition Controller and Linear Discriminate Analysis for MFL Defect Detection. *JCIT*, 4(1), 11-19.
- Saeedreza, E., Sadr, A., & Moussavi, S. Z. (2007). Rapid face recognition by regional feature extraction. INISTA conference 20 – 23, pp. 262-269. Istanbul Turkey
- Saeedreza, E., & Moussavi, S. Z. (2007). Semantic Supervised clustering to land Extraction on satimage database. *journal of Global engineering science and technology* (GESTS)). Seul korea March, pp.117-125.
- Shcherbinin, V. E., & Pashagin, A. I. (1972). *Defektoskopyia*, 874–82.
- Turk, M., & Pentland, A. (1991). Eigenfaces for Recognition. *Journal of Cognitive Neuroscience*, 3, 71-86. <http://dx.doi.org/10.1162/jocn.1991.3.1.71>
- Uetake, I., & Saito, T. (1997). *NDT & E Int*, 30, 371–7. [http://dx.doi.org/10.1016/S0963-8695\(97\)00002-9](http://dx.doi.org/10.1016/S0963-8695(97)00002-9)

Table 1. Observed results

DATA TYPE	FEATURE EXTRACTION	CLASSIFICATION					
Result of application of feature extraction and classification done in data type1,2,3	Neural Network PCA	MLP1 Accuracy percent			MLP2 Accuracy percent		
	Data Type	Data1	Data2	Data3	Data1	Data2	Data3
	2 first Eigen vectors	74	64	61	73	69	58
	3 first Eigen vectors	76	70	81	78	48	56
	4 first Eigen vectors	77	73	85	79	52	63
	5 first Eigen vectors	65	75	88	86	65	68
	6 first Eigen vectors	80	78	90	88	68	66
	9 first Eigen vectors	96	82	87	90	82	73
	12 first Eigen vectors (2 times of <i>P</i>)	92	88	92	95	84	85

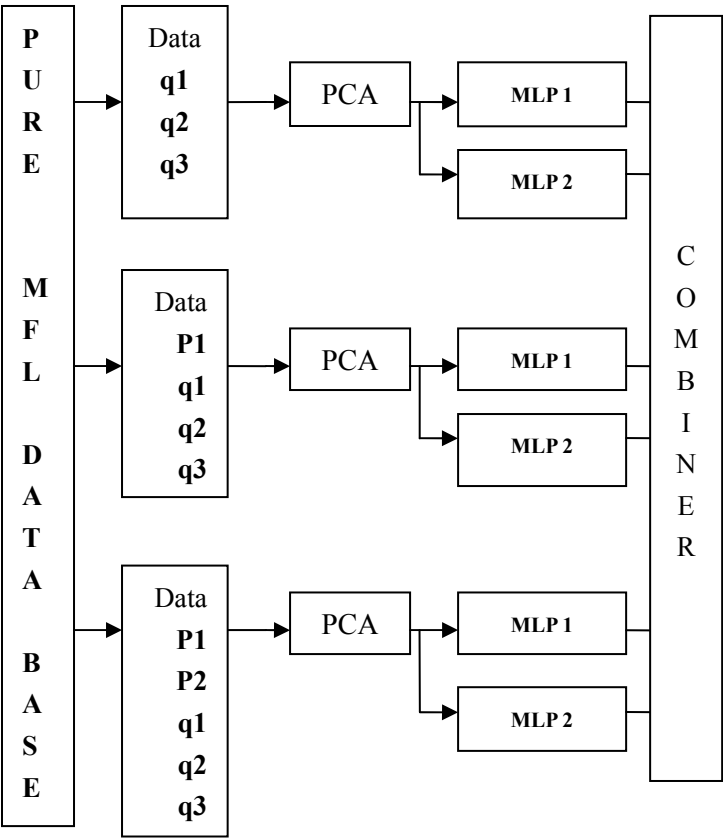


Figure 1. Purposed Algorithm