FACTA UNIVERSITATIS (NIŠ)
SER.: ELEC. ENERG. vol. 19, December 2006, 371-377

Crack Sizing by Using Pulsed Eddy Current Technique and Neural Network

Ivaylo Dolapchiev and Kostadin Brandisky

Abstract: A neural network approach for solving an inverse problem of identification of crack width and depth is proposed. Radial Basis Function (RBF) neural networks (NN) perform the identification. It was trained using information from numerical simulated pulsed eddy current (PEC) nondestructive testing (NDT). The capability of the RBF NN was checked with information from numerical and physical experiment. The obtained results illustrate the efficiency of the approach.

Keywords: Nondestructive testing, inverse problem, neural networks.

1 Introduction

The measuring of surface crack dimensions in metal structures is a task that is usually accomplished by NDT methods. In contrast to the classical eddy current NDT methods, PEC measurements excite the probe's coil with a repetitive square wave pulse [1]. The resulting transient current through the coil induces transient eddy currents in the test piece, that are associated with highly attenuated magnetic pulses propagating through the material.

This work investigates the PEC method and a NN based inversion as an approach to the nondestructive crack sizing. The interaction between eddy current probe and the device under control is modeled numerically. The prepared model consists of a sample with an artificial crack and a probe. The coil of the probe is supplied by square wave voltage source. The forward problem is solved by means of the finite element method (FEM) and transient solver. By changing the width

Manuscript received June 22, 2005. An earlier version of this paper was presented at seventh International Conference on Applied Electromagnetics ΠEC 2005, May 23-25, 2005, Niš, Serbia.

I. Dolapchiev is with Technical University of Sofia, Faculty of Electrotechnics, 1000 Sofia, Bulgaria (e-mail: ivailodo@tu-sofia.bg). K. Brandisky is with Technical University of Sofia, Faculty of Automation, 1000 Sofia, Bulgaria (e-mail: kbran@tu-sofia.bg).

and the depth of the crack, two data sets were built – one with “time-current” data values obtained from forward problem solution and another with crack dimensions.

A Radial Basis Function (RBF) neural network is used to approximate nonlinear relationship between the probe current attenuation at the end of the excitation pulse and crack parameters.

2 Forward Problem Definition

The FEM is used as a forward problem solver to collect information for field distribution in the region under investigation. This region contains an eddy current probe, disposed over a specimen with crack. The probe consists of ferrite core coaxially placed in a pancake coil. Because of the symmetry of the model only one fourth of the investigated region is considered. The interaction between electromagnetic field, excited from the probe, and the specimen is analyzed numerically in 3D.

During the analysis all used materials are accepted to be linear and homogeneous. Electromagnetic field is excited by the coil, supplied by a repetitive square wave pulse voltage source and attenuates entirely at the boundaries of examined region The resulting transient magnetic field distribution is governed by partial differential equation (1), which includes the effect of magnetic field variation with time.

$$\nabla \times \left(\frac{1}{\mu_0 \mu_r} \nabla \times \vec{A} \right) + \sigma \frac{\partial \vec{A}}{\partial t} = \vec{J}_e. \tag{1}$$

The numerical solution of equation (1) was performed at zero value boundary conditions using FEM and commercial software package MAGNET [2]. To study the response of the pulsed eddy current probe to crack’s width and depth, a series of simulations were carried out. The problem was solved for full combinations of 3 values of crack’s width and 10 different values for crack’s depth. Figure 1 shows the magnetic flux density plot for one of these simulations, at the end of the voltage pulse. The dark gray color at the figure corresponds to the high values of the flux.

3 Using RBF Neural Network for Solving the Inverse Problem

The neural network approach for the described inverse problem solution requires input and target data sets for the training. The information in the input data set is collected either by data acquisition system during physical experiments or by numerical simulations. In the examined problem, this set was formed with “time–current” information for probe’s coil. The target data set contains data for crack parameters.

The RBF neural network was preferred to the most popular multi-layered perceptron networks (MLP). The neurons, used in RBF NN, respond to relatively small regions of the input space, which allows such networks to have more neurons than the MLP networks for the same tasks. RBF networks provide fast training rate and good abilities to approximate any given nonlinear function even though in multi-dimensional space. The accuracy of approximation depends on the number of the hidden neurons [3]. During the training process, the values for their weights and the biases are determined. Despite of the large number of neurons, RBF network is trained very quickly.

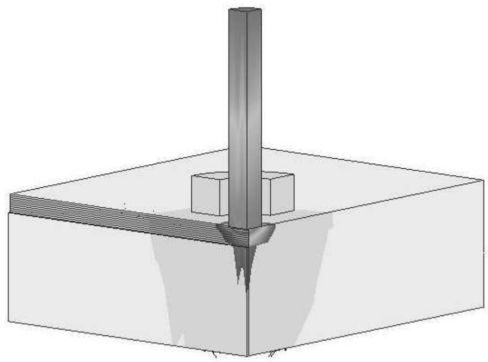

Fig. 1. 3D plot of flux density distribution

For the purpose of the described inverse problem solution, two different RBF networks were formed. They use identical input data set with information for probe current values at fixed time steps. This information was prepared using results from numerical simulated experiments.

Both networks are with approximately 100 inputs and a single output. They differ in neurons parameters and the used target data sets. The first target data set contains information for crack's width and the second one was with information for crack's depth. Therefore, the networks were trained to different crack parameters determination.

4 Physical Experiments

To test the abilities of the created neural networks a physical experiment was conducted. An inductive transducer consisting of cylinder ferrite core and a pancake coil at its end was created. The transducer was supplied by a square wave voltage source. A shunt resistor connected in series with the coil was used to measure the changes in coil's current. The current values are measured at equal time steps by means of digital storage oscilloscope. The probe is placed in a plastic holder to guarantee its perpendicular position to the sample's surface.

The specimen under test is manufactured for the adjustment of non-destructive testing devices. It represents a thick flat steel slab with three transverse cracks. They have equal width of 0.2mm and 0.2mm, 0.5mm and 1mm depth. The conductivity and permeability of the slab material are known.

The voltage source used ensures pulse amplitude of 1V and frequency of 1kHz with 30% duty cycle. At this excitation, the values of potential drop over the shunt resistor were measured in 2μs time steps. The speed of probe current decay differs depending on crack dimensions. In order to extract information about the influence of crack to the probe current decay, the following experimental scheme was accomplished, Figure 2.

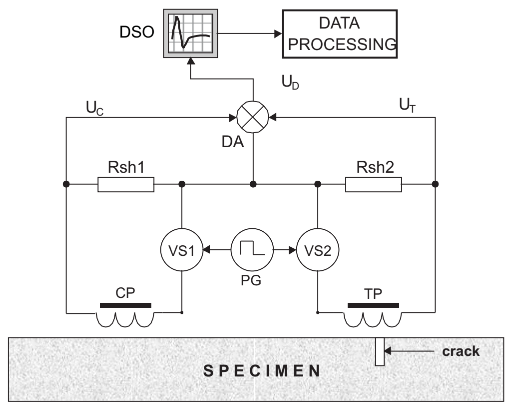

Fig. 2. Schematic view of the experimental setup

Two identical probes were used – one placed over the crack and another on the section of the specimen without cracks. Both probes were supplied by two identical voltage sources VS1 and VS2 that are controlled by pulse voltage generator PG. The voltage drops U_C and U_T, over the shunt resistors Rsh1 and Rsh2, are proportional to the currents in the probes. The attenuation of the current in the compensation probe CP depends on the electromagnetic properties of the specimen's material. The current in the testing probe TP attenuate in a manner that depends on the specimen material properties and on the crack dimensions.

During the experimental preparation, the resistances of the shunt resistors were equalized. In this manner the voltage U_D obtained as a difference between the voltage drops U_C and U_T, is proportional to the crack parameters. Its values were magnified by the differential amplifier DA and measured by means of digital storage oscilloscope DSO. The obtained in "time–voltage" information for probe's current behavior is prepared and saved for further neural network processing.

5 Results

The physical experiment was simulated numerically using FEM. The described forward problem was solved at different values of crack dimensions, and the obtained “time-current” values were used to reconstruct the voltage drop U_T over the shunt resistor Rsh2. The information for voltage attenuation over the shunt resistor of the compensation probe U_C was prepared using the same approach. In order to collect this information the same forward problem was solved but the used specimen was without crack. The voltage U_D was obtained numerically as a difference between U_C and U_T, at each time step. This “time–voltage” information depend on crack parameters and corresponds to the readings of the digital storage oscilloscope at the experimental bench.

The numerically obtained information allowed charting the variation of the measured voltage U_D with respect to crack depth and width. Figure 3 shows the influence of crack depth on the voltage variation at fixed width of the crack, and Figure 4 represents the influence of the crack’s width if its depth did not change. Both charts display voltage U_D 100μs after the end of the excitation pulse.

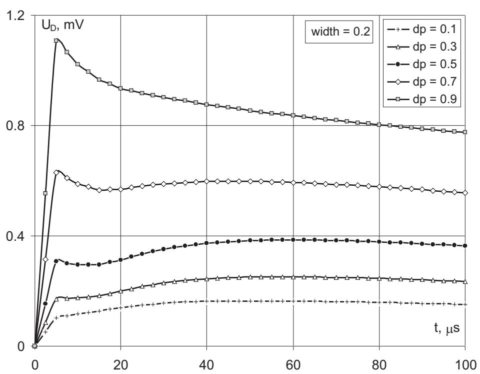

Fig. 3. The influence of crack depth on the voltage U_D

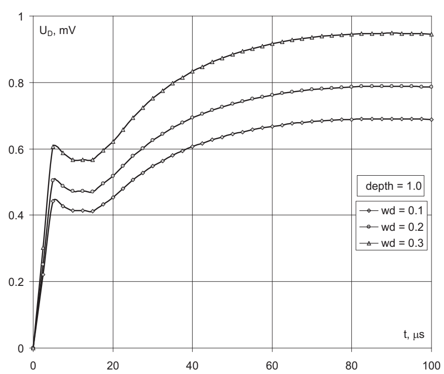

Fig. 4. The influence of crack width on the voltage U_D

The training process of the RBF neural network requires two data sets. The input data set contains information for the voltage UD at previously defined time range and fixed time step. The target data set contains information about crack dimensions. Both data sets were prepared numerically as it was described above. The information in the data sets corresponds to the results from ideal physical experiment.

To facilitate the identification of crack parameters, two RBF NN were prepared – one for width and another for depth identification. Both networks were trained with identical input data but with different target data sets.

In order to test their abilities and to adjust their parameters, new testing data sets were prepared. These sets were built in the same manner using the numerical model and forward problem solver. At this stage, the forward problem was solved for cracks, different in their dimensions from the cracks that formed the training target data sets. In addition to that, these results were processed to simulate the real measurement conditions. Because in practice measurements are influenced by disturbances, which induce significant noise in the collected data, a normally distributed random noise was added to the obtained voltage values.

The obtained noisy input data sets with approximately 40dB signal-to-noise ratio were applied to the RBF networks. The relative accuracy of their identifications is shown at Figure 5 and Figure 6.

The standard specimen with three cracks was used to conduct the physical experiments. Two identical ferrite core probes CP and TP were placed over the specimen. The CP was fixed far from the cracks and TP. The TP moves over the surface and at crack positions, the voltages U_C and U_T were digitized and saved. After the U_D calculation the input data set was formed and applied to the networks.

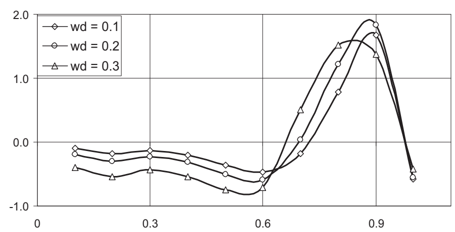

Fig. 5. Relative accuracy of RBF 1 – depth identification at different widths, %

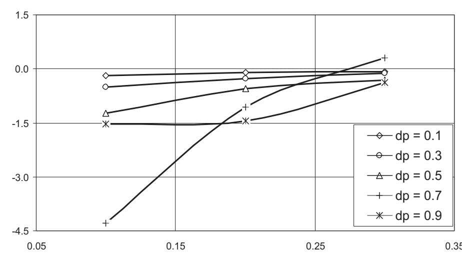

Fig. 6. Relative accuracy of RBF 2 – width identification at different depths, %

The determined from RBF 1 depth and from RBF 2 width of the crack differ from the expected values of the same parameters. The relative accuracy of determination δ was up to three times worse than the worst results obtained in the testing stage of the neural network preparation. The expected and obtained values together with the relative accuracy are shown in Table 1.

Table 1. Expected and obtained values of crack parameters.

	Depth			Width		
Crack	Exp	RBF 1	δ	Exp	RBF 2	δ
	mm	mm	%	mm	mm	%
#1	0.2	0.207	3.5	0.2	0.195	2.5
#2	0.5	0.484	3.2	0.2	0.206	3.0
#3	1.0	0.945	5.5	0.2	0.185	7.5

6 Conclusion

This work presents an investigation of the use of RBF NN for the inverse problem solution in the field of PEC NDT. The solution of the forward problem was obtained using 3D FEM transient solver. The investigation of the influence of crack's width and depth on the field decays was done at constant conductivity and permeability of the specimen.

Field attenuation depends not only on the crack parameters but also on the conductivity and permeability of the specimen. To suppress the influence of specimen material parameters on the output voltage a differential measuring circuit is proposed. The circuit works properly if the shunt resistors, ferrite probes and voltage sources used are identical.

With these restrictions on the investigation, it was determined that crack's dimensions change the speed of probe's current attenuation. This allows suggesting that crack's sizes can be defined by suitable processing the information for the probe's current. The results from numerical simulation of the experiment show that the correlation between the voltage U_D and crack dimensions is non-linear. This allows artificial NN to be used as a tool for inverse problem solution. The obtained two RBF NN were adjusted and tested with numerically computed data from the forward problem solution.

The applied data set at the testing stage of the RBF preparation demonstrates their abilities to perform identification with acceptable accuracy. The conducted physical experiment showed worse accuracy. This is due to the errors and disturbances in the measurements as well as to the insufficient information for NN training stage.

References

[1] W. William and J. Moulder, "Low frequency pulsed eddy currents for deep penetration," *RPQNE*, vol. 17, pp. 291–298, 1998.

[2] "Infolytica corporation," MAGNET 6.1 - Users Manual, 2004.

[3] S. Haykin, *Neural networks.* A Compressive Foundation, New Jersey: Macmillan College Publishing Company, 1994.