APPLICATION OF NEURAL NETWORKS IN MULTIFREQUENCY EDDY-CURRENT TESTING

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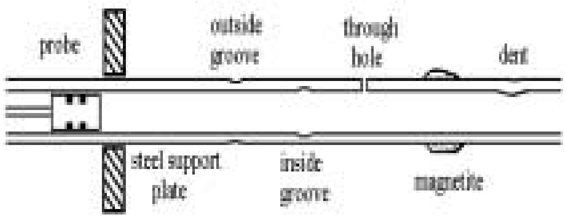
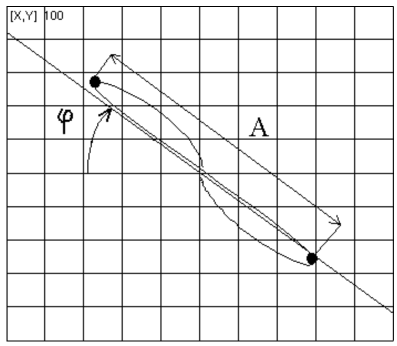
The nondestructive defectoscopy of steam generator tubes of nuclear power plants by multifrequency eddy current method is the field, in which the use of classifiers, based on neural network is very perspective.One of the fields is classification of indications into classes, that are characterized by the signal shape, eventually by the signatures relating to the signal shape. The contribution concentrates on the choice of suitable neural network structures and of the suitable representation of indications.

1. Introduction

Eddy current testing is one of the methods of nondestructive testing. In our case it is testing of heat-exchanger tubing using a differential probe [1]. Tubes are made from nonmagnetic material. The shape of output signal from the probe reflects properties of tested material [2].



a.



b.

Fig.1. a/Defect types, b/ Parameters of curve corresponding to 100% defect

The fundamental problem is to determine according to the signal shape, whether there is some defect, structural element, roughness or impurity in the tube.

The measurement has been accomplished at four frequencies. Low frequencies are more suitable for evaluation of identifiable anomalies at the outside wall of the tube, e g of the presence of construction elements of the steam generator. At high frequencies there are dominant signal components corresponding to the changes of internal tube wall, e g to the changes of profile tube. Middle frequencies enable to obtain phase separation of 2D curves (fig. 1.b) corresponding to defects that are important for quantification of percentual material drop.

The contribution treats the topic of classification of indications into defined classes. Classification is based on the identification of the shape of 2D curves by neural network. From this point of view the choice of suitable descriptors of 2D curves plays an important role. Techniques based on Fourier transformation and Fourier descriptors belong to the frequently used methods. It is necessary to transform the obtained parameters in order to obtain descriptors that are invariant to the shift, rotation, scale and to the choice of boundary values at numerical calculation of parameters.

2. Data representations

The choice of suitable representation of indication data is very important. Properties of data representations to be used as an input of neural classifier depend on the measurement frequency of original data representation. .The convenience of representation is compared in terms of separability of input data into disjunctive clusters.

2.1 Fourier transformation

The indication can be then represented by vector of the most significant Fourier coefficients. Indication curve can be defined by parametrized representation *f(t)=x(t)+i.y(t),* where $t \in \langle \alpha, \alpha + \tau \rangle$. Fourier coefficients are usually defined by the following formula:

$$a_k = \frac{1}{\sqrt{\tau}} . \int_{\alpha}^{\alpha+\tau} g(t)\, dt \quad | \; k \in Z \qquad (1)$$

where $\omega = \frac{2\pi k}{\tau}$ and $g(t) = f(t).e^{-i\omega t}$.

To define a representation independent of the choice of starting point, on position, rotation and scale of curve let us define invariant Fourier based (1) coefficients.

$$b_1 = \frac{|a_1|\, a_2}{a_1^2} \qquad , \; b_j = \frac{a_{1+j} a_{1-j}}{a_1^2} \qquad \text{for } j \geq 2 \qquad (2)$$

Descriptor b_1 depends on the curve rotation, but other descriptors are independent of all mentioned unacceptable factors [2].

2.2 Wavelet functions

A wavelet is a waveform of effectively limited duration that has an average value of zero. Fourier analysis consists in decomposition of the signal into sine waves of various frequencies and similarly, wavelet analysis consist in decomposition of the signal into shifted and scaled versions of the original wavelet.

Instead of other signal analysis techniques wavelet analysis is capable of revealing aspects of data like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. It affords a different view of data than the traditional techniques and therefore wavelet analysis can often compress or de-noise a signal without appreciable degradation [3], [4].

2.3 Other parameters

Of course, we can use different types of 2D-curve natural parameters [5]. The output signal from the probe consists in two orthogonal parts (called real and imaginary parts).

The following list contains representations based on mentioned natural parameters:

- standard deviation of real and imaginary parts of indication signal and their covariance coefficient (3 numbers)
- peak-angle-peak representation (peaks angle a their distances in X-axis and Y-axis direction [5]

3. Neural network classifier

Network topology depends on the choice of input data representation. The dimension of space of indications data is equal to the size of network input layer. The size of output network layer depends on the number of tested classes [6], [7].

For classification are usually used feed-forward supervised NN. The most popular is the multilayer perceptron (MP). MP containing one hidden layer is adequate for approximation of any arbitrary continuous function [6]. The input space of signature vectors of indications must be separable into disjunctive subspaces (clusters). Every cluster then contains indications of the same class.

Training of typical feed-forward MP is quite difficult because it is difficult to obtain a big amount of real data of indications. We are forced to use the data of artificial indications. Probabilistic neural networks (PNN) can be used to solve this classification problem. Their design is straightforward and does not depend on training. When an input is presented, the first layer computes distances from the input vector to the training input vectors, and produces a vector whose elements indicate how close the input to the training input is. The second layer sums these contributions for each class of inputs to produce its net output as a vector of probabilities. Finally, a compete transfer function on the output of the second layer picks the maximum of these probabilities, and produces one for that class and zero for the other classes.

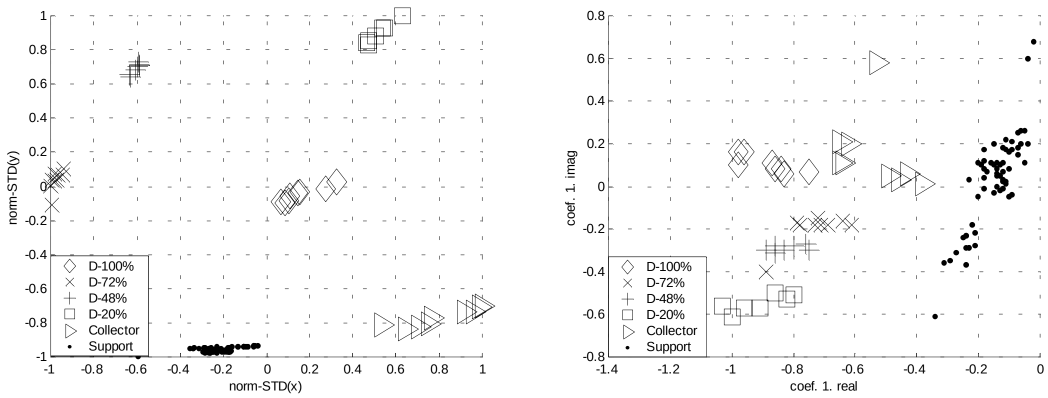
4. Comparison of representations

We have built database of indications. These indications were then transformed by defined algorithms to desired representation.

Tab.1. Groups of indications in the database

group 10 – defect – 100%	group 17 – defect 100% + support edge
group 11 – defect – 72%	group 18 – support plate + defect 100%
group 12 – defect – 48%	group 19 – defect 48% + support edge
group 13 – outside groove – 20%	group 20 – support plate + defect 48%
group 15 – collector	group 21 – outside groove 20% + support plate
group 16 – support plate	group 22 – support plate + outside groove 20%

Representations were compared using the same subset of database indications and following figures show selected projections of data clusters for some representations.



a. b.

Fig.5. a/ Standard deviation dependency, b/. First complex invariant based on Fourier coefficients

One can see that representation (a) gives very compact class clusters. Situation with invariants based on Fourier coefficients (b) is more complicated. Data analysis shows existence of class clusters, but these clusters are not compact and regular. Fig. 5.b shows projection of the first coefficient and results for the rest of the coefficients are worse).

Tables 2. and 3. show that PNN gives very good results using representation (a). A PNN is guaranteed to converge to good classification results providing it is given enough training data. Proof of the last statement is in the table 2. PNN gives very bad results while using only calculated centres of the data clusters.

Tab.2. Results of networks testing for representation (a)

networks\training set	***all***	***centres***
PNN-100/200kHz	100 / 98.6%	100 / 95.6%
MP-100/200kHz	81.2 / 91%	98 / 87.8%

Tab.3. Results of networks testing for representation (c)

networks\training set	***all***	***centres***
PNN-100/200kHz	100 / 100%	30 / 37.5%
MP-100/200kHz	68 / 64%	36 / 37.3%

Representation (a) used together with PNN gives the best results. From the next table (table 4. one can see that the frequency of measurement is very important. Table includes informations on error of classification. Entry 16 / 15 means that indication of support plate (group 16 - see table 1) was classified as collector.

Experiments show that errors of classification depend on the measurement frequency . Low frequencies give good results for support plate and collector and high frequencies are suitable for internal defects. It is evident, that using results of the classification of all signal frequencies will increase classification success and stability. One of the possible solutions is to define modular neural network where each module is implemented by neural classifier. The result of calculation of the major net is a combination of the original input and outputs from individial modules. At the input of modules is the same indication but in different frequency (representation may be different too).

Tab.4. Results of networks testing for representation (a) using different frequencies

Freq	***all***	***centres***
25kHz	100%-	97.3% (12 / 13; 13 / 21)
100kHz	100%-	100%-
200kHz	98.6% (17 / 10)	95.6% (10 / 17; 13 / 21)
700kHz	89% (16 / 15 ; 12 / 19; 13 / 21)	88.7% (16 / 15; 12 / 19; 13 / 21)

5. Conclusion

Results presented in the contribution show, that the success of indications classification using neural networks depends on the choice of data representation. In the case of eddy current method success of classification depends on the measured frequency.

References

[1] Palanisamy, R. & Loyd, W.: *Finite Element Simulation of Support Plate and Tube Defect Eddy Current Signals in Steam Generator NDT.* Materials Evaluation, Vol. 39, June 1981

[2] Yahn, Ch.T. & Roskies, R.Z.: *Fourier Descriptors for Plane Closed Curves*. IEEE Transactions on computers, March 1972

[3] Strang, G. & Nguyen, T.: *Wavelets and Filter Banks.* Wellesley-Cambridge Press, 1996

[4] Alvarez Hamelin, J.I.; D'Attelis, C.E.; Mendonca, H. & Ruch, M.: *A New Method for Quasi On-line Eddy Current Signal Analysis: Wavelet Transform*. INSIGHT, Vol. 38, No.10, 1996, pp. 715-717

[5] Charlton, C.: *Investigation into the Suitability of a Neural Network Classifier for Use in an Automated Tube Inspection System*. British Journal of NDT, Vol. 35, No. 8, 1993

[6] LiMin, Fu: *Neural Networks in Computer Intelligence*. McGraw-Hill Companies, 1994.

[7] Rajagopalan, C.; Baldev, Raj & Kalyanasundaram, P.: *The Role of Artificial Intelligence in Non-destructive Testing and Evaluation*. INSIGHT, Vol. 38, No. 2, 1996