

# DEVELOPMENT OF A SYSTEM FOR MONITORING AND DIAGNOSIS OF STEAM GENERATOR TUBES USING ARTIFICIAL INTELLIGENCE TECHNIQUES ON EDDY CURRENT TEST SIGNALS

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## ABSTRACT

New classification and feature extraction methods for steam generator tube defects are being developed by IPEN/CNEN-SP in cooperation with UTK to improve a monitoring and diagnosis system for classification and characterization of steam generator tube defects using Eddy Current Testing (ECT) signals. The first methodology being developed uses a set of feature extraction methods applied to different tube defect type ECT signals and each obtained feature vector is projected into a bi-dimensional map obtained by a Self-Organizing Map (SOM) neural network. This methodology allows an optimal feature extraction method selection for the defect type classification. Other approach is being developed using tubes with different manufactured defect types which are tested using MIZ-17ET equipment with 4 sets of probes (two different diameter). A fuzzy inference system will be used to build a knowledge base for these defects. These methodology and algorithms will be integrated into an automated diagnosis system being developed with UTK, which is designed to read both on-line acquired data, as well as stored data files. These commercial software tools are the ones usually utilized in nuclear power plants.

**Keywords:** ECT, eddy current, SOM, feature extraction, classification.

## I. INTRODUCTION

The IPEN/CNEN-SP and The University of Tennessee, Knoxville (UTK) are working on a cooperation project to develop an automated diagnosis system for steam generator tube defects based on eddy current signal analysis.

The original project scope is very large and includes many steps that vary from data acquisition to the final decision (to plug or not the steam generator tube). The system main features are: filtering, calibration, defect simulations, artificial intelligence techniques for automatic recognition and characterization of steam generator tube faults. UTK Nuclear Engineering Department has been the pioneer over the last ten years in the integration of different artificial intelligence methods to get an automated and precise steam generator tube defects diagnosis.

The classification techniques development is being done through the study of different algorithms that composes the EDDYAI system being developed at the Nuclear Engineering Department (UTK). A new feature extraction technique was developed using LPC (Linear Predictive Coding) and Self Organizing Maps (SOM), which was communicated at MARCON 2001 [1].

Fault detection in tubes is one of the main aspects of steam generator inspection routine in order to prevent leakage. The decision of plugging or not each inspected tube usually is done based on specialist inspector knowledge being vulnerable to evaluation errors, which is a characteristic of the human dependant inspection methods.

These methodology and algorithms will be integrated into an automated diagnosis system being developed with UTK, which is designed to read both on-line acquired data, as well as stored data files.

## II. METHODOLOGY

**Eddy Current Testing.** The eddy current test (ECT) has been the most used inspection technique for decades as it has considerable advantages to the other non-destructive evaluation techniques (NDE) for this application. The ECT is based on the introduction of a sounding lead, which basically consists of a coil that generates a magnetic field. This field induces continuous circular eddy currents [2] in the electrically conductive sample and these currents induce back a secondary magnetic field in the lead.

ECT can be applied to metallic sheets, tubes and provides conductivity measurements, discontinuity detection

and can be used to determine metallic sheets thickness. It has been used in many industry branches to quality control over newly produced objects.

The signal to be analyzed is the current produced by this secondary magnetic field (example shown in figure1).

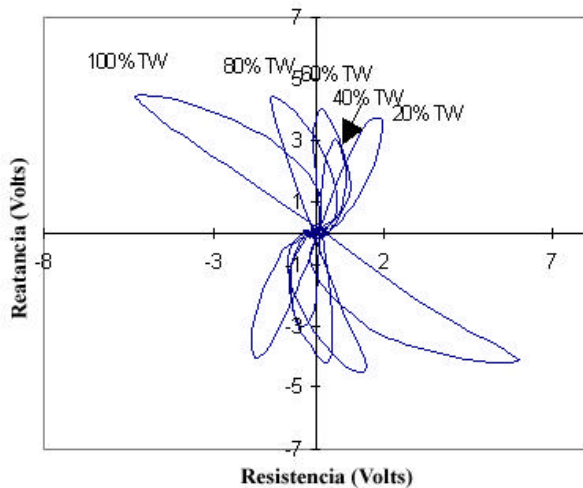


Figure 1. Impedance Plane of a Typical ECT Signal [3].

Part of data used to this development was acquired from EPRI's (Electric Power Research Institute) Performance Demonstration Database (PDD) and include typical signals from Stress Corrosion Cracking (SCC), Inter Granular Attack (IGA), Pitting, and Wear (caused by interaction between anti-vibration bars and tubing) from actual ECT measurements in operating steam generators.

Typical steam generator tube defects are pitting (PIT) (Figure 2a), stress corrosion cracking (SCC) (Figure 2b), inter-granular attack (IGA), anti-vibration bar damage (AVB), mechanical fretting caused by tube-support plate interaction, and others. A set of different power plant operational conditions over many years cause these tube degradation. The usual operational conditions include high pressure, temperature, and flow with severe water chemistry reactions.

Pitting (PIT) defect is due to galvanic differences in the tubing and assumes volumetric characteristics. Most of these defects are associated with acid chemical reactions. A typical PIT signal is shown in Figure 2a. Stress corrosion cracking (SCC) is caused by simultaneous actions of chemical corrosion and mechanical stress. The main physical characteristics of SCC are multiple major cracks with branching and two-dimensionality. A typical signal is shown in Figure 2b. Anti vibration bar (AVB) damage is due to mechanical interaction between the tubes and their supports. It consists of material removal characterizing a volumetric defect. Finally, the inter-granular attack (IGA) is a defect mainly caused by chemical corrosion. Mechanical stress has a less significant contribution and its physical characteristics may be volumetric or two-dimensional.

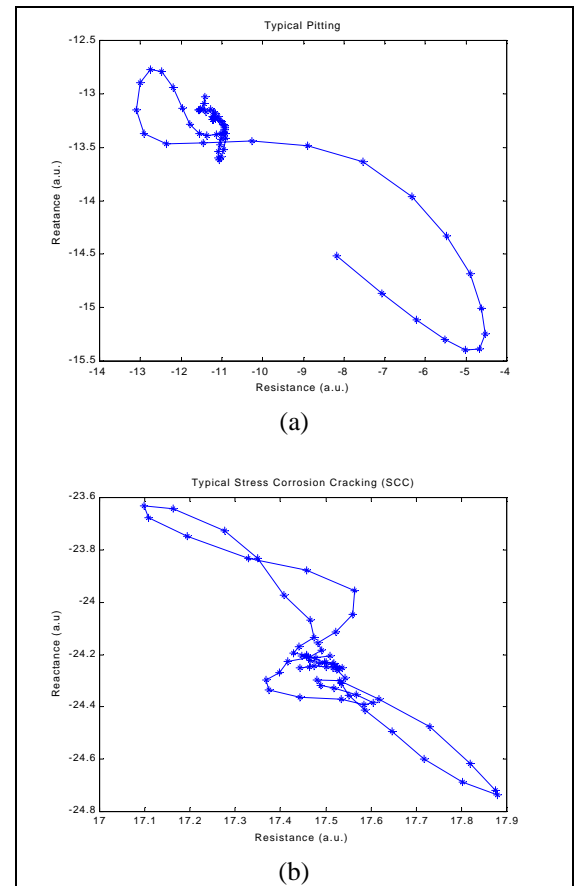


Figure 2. Typical Impedance Plane Plots (Lissajous like Figures, Arbitrary Units) of ECT Data from Steam Generator Tube Defects: (a) PIT and (b) SCC.

**Classification Techniques.** The first IPEN/CNEN-SP participation was the development of a “stand-alone” module to eddy current signal pre-processing using Wavelets Multi Resolution Analysis (MRA). This module allows the user to select specific frequency bands to attenuate and choose either how much attenuation is needed for each frequency band. This filtering technique is called de-noising and has been extensively used in signal analysis and processing lately [4]. The developed stand-alone module may be incorporated to the system being developed by the University of Tennessee (EDDYAI) [3,4].

A new approach based on feature extraction methods for steam generator tube defects is being developed by IPEN/CNEN-SP to improve a classification and characterization system based on different feature maps extracted and trained from Eddy Current signals. A set of feature extraction methods is applied to different tube defect type ECT signals and each obtained feature vector is projected into a bi-dimensional map obtained by a Self-Organizing Map (SOM) neural network.

This technique is currently being improved to obtain a classification system based on different feature maps extracted and trained from Eddy Current signals. These maps show different clustering distributions that depend on the importance that each of the features has to characterize the defect type. An estimate of the characterization

importance of each feature is done through the comparison between the clusters average distance on those maps. This methodology allows an optimal feature extraction methods selection for the defect type classification. The set of methods consists of Linear Predictive Coding (LPC), Wavelet Zero-Crossings (WZC), Center of Gravity, Signal Segments, Phase, and different combinations of these feature vectors.

**Self-Organizing Maps (SOM's).** The Self-Organizing Map is a pattern recognition method that represents the points in the source space into points in a target space; such as the distance relations and proximity are preserved. Such maps have a general learning and have different applications. A SOM can be formally described as an ordered and smooth non-linear mapping of manifolds [5]. The training algorithm evaluates new values for each node (and its neighbors) comparing each input sample with each of the feature vector components. The nodes are distributed initially using a topological function and are changed obeying Kohonen rule [5].

Suppose that the set of input variables  $\{\hat{i}_i\}$  is definable as a real vector  $x = \{\hat{i}_1, \hat{i}_2, \dots, \hat{i}_n\}^T \in \mathbb{R}^n$ , each element in the SOM array is also associated with a parametric real vector (model):

$$m_i = \{\hat{i}_1, \hat{i}_2, \dots, \hat{i}_n\}^T \quad (1)$$

This mapping implementation is done by an algorithm that attributes new values for each node (and its neighbors) in each iteration comparing each input sample  $x(t)$  with all the  $m_i$ , optimizing the distance measure. If the general distance between  $x$  and  $m_i$  is  $d(x, m_i)$  the input vector SOM image is defined as the matrix element  $m_c$  that better fits the input vector ( $x$ ), where  $c$  is the index:

$$c = \arg \min_i \{d(x, m_i)\}. \quad (2)$$

It has been proved that if the  $x(t)$  and  $m_i$  are Euclidean vectors and a locally smoothed distance measure is used, then the process converges [5]. The nodes are arranged initially at positions that obey a topology function and are updated using the Kohonen rule and some updating algorithms. An example of this topological arrangement is shown in Figure 3 with natural speech spectrum in a two-dimensional map.

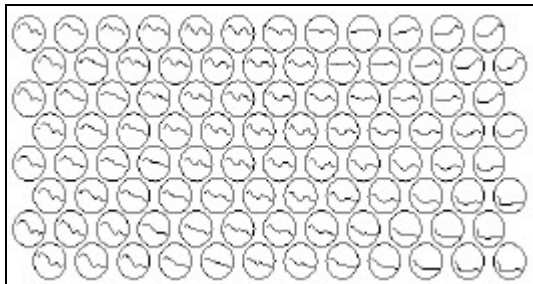


Figure 3. Hexagonal Grid of Natural Voice Spectrum [5].

**Algorithm implementation.** During the training phase the neuron winner and its nearest neighbors (in an Euclidean sense) are adjusted to the input vector. The sequence is as follows:

- 1) Initialization of weights with small values.
- 2) Finding the winner through  $c = \arg \min_i \{d(x, m_i)\}$ .
- 3) Weight update using Kohonen rule:  $\Delta w(t_{k+1}) = \alpha(t_k) (x(t_k) - o(t_k))$ , where  $x$  is the input vector and  $o$  is the output vector.

**Feature Extraction Methods.** The following feature extraction methods are used in this work.

**Signal Segmentation.** Sets of 64-point vectors are obtained by sampling around the defect center point. This point is the median sample of the degradation area signal. The affected area generally contains 200 to 500 samples and the central sample is also used for phase estimation.

**Phase.** This is the main feature used during ECT inspection. The vectors are obtained from the ECT Lissajous figure formed in the impedance plane. It takes into account that the ASME calibration has been performed with 40-degree angle for a 100% through hole. The phase is defined as

**LPC.** The LPC technique is usually applied to voice recognition problems. The basic principle of this analysis is that a signal sample can be approximated by a linear combination of past samples (Eq. 3). The squared error minimization in a finite interval can produce a set of coefficients that are usually used as coding parameters. These coefficients are used in the inference system as one of the features.

$$x(k) = \sum_{i=1}^n a_i x(k-i) + w(k) \quad (3)$$

where the  $\{a_i\}$  are model parameters. The  $\{w(k)\}$  series represents the unknown noise.

**Wavelet Zero-Crossing (WZC).** In the last decade the wavelet transformation has become a popular tool for signal processing. This technique was used by Upadhyaya et al [6] to establish a fuzzy inference system to classify ECT defect types based on the discontinuities detected on a set of signals.

By definition the function  $y(x)$  is said to be a wavelet if:

$$\int_0^{+\infty} \frac{|\Psi(w)|^2}{w} dw = \int_{-\infty}^0 \frac{|\Psi(w)|^2}{w} dw < +\infty \quad (4)$$

Using  $y(x)$  mother wavelet, the wavelet transformation of a function  $f(x)$  at the scale  $s$  and position  $x$  is defined by the following convolution:

$$W_s^y f(x) = f * \mathbf{y}_s(x) \quad (5)$$

The wavelet transformation decomposes a signal into components using a dyadic scale where  $s = 2^j$  is used. It is rarely computed for continuous scale. The wavelet transformation of a signal is proportional to the first derivative of the signal smoothed by  $\theta(x)$ , if the wavelet is the first derivative of a smoothing function, and it is proportional to the second derivative of the signal smoothed by  $\theta(x)$  and if the wavelet is the second derivative of a smoothing function [7]:

$$W_s^y f(x) = f * \left( s \frac{d}{dx} \mathbf{q}_s \right) (x) = s \frac{d}{dx} (f * \mathbf{q}_s)(x) \quad (6)$$

If a discontinuity has a larger localized singularity than the background noise it is possible to separate the noise from the useful part of the signal. In this way, the number of discontinuities can characterize the signal regularity. Zero-crossings localization in wavelet representation can be considered as the inflection points of the original signal. A more stable representation by integrating the wavelet representation between two consecutive singular points:

$$c_n = \int_{z_{n-1}}^{z_n} W_{2^j}^y f(x) dx \quad (7)$$

### III. PRELIMINARY RESULTS

The classifier uses the SOM's selected features as the input space for a Fuzzy Inference system, which outputs the defect type and its corresponding size (percentage throughwall depth). The called SOM-FUZZY system uses solely intrinsic defect ECT signal information. Important correlation between the inference results and the related non-intrinsic information (such as defect tube localization and frequency channel) are being made. The development of other related techniques and applications are being implemented.

Some preliminary results show important clustering occurring for different defect types (see Fig. 4). This map is relative to segmented inductive signal. The other maps obtained will be used as a basis for a fuzzy inference system.

**Simulated Defects.** Another step has been taken recently to obtain Eddy Current Test (ECT) signals from simulated cracks in tubes using the recently acquired MIZ-17ET equipment with 4 probes (two different diameters) (figures 5 and 6). He has elaborated a set of manufactured tubes with different simulated defects in order to acquire raw data from an analog output using Labview. Several experimented inspectors have been consulted to gather field actual data. A fuzzy logic inference system will be used to build the knowledge base which is similar to that presented in your previous reports.

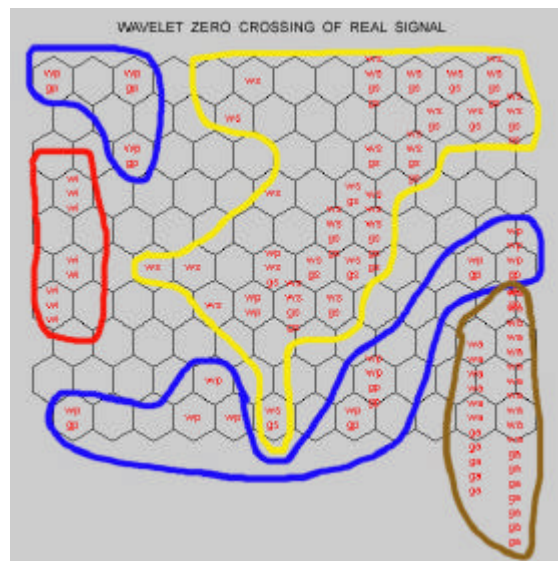


Figure 4. Kohonen Map with Distribution of Wavelet Zero-Crossings of ECT Resistive Signal Clusters: ws, gs – SCC (yellow line); wi - IGA (red line); wp, gp – PIT (blue line); wa, ga – AVB (brown line).



Figure 5. MIZ-17ET Eddy Current Test Equipment.



Figure 6. Experimental ECT Setup.

### ACKNOWLEDGEMENTS

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