Novel signal processing scheme to Integrate DCS and defect detection in power plants

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Sep. 2015

Abstract

Non-destructive testing of power stations pipelines plays an important role in minimizing fault and defect occurrence in power plants and therefore results for continue of operation for more times. In the present work various intelligent schemes to infer the fault detection of metal pipelines are proposed. NDT signal processing involves capturing MFL (Magnetic Flux Leakage) reflux from metal surface of pipelines with the measurement of various parameters like diameter, depth and radius of metal pipeline defects.
NDT-MFL database for this research and previous works was from Applied Magnetics group (AMG) in department of physics from Queens in Canada. This database concludes signals of MFL that measured from outside and Inside of a power plant flow pipelines.
Database signals are pre-processed to reduce noise. This step is done right before any further processing on gathered data. The conventional classification and clustering techniques in this paper include the Euclidean distance classifier (L_2-norm classifier) and Bayesian. The intelligent classifier includes the Radial Basis Function Network (RBF), Back Propagation Algorithm (BPA) and parallel architecture with RBF and BPA (PRBFBPA). Also a Combination of Fisher linear discriminate with is employed in the application of MLP and RBF.
For better and optimal decision on MFL samples, parameter values of defects are categorized. By this way defects are categorized in a few groups with the same parameter range. This makes the algorithm to perform a more exact classification.
The proposed algorithm can be integrated with the distributed control system (DCS) that is used for automation of the power plant. The inferred parameters can be displayed in the centralized control room. The major contribution of this research work is to develop an indigenous online intelligent scheme for inferring the process parameters and defect emissions in the centralized control room directly from the metal pipelines.

Keyword
Magneticflux leakage (MFL), Non destructive Testing (NDT), Principal Component Analysis (PCA), Multilayer Perceptron (MLP).

1. Introduction

Metal pipelines are one of the vital parts in power plants. As a part of inspection procedures these metal parts are a subject for consideration. After a visual check, a technical method is required to provide more precise information of the line. These methods used defect detection algorithms [1, 2, and 3]. 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 in a visual check procedure So finding an intellective effective algorithm to recognize pipeline defect quantitatively is an important need [3]. For this reason we applied a mathematical relation between magnetic field applied on the surface of a metal and try to recognize defects via the reflux of the emitted flux. Samples from defects which are sorted in the surface by their various radial and depth from MFL reflux are stored and an MFL database is prepared from simulated defects. Some processes are done on this pure database to be ready for being processed in the algorithm. The algorithm that will be presented in the reset on this research effort is an artificial neural network based one to specify the best classification approach regards to defect classification [4]. 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. Particulars of this record will lead to both an annealed and annealed data plots of rising defect depths from 3mm to 7mm, resulting in a total of 10 plots for each one**.**

3. MFL Formulation for magnetic field simulation

If a material is magnetized near saturation, the MFL field generated by a subsurface flaw is specified in eq. 1:

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

Where m is the dipole moment per unit length this is measured in eq. 2:

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

Plank coefficient is h, Applied magnetic field of 1 Tesla is Ha [6]. Defect radius is defined by a [7, 8]. If the MFL on the surface of a sample is intended, the variable y is constant and is equal to the depth h of the defect so the magnitude of h could denote the depth of defect. If system and material properties could be defined in $p=2h$ (m-$2H_a a^2$) and $q=h^2$, we gain following simple fit function for the magnetic flux leakage on the surface of a sample. This latter is illustrated in eq. 3:

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

Reflux signal of emitted magnetic field on sample surface is deliberate by induction coils. for this reason the intended signal is derivation of $f(x)$ in x direction times the velocity of measuring device. With regards to previous equation, the MFL signal becomes as Eq. 4. In this family member we try to calculate the rate of calculated signal in time. So with acknowledge of velocity that is the rate of measuring machine distance in time, and by timing this term to deviation of $f(x)$, the rate of depth in time will be achieved.

$$F(x) = \nu . f'(x) = \nu \left(\frac{p}{(q + x^2)^2} - \frac{4px^2}{(q + x^2)^3} \right) \qquad (4)$$

On the supposition that the velocity is constant, a new parameter P can be defined as eq. 5.

$$P = \nu . p = 2h\nu(m - 2H_a a^2) \qquad (5)$$

4. Feature extraction for recognition

Principal Component Analysis (PCA) is a well-known statistical technique for feature extraction. Each M × N MFL signal in the training set was row concatenated to form MN×1 vector x_k. Given a set of training signals $\{x_k\}$, k=0, 1,…, N_T the mean vector of the training set was obtained as eq. 6 [30].

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

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

$$\lambda = V^T \sum\nolimits_x V \qquad (7)$$

Where $\sum_x X X^T$ is the covariance matrix, V is the eigenvector matrix of $\sum_x$ and λ is the equivalent slanting matrix of Eigen values. As the PCA has the property of packing the most energy into the slightest number of principal components, eigenvectors matching to the m largest Eigen values in the PCA are selected to shape a lower-dimensional subspace. It is confirmed that the residual reform error generated by discarding the N_r-m components is low even for small m [37].

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 Eigens.

4.1 Recognition of defects

The recognition of power plants flow pipeline decays in this paper includes preprocessing and categorization study. The former can be accomplished by recognizing and classifying typical features of signals from magnetic flux signals in types of numerical forms. move toward is to classifying and performing a liable decision. Many procedures like Learning Vector Quantization (LVQ) [9], Self Organized Machine (SOM) [10] and multilayer perceptrons are approaches for classification.

4.2 Classification for recognition

In this study dissimilar classifiers are mutual with each other to assess a liable categorization. These networks are basically similar to each other but are not theoretically similar. MLP in abbreviation Multilayer Perceptron in this paper is known with intrinsically back propagation algorithm. So this network is named BPA-MLP. Fundamental work of MLP is to changing weights between layers and each layer has (m) nodes. Number of input nodes is depended on measurement the database. Quantity of nods located in hidden layer is subject to change by complicated rate of the expert. In this paper an approach is exposed in follow that specifies the number of each layer. this equations for this reason is earned experimentally but the consequence of this employment is satisfied. In training situation the weights are subject to change until reaching the best weights. The amount of training situations is determined by the amount of epochs it is kept done until fewer mistakes come into view in output.

With the acknowledge of MLP, here is another type that is widely used in classification algorithms and is employed in this study. Radial Basis Function, RBF. This type of network is used radial Euclidian distance among the basic data to specify the output with the information that the radial distance change during training phase to specify the best output [11].

The MLP structural design is the most popular in practical applications. Each layer uses a linear mixture function. Inputs are fully linked to the first hidden layer, each hidden layer is completely connected to the next, and the last hidden layer is completely connected to the outputs often with a bias node at the input. This node could take part in a hidden role in evaluation the output.

Radial basis function (RBF) networks usually have only one hidden layer for which the combination function is based on the Euclidean distance between the input vector and the

weight vector. Some types of RBFs have a "width" associated with each hidden unit or with the entire hidden layer; instead of adding it in the combination function like a bias, the Euclidean distance could be divided by the width.
Fisher Linear discriminate FLD, known as a Gaussian conditional density model. This model tries to apply a linear limit between samples with a Gaussian gathering theory [13, 14]. This model is conceptually near to principal component analysis PCA. FLD applies measured variance between the samples however PCA tries to establish boundaries with covariance analysis. Another method that is used in this paper is to estimate Bayesian and RBF on samples via WEKA, WEKA contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces for easy access to this functionality [10]. Weka supports several standard data mining tasks, more specifically, data preprocessing, clustering, classification, regression, visualization, and feature selection. In this paper weka is used to evaluate a decision for boundary classification in for Bayesian and RBF networks. Bayesian network is specified by an expert and is then used to perform inference. This structure tries to perform a decision on samples via a graph and statistic of each node on the others. Automatically learning the graph structure of a Bayesian network is a challenge pursued within machine learning. The basic idea goes back to a recovery algorithm developed by Rebane and Pearl [12]. Bayesian sometimes provide a liable decision with regards to inherent features of applied samples and their gathering. However the application of all described networks are collected in a table with several times training.

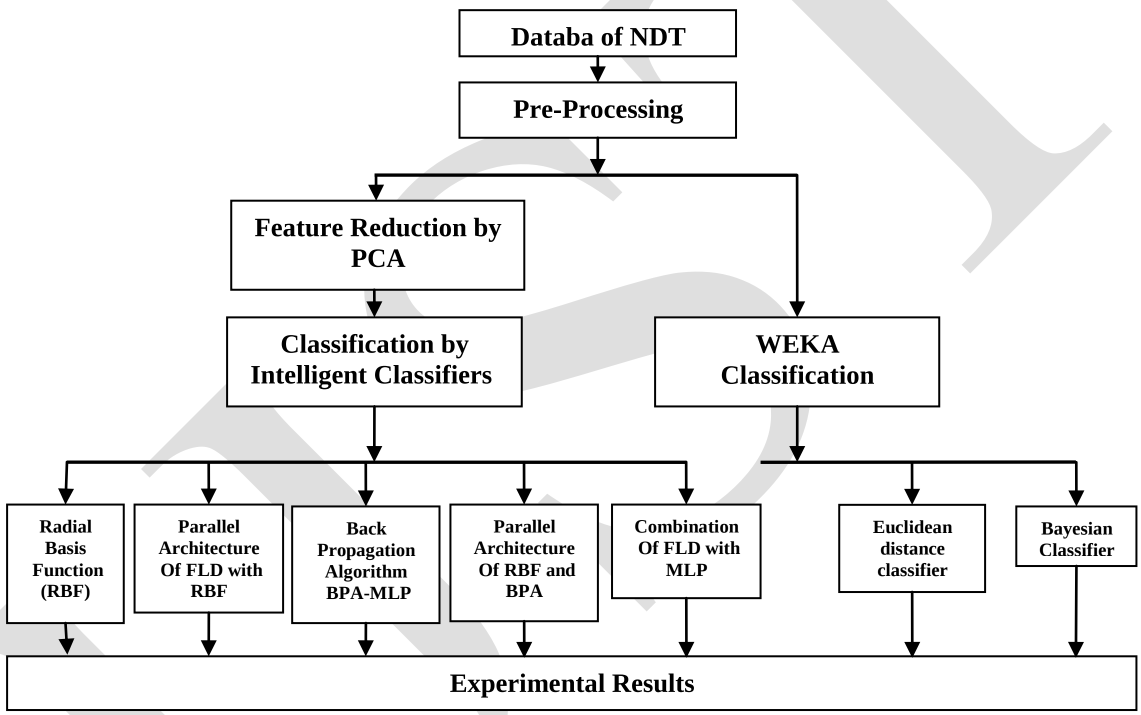

Figure 1. Devised algorithm

In this diagram Fig. 1, pre-processing is applied to the basic database. This section is discussed in follow and as a brief it starts to extract different kinds of defects from physical formulation and normalization then classes known as experts perform a decision on their inputs.

6. Results and discussion

In order to examine the statistical distribution of the error rate, seven main neural networks with an identical structure are trained in each class several situations are combined with same transfer function (but with different number of neurons that are referred to initial state) refer to previous efforts [18,19,20], this idea provides a better decision on NDT database. This effort provides expert classes by which are trained to recognize 5 different categorize of defects. And the

Error rate and accuracy of each class is reported and compared with others. The following experimental rule was used to define the structure of the network:

$$N_{input} = 2 \times P$$
$$N_{hidden} = approx(N_{in} + N_{out}) \qquad (16)$$
$$N_{out} = 2 \times P$$

CLASSIFICATION

Parameters and measurements

WEKA

	Euclidian			Bayesian	
Data Type	Mean Error	Precession	Data Type	Mean Error	Precession
I	10e-2	90	II	10e-3	83
II	10e-1	66	I	10e-2	75
Data Type	Sensivity	F-measure	Data Type	Sensivity	F-measure
I	0.8	0.75	II	0.9	0.8
II	0.8	0.73	I	0.85	0.77
Data Type	Error type I	Error type II	Data Type	Error type I	Error type II
I	15%	20 %	II	12%	17%
II	16%	25%	I	14%	17%

FLD-WEKA

	Euclidian			Bayesian	
Data Type	Mean Error	Precession	Data Type	Mea Error	Precession
I	10e-3	93	I	10e-3	80
II	10e-3	87	II	10e-2	73
Data Type	Sensivity	F-Measure	Data Type	Sensivity	F-Measure
I	0.9	0.97	I	0.85	0.77
II	0.95	0.95	II	0.9	0.8
Data Type	Error type I	Error type II	Data Type	Error type I	Error type II
I	12%	15%	I	9%	10%
II	14%	17%	II	11%	14%

Least mean error –WEKA 10e-3 DataType I
Least mean error –FLDWEKA 10e-3 DataType I & II
Sensivity (recall)-WEKA
Sensivity (recall)-FLDWEKA

Intelligent classifiers and Parameters –Fully data type P1-P2-Q1-Q2-Q3

PCA	BPA-MLP	RBF || FLD	RBF	BPA-RBF	MLP || FLD
	NET. MAKEUP	NET. MAKEUP	NET. MAKEUP	NET. MAKEUP	NET. MAKEUP
NET / PC	NET. HIDD. NODES 10 04 04 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05
2	55	35	45	60	73
4	63	30	30	63	80.1
6	70	33.3	50.3	80	86
8	85.3	66	56	85.5	89.3
10	75	69.1	70	86	91
	NET. HIDD. NODES 10 06 06 05	NET. HIDD. NODES 10 06 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05
2	50	45	55	63	75
4	61	50	63	70	81
6	90.2	63.9	66	81.8	87
8	89	75	95	89	93.7
10	70	73	80	94	89
	NET. HIDD. NODES 10 08 08 05	NET. HIDD. NODES 10 08 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05
2	65	43	60	70	71
4	73	52	78	77	79
6	82	66	94.1	85.5	80
8	93.3	79.8	91	93.1	89.1
10	81	80	88	94	83
	NET. HIDD. NODES 10 10 10 05	NET. HIDD. NODES 10 10 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05
2	77	77	89	88	88.3
4	84	81.3	90	91	93
6	94	90	91	90	94
8	75	94.3	93	92.3	87
10	71	87	87	89	75
	NET. HIDD. NODES 10 12 12 05	NET. HIDD. NODES 10 12 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05
2	58	75	45	71	66
4	61	66	66	67	70
6	80.3	89	95	80	90
8	85	94	94	93.3	91.7
10	70.3	85	85	87	91
	NET. HIDD. NODES 10 14 14 05	NET. HIDD. NODES 10 14 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05
2	86	67	59	88	89
4	94.3	87	66	88.1	91.5
6	95	93.3	91.3	87.3	90
8	90.1	88	89	85	92.3
10	88	89.1	77	90.3	88
	NET. HIDD. NODES 10 14 14 05	NET. HIDD. NODES 10 16 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05	NET. HIDD. NODES 10 04 05
2	70	89	82	71	77
4	73	90.2	88	86	80.2
6	91	93	91	93	87
8	89	75	90.2	95	94
10	75	71	80	88	91

Table 1. observed results

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. Furthermore, maximum or minimum of the average of output of each network in ten times training and the best achievement is reported in table 1. for comparison with others. 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):

$$P = \nu . p = 2h\nu(m - 2H_a a^2) \qquad (17)$$
$$q = h^2$$

1= 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]

Issue 6 volume 5, September-October 2016
ISSN 2249-9954

Preparation and training phase applied by iterations for five classes named P1, P2 up to q3. These are all merged to each other in training set of non-WEKA

Classifiers. In non-WEKA, BPA-MLP is the first attempt to apply classification. Next one is the application of RBF on the FLD. Third one is a pure RBF function with the Gaussian activation function. Forth one is the RBF with the Back propagation concept and finally is the application of MLP on the Fisher linear discriminate function. For WEKA clusters data type I and II are selected for training classifiers. Two types such as Euclidian and Bayesian are applied and results are summarized in table 1.

6.1 Historical discussion

If we would like to have a discussion on what is done before, we would observed some of published researches that are based on the analytical model of MFL signals from magnetic charge [23, 24-27]. But for an exception, reference [22] is just discussed a single defect. The often encountered sensible situation of two nearby defects is also discussed only by Uetake and Saito [28], but their effort 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 [29, 30, and 31]. In oppose of the significant progress made in this area to include non-linear material properties [32, 33, 34], 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 [30-33] and from side to side analytical methods based on dipolar magnetic charge [37, 41]. Two of the arithmetical analysis studies [30, 42] correctly predicted that the amplitude of the normal MFL signal Component increases with defect depth and 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 seven classes which each of them tries to learn a defect with determined characteristics. This structure is an estimate of five large groups of defects recognition.

7. Conclusion

This study provides an algorithm to recognize defects of pipes by a non destructive testing and MFL procedure. The mentioned algorithm provides a powerful structure to find out defects in five main groups. Seven expert classes are combined with each other to maintain is algorithm. The efficiency of the model was confirmed through experimental results and is reported in table1. A clear advantage of the method presented here is the low number of parameters that have to be considered with the advantage of its output error rate. This study estimates defects in five groups with different shapes and features. In this case all the defects ranged to depth of 2 till 4 millimeter and radius of 1 up to 1.5 millimeters. Expert in the mentioned algorithm are trained in ten times to achieve the best setting for the weights. Seven classes are finalized for this structure. PCA as a well known feature extraction function is employed for data compression by the means of Eigen values. The result of all are shown and discussed in table 1. The accuracy rate of 95 percent shows the efficiency of the mentioned algorithm.

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