Eddy Current Flaw Detection with Neural Network Applications

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ABSTRACT

Eddy current inspection is a fast and effective method for detecting and sizing most of the flaws in conducting materials. The inverse problem solution i.e. inferencing about possible defect, based on the measurement signal from the eddy current probe, is a difficult task In this paper an implementation of artificial neural networks for multi-frequency eddy current testing on conducting layers (aluminum, copper) and ferrous tubes has been presented.

Keywords: eddy current testing, flaw detection, artificial neural network, Radial Basis Networks

1. INTRODUCTION

Eddy current phenomenon is described by three-dimensional, nonlinear partial differential equations with very complicated boundary conditions[1]. Modeling analysis methods are very difficult to apply for test data analysis. Usually, a visual observation technique is currently used for analysis of eddy current test data. This technique requires highly trained personnel. Human error in performing the analysis of test data is the main drawback for its successful application. So it is very important an automating eddy current analysis and flaw depth estimation.

The amplitude and phase of the eddy current measurement signal depends on several parameters e.g.: conductivity of materials, magnetic and electrical permeability, frequency of the excitation current, distance between probe and specimen, material errors as discontinuity, non-homogeneity. The inspection requires standard calibrations specimens (bar or tubes) with natural or artificial defects to initial instrumentation set–up. The specimens should be identical in material and form to be tested.. Artificial discontinuities are frequently made using electrodischarge machining (EDM) technique as rectangular notches or holes with various size and depth. (Tab.1). The specimens are further applied as standards for training of the neural network.

2. TESTING SYSTEM

The testing system allows for automatic scanning of the surface of the conducting material under test on previously planned trajectory, for instance in a line by line manner. In fact, the following measurements were performed in a uniformly distributed grid points over the testing surface. The eddy current probe has scanned the surface of the tested conducting material in XY plane, being driven by programming 2 step engines, each for one coordinate axis. The control link between axis drives and a Pentium II PC computer was established via a specialized card suitable for incremental control.

To eliminate the influence of the material properties, a difference measuring system was established consisting of two eddy current coils.
The scanning probe was excited by the signal coming from sinus wave generator with the adjustable frequency.

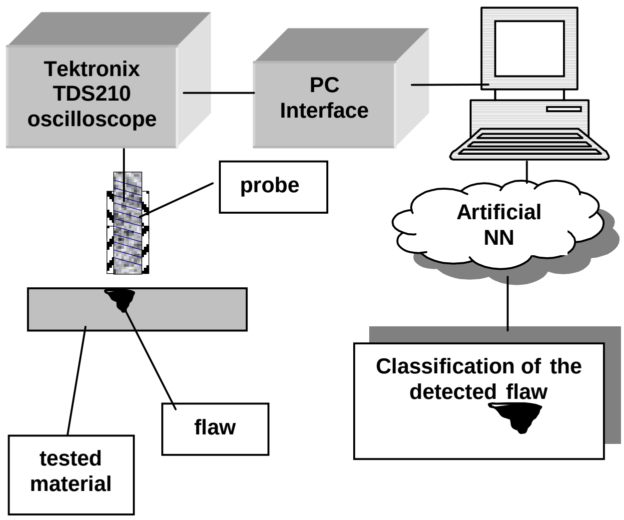

Fig.1. Experimental testing system

The output electrical signal picked up from the probe, after amplification, was compared with the primary i.e. excitation waveform, and after that, amplitude ratio and a phase shifting were evaluated. The data was stored in the memory for the further use by the neural network based application detecting the presence of the flaw. The data acquisition module used Tektronix TDS-210 oscilloscope, controlled from the Pentium II PC with a serial RS232C interface. The calibration of the crack detection system has been effected with sets of specimens fabricated as bars from aluminum, messing and copper with dimensions (400mm × 30mm × 5mm) and ferrous tubes with 3m length. An exemplary kind of specimen bar is shown in Tab.1.

Tab. 1. Dimension of notches in aluminum specimens

flaw No.	**width** [mm]	**depth** [mm]
w/o	-	-
1	0.8	0.2
2	0.8	0.4
3	0.8	0.6
4	0.8	0.8
5	0.8	1.0
6	0.8	1.5
7	0.8	2.0
8	0.8	2.5
9	0.8	3.0
10	0.8	3.5

3. INVERSE PROBLEM SOLUTION WITH NEURAL NETWORK APPLICATION

In eddy current testing it is observed distinct deviation of the magnetic field, correlated with the presence of the material crack under testing probe. The similar results can be obtained on the theoretical studies [1,5]. However in many applications the inverse problem solution is the fundamental task. The magnitude and phase of the output signal picked by the probe above the flaw are non-linear functions of a number operating parameters. They are especially sensitive of distance variation between sensor and testing material and also very effected by other noise signals.

It is used for localization and the shape classification of the material cracks. Because of very sensitive, noisy nature of eddy current signal, it is a common approach employing ANN for solving the problem. Nevertheless the applications with ANN has so many advantages as drawbacks. The paper references [2,3,4] are related to research works performed with very different types of ANN, beginning from Multi Layer Perceptron (MLP), trained with Levenberg-Marquard method, competitive networks learned with Kohonen rule and classifying networks based on self - organizing map with various modifications.

Due to increase the performance, i.e. the rate number of successfully detected discontinuities by the testing algorithm, a multi-frequency method was established. Depth of the penetration by the eddy current testing depends on reciprocally from the square root of the excitation frequency of the probe Eq.(1).

$$\delta = \frac{1}{\sqrt{\pi f \mu \sigma}} \tag{1}$$

where,
δ - penetration depth of eddy current,
μ - magnetic permeability,
σ - electrical permeability,
f - frequency.

The testing was performed at the three distinct frequencies: 10, 14 and 20 kHz, being in different grade sensitive to material cracks of various depth. After measuring, test signal has been processed to extract the properties of interest: the relative amplitude and phase shift. Two practical approaches have been tested with Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) networks. The input vectors consisting of three components: amplitude, phase and frequency have been initially normalized to the range of values between [-1 and 1] with the formula (2)[6]:

ynorm =2*(y-ymin)/(ymax-ymin) (2)

where,
ynorm - normalized value,
ymin - minimal value,
ymax - maximal value,
y - current value of the component variable.

A general architecture of a multi-layer neural network is shown in Fig.2. The prepared sequence of learning vectors, coming from measurements performed on specimens, were initially divided in three equally numerous series. The first of them was further employed in training of the network, being applied directly to the input layer, the second has been used as a testing one.
The neural network was learned with a selected record, using backpropagation (BP) algorithm with adaptive rate of learning during a period of 200 epochs.

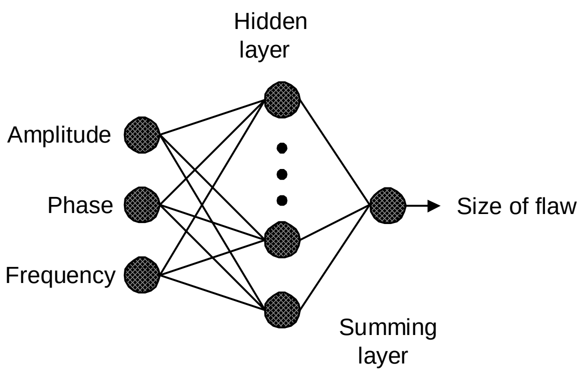

Fig. 2. Architecture of the multi layer network for detecting size of discontinuity

The number of neurons has been determined experimentally on network training results, based on evaluated MSE and RMAE - learning performance indices [6], defined in Eq.(3) and Eq.(4) respectively.

Mean Square Error MSE:

$$MSE = \frac{1}{nw}\sum_{w=1}^{nw}(d(w) - d_{wyj}(w))^2 \qquad (3)$$

and
Relative Mean Real Error

$$RMAE = \frac{1}{nw}\sum_{w=1}^{nw}\frac{|d(w) - d_{wyj}(w)|}{|d(w)|}\cdot 100\% \qquad (4)$$

$d(w)$ –real flaw depth for w-th specimen,
$d_{wyj}(w)$ – NN estimated for w-th specimen,
nw – number of specimens.

To build the ANN of suitable size, a sequence of training courses have been carried out, using the same learning data record. The results have been shown in the Tab.2. In the Levenberg-Marquard method, the weights update law is described by the Eq.(5), where **J** is the Jacobian matrix of derivatives of each error to each weight, **k** is a scalar and **e** is an error vector

$$\mathbf{\Delta W= (J^T J+kI)^{-1} J^T e} \qquad (5)$$

As we can see below (Tab2), the learning have been completed after **k** reached its maximum value, error goal was met or given number of epochs elapsed.

Tab.2. Training results for various topologies

Topo-logy	Number of epochs			MSE error Learning patterns		
3-1-1	19(1)	23(1)	21(1)	0.0211	0.0211	0.0211
3-2-1	58(1)	93(1)	500(1)	0.0057	0.0057	0.0047
3-3-1	500	500	500	0.0026	0.0024	0.0023
3-4-1	500	500	500	0.0036	0.0014	0.0017
3-5-1	104(2)	500	500	0.0001	0.0001	0.0015
3-6-1	237(2)	123(2)	204(2)	0.0001	0.0001	0.0001

(1) training completed due to reaching the maximum value of **k**,
(2) training completed due to reaching the MSE error value below 1E-4

Tab.3. Checking the generalization features of previously learned network

Topology	MSE error [mm^2] Test patterns		
3-1-1	0.1041	0.1041	0.1041
3-2-1	0.0575	0.0575	0.0095
3-3-1	0.0106	0.0385	0.0211
3-4-1	0.0925	0.0077	0.1306
3-5-1	0.1634	0.3014	0.0322
3-6-1	0.3819	0.0571	0.0718

The error goal was settled on relatively high value equal 1E-4, allowing to shorten the learning time for the over-fitted network. After training the generalization property of the network had been checked, following the evaluation the network outputs for the test patterns.(Tab.3).

Too much of neurons caused, that existence an extra degrees of freedom of the network had been observed, at the expense of useful generalization.
Introduction of the excessive hidden layer resulted in increasing the time of learning and more frequent completing the training in a local minimum.

As an optimal MLP network, this one with three sigmoid neurons in hidden layer and one linear neuron in output layer, was favored.

In the next stage, the RBF network was tested, consisting of input layer with three neurons, hidden layer with RBF neurons Eq.(6), and the linear output layer evaluating the size of flaw.

a=radbas(||dist|| b) (6)

where,

radbas(n)=exp(-n ^{2})
||dist||=dot product(p-w),
a -neuron's output,
b - bias (dilution),
p -input vector,
w -weight vector.

The optimal number of RBF neurons has been chosen after analysis of MSE and RMAE indices, which in turn were additionally related with a RBF bias (dilution) parameter.

Tab.4. Values of errors after training versus dilution parameters and number of neurons in a radial layer

Value of dilution	Number of neurons in a radial layer	Training record MSE [mm^2]	 RMAE [%]
0.1	15	0.0020	3.27
0.2	13	0.0014	4.89
0.3	16	0.0014	3.14
0.4	11	0.0038	6.52
0.5	11	0.0027	4.82
0.6	10	0.0032	5.19
0.7	7	0.0038	5.39
0.8	7	0.0034	5.77
0.9	8	0.0036	5.40
1	9	0.0033	5.21
2	9	0.0027	4.97
3	9	0.0039	5.09
4	10	0.0040	5.59
5	10	0.0039	4.81
6	10	0.0036	6.24
7	10	0.0040	5.41
8	10	0.0040	5.36
9	10	0.0040	4.67

The training courses of RBF networks confirmed having the shortest learning time versus MPL. So it was the main reason to prefer applying them in a task of mapping the dependence between record of eddy current measurement signal and size of flaw.

Tab.5. Simulation RBF with test record

Value of dilution	No. of neurons	Test record	
		MSE	RMAE
0.1	15	1.2998	36.00
0.2	13	0.1480	15.97
0.3	16	0.0338	7.24
0.4	11	0.0575	11.83
0.5	11	0.0556	12.06
0.6	10	0.0592	14.75
0.7	7	0.0274	12.55
0.8	7	0.0206	11.60
0.9	8	0.0155	9.46
1	9	0.0135	10.14
2	9	0.0238	8.92
3	9	0.0083	7.66
4	10	0.0106	10.70
5	10	0.0127	10.03
6	10	0.0435	16.11
7	10	0.0140	10.82
8	10	0.0136	10.47
9	10	0.0117	9.70

The feature of the simple RBF net structure and fast on-line learning ability makes the proposed approach particularly feasible for embedding in real-time operating flaw detectors classifiers. The simulations performed in a Matlab package environment confirmed that RBF Artificial Neural Networks (ANN) over-performed MLP (Multi Layered Perceptron) resulting in a lower training time.

Verification of the trained network has at finally carried out on the third record of flaw patterns (Fig.3.)

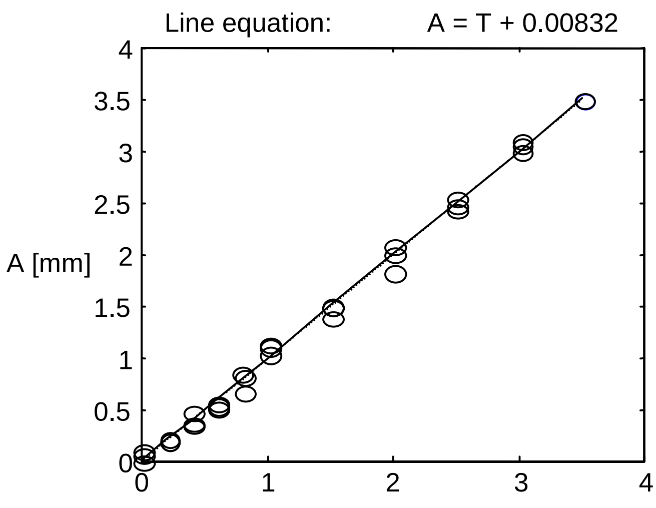

Fig.3. Depth of flaw evaluated by ANN (A) versus real value of depth specimen (T)

The obtained results, for tested at the end ANN RBF network, represent relatively good accuracy of mapping the crack dimension. The fitting accuracy describes the correlation coefficient R= 0.998.

4. CONCLUSIONS

The artificial neural network methods are very attractive solution for fitting the nonlinear function dependencies between geometrical properties of the investigated defect based on the measurement records acquired in the closest neighborhood of the interesting spot.

From among many successfully implemented ANN applications in other branches of industry, engineering medicine and others domains, only few of them can be applicable for solving the inverse eddy current problem.

Concluding we can say that: the estimation of defect parameters, such as flaw size and depth, defect type, could be performed with a satisfactory accuracy applying neural network computation.

The further improvements of the flaw detection system can be done by extending available set of flaw patterns, making the training algorithm and finally the ANN more robust and flexible for not known materials.

5. REFERENCES

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