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Classification of Steam Generator Tube Defects Using Linear Predictive Coding and a Self-Organizing Neural Network

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Abstract

The objective of this work is to develop a new approach in classifying steam generator tube defects using Eddy Current Test (ECT) data. Linear Predictive Coding (LPC) coefficients obtained from ECT signals were used as feature space vectors in a Kohonen Self-Organizing Map (SOM) neural network. The data were extracted from EPRI's (Electric Power Research Institute) Performance Demonstration Database (PDD) and include typical signals from actual ECT measurements in operating steam generators. The development of other related techniques and applications are discussed. This inference algorithm will be integrated into an automated diagnostics system called EDDYAI, which is designed to read both on-line acquired data as well as stored data files. The integrated system should help ECT experts in simplifying extensive data analysis for making decisions about the integrity of steam generator tubing. On-line data processing and automated decision-making are being developed in order to enhance the reliability of eddy current testing as a condition-based maintenance technology.

Introduction

The efficiency of steam generators can be directly related to the power that a nuclear power plant generates. This efficiency is greatly affected when a portion of the thousands of steam generator tubes begins to present defects that may require their plugging. The usual maintenance routine of steam generator tubes consists of periodic inspection using ECT. The ECT testing technology in nuclear power plants is highly developed, including probe design and automated robot controlled systems for probe positioning. The ECT measurements are generally analyzed by multiple teams of experts that take into account safety and economical reasons to decide whether or not the tubes should be repaired or plugged. Fatigue among personnel is a common issue in this kind of data analysis. The analysis is based on comparing extensive database of previous tube defects with the actual measurements. The need for a quick decision after analyzing a large amount of previous and actual data led The University of Tennessee, Nuclear Engineering Department to develop the EDDYAI project for automating the analysis process. This system should enhance the reliability of ECT as a condition-based maintenance technology.

The purpose of research is to develop programs that should be able to locate, size and classify tube wall degradation with a very high accuracy and with minimum user assistance. It should be a little conservative so that every possible location of tube wall degradation is flagged. The final decision should be made by the user.

This paper intends to propose a new approach to ECT signal classification that will be integrated into the EDDYAI system to improve its efficiency in the automated diagnostics of steam generator tube defects. The proposal consists of using LPC coefficients obtained from the signal as feature space vectors in a Kohonen Self-Organizing Map (SOM). The defects would be classified based on the Euclidean distance from different trained SOM LPC feature maps to the corresponding LPC coefficients of the unknown defect signal. Both measured distances (test errors) and the LPC feature map coordinates could be used as input to a single layered feed-forwarded neural network, characterizing a Learning Vector Quantization (LVQ) neural network.

The data were extracted from EPRI's (Electric Power Research Institute) Performance Demonstration Database (PDD) and include typical signals from actual ECT measurements in operating steam generators. The development of other related techniques and applications are discussed.

Eddy Current Testing

Eddy current testing is the most used non-destructive evaluation method used for the inspection of nuclear power plant steam generators. It has also been extensively used in many different industrial sectors in quality control of recently produced metal pieces. The test can be applied on cylinders, tubes, flat metal sheets and can provide conductivity measurements, detect discontinuities and even determine the thickness of metal layers in objects.

The technique is based on circular electrical currents (eddy currents) induced on the metal sample by a magnetic field generated with an electromagnetic probe. These induced currents give rise to an opposing magnetic field (secondary) that opposes the primary probe field and changes its electrical impedance. The impedance change of the primary probe is the main measure to detect discontinuities or defects in the sample.

The tube defects are caused by long-term operation conditions that include high pressure, temperature, flow and severe water chemistry reactions. The main defect types are pitting (PIT), stress corrosion cracking (SCC), inter-granular attack (IGA), anti-vibration bar damage (AVB), mechanical fretting caused by tube-support plate interaction, and others. After a significant efficiency loss over the years, steam generators have to be replaced. This is an extremely costly operation and entails long periods of downtime.

The ECT signals are typically composed of a real part and an imaginary part. Typical impedance plane plots (Lissajous like figures) of ECT data from typical steam generator tube defects are shown in Figures 1 and 2.

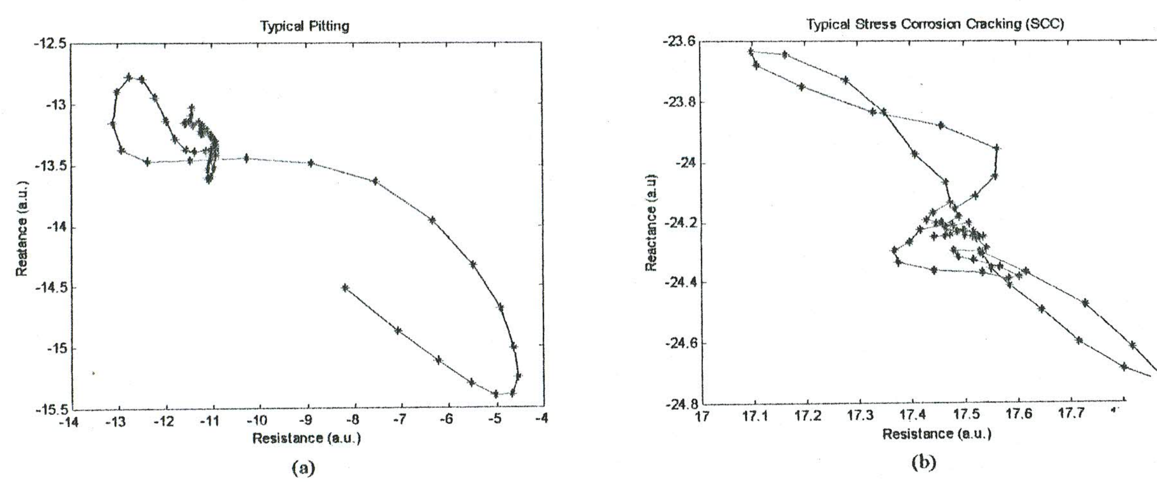
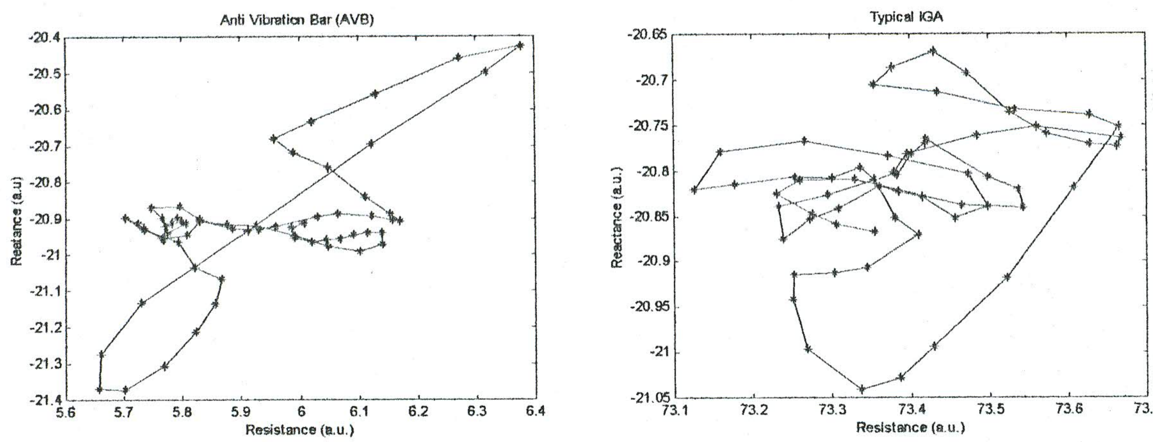


Figure 1. Typical signals of Pitting and Stress Corrosion Cracking.



(a) (b)

Figure 2. Typical signals of Anti Vibration Bar and Inter-granular Attack

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 1a. 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 1b. 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. A typical signal is shown if Figure 2a. 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. A typical IGA signal is shown in figure 2b

Multi-frequency analysis is a common feature of Eddy Current Test. The tests are done with different excitation frequencies in order to increase the accuracy of defect detection. The higher the frequency applied, the lower the penetration of eddy currents in the material, thus enabling the detection of inner diameter defects (as the probe is usually inserted inside the tubes). The data used in this study contain different frequency channels.

Linear Predictive Coding (LPC)

LPC is a signal analysis technique mostly applied in speech recognition tasks [4]. The basic principle of this analysis is that the signal sample can be approximated as a linear combination of past samples. By minimizing the sum of the squared differences (over a finite interval) between the actual samples and the linearly predicted ones, a unique set of predictor coefficients can be determined. It has been used as feature extraction for signal recognition [5] and image compression [6]. An autoregressive one-step predictor model of a discrete signal x(k) has the form

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

where $\{a_i\}$ are the model parameters. The model parameters and the model order, n, are estimated using least squares techniques. The sequence $\{w(k)\}$ represents uncorrelated noise.

Self-Organizing Map (SOM)

Self-organizing feature map of Kohonen [7] is a pattern recognition method closely related to multidimensional scaling. The main goal is to represent all points in the source space by points in a target space, such that distance and proximity relationships are preserved as much as possible. The sample storage is relatively small, requiring less complexity than the multidimensional scaling. The learning of such self-organizing maps is very general and can be applied to virtually any source space, target space, and continuous nonlinear mapping [8].

Formally the SOM may be described as a nonlinear, ordered, smooth mapping of high-dimensional input data manifolds onto the elements of a regular, low-dimensional array [7]. The implementation of this mapping resembles the classical vector quantization, differing mainly in the mapping ordering which describes the distribution of the input space.

Suppose that the set of input variables $\{\xi_i\}$ is definable as a real vector $x = \{\xi_1, \xi_2, ..., \xi_n\}^T \in R^n$, each element in the SOM array is also associated with a parametric real vector (model):

$$m_i = \{\mu_1, \mu_2, ..., \mu_n\}^T$$

Assuming a general distance measure between x and m_i to be $d(x,m_i)$ the image of an input vector x on the SOM array is defined as the array element m_c that better matches with x, i.e., that has the index [7]:

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

The SOM algorithm provides new values for each node (and its neighbors) in each iteration comparing each input sample x(t), where t is an integer-valued index, with all the m_i optimizing the distance measure. It has been proved that if the x(t) and m_i are Euclidean vectors and a locally smoothed distance measure is used the process converges [9]. The nodes are arranged initially at positions that obey a topology function and are updated using the Kohonen rule [10] and some updating algorithms [11].

Outline of the Method

The methodology of this study is shown schematically in Figure 3.

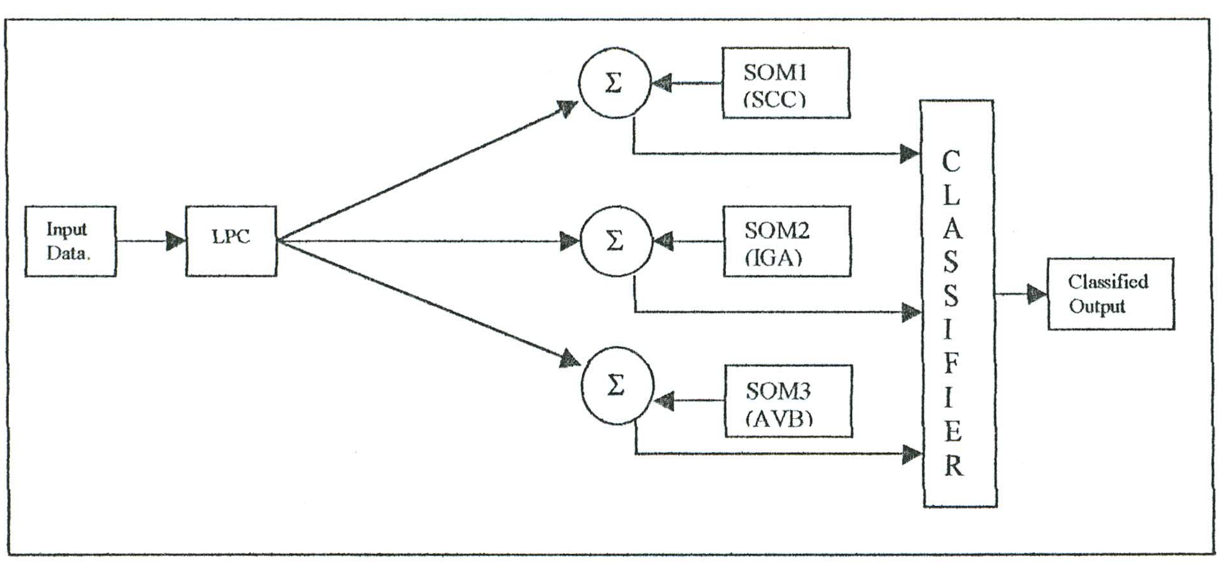


Figure 3. Clustering and Classification Method.

The classification method resembles a model-based prediction procedure. A set of characteristic signals is used to train an LPC-feature SOM map for each defect type. The Euclidean distance measure between the new signal sample and the individual trained maps are evaluated and used as input parameters for a classifier. Different training parameters, distance measure definitions and classifier types are being tested. Most of the initial tests are being made using the MATLAB Neural Network Toolbox v.5.3.

The LPC feature map coordinates are used in a feed-forward neural network layer as the final classifier. The Euclidean distances from different maps to the unknown signal and the predictor errors as input, are considered. This second approach would require two different training phases. The first one to train each characteristic defect SOM map, and the second one to train the final classifier.

Finally, the use of all the data (with different defect types) to generate only one general SOM map will be tested.

Results of Application to ECT Data

The data were taken from EPRI's Performance Demonstration Database (PDD) and include typical signals from actual ECT measurements in operating steam generators. Typical signals taken from different frequency channels were grouped by defect type and used to generate the training data set. These signals were initially submitted to an LPC regression model, generating a set of LPC coefficients for each defect type. The number of coefficients was selected taking into account the predictor error level and computational effectiveness.

Typical LPC-SOM feature maps obtained for a training set are shown on Figure 4. The graphical representation showed similar patterns for different training sets having the same defect type. These maps were obtained using nine LPC coefficients and a (3x3) SOM matrix, using hexagonal topology.

Concluding Remarks

Based on the current results of application to ECT data, there is strong evidence that the LPC feature map can be used as an important parameter set for steam generator tubing defect classification. A systematic and extensive testing of the proposed techniques, with different input data settings and training parameters, is being developed.

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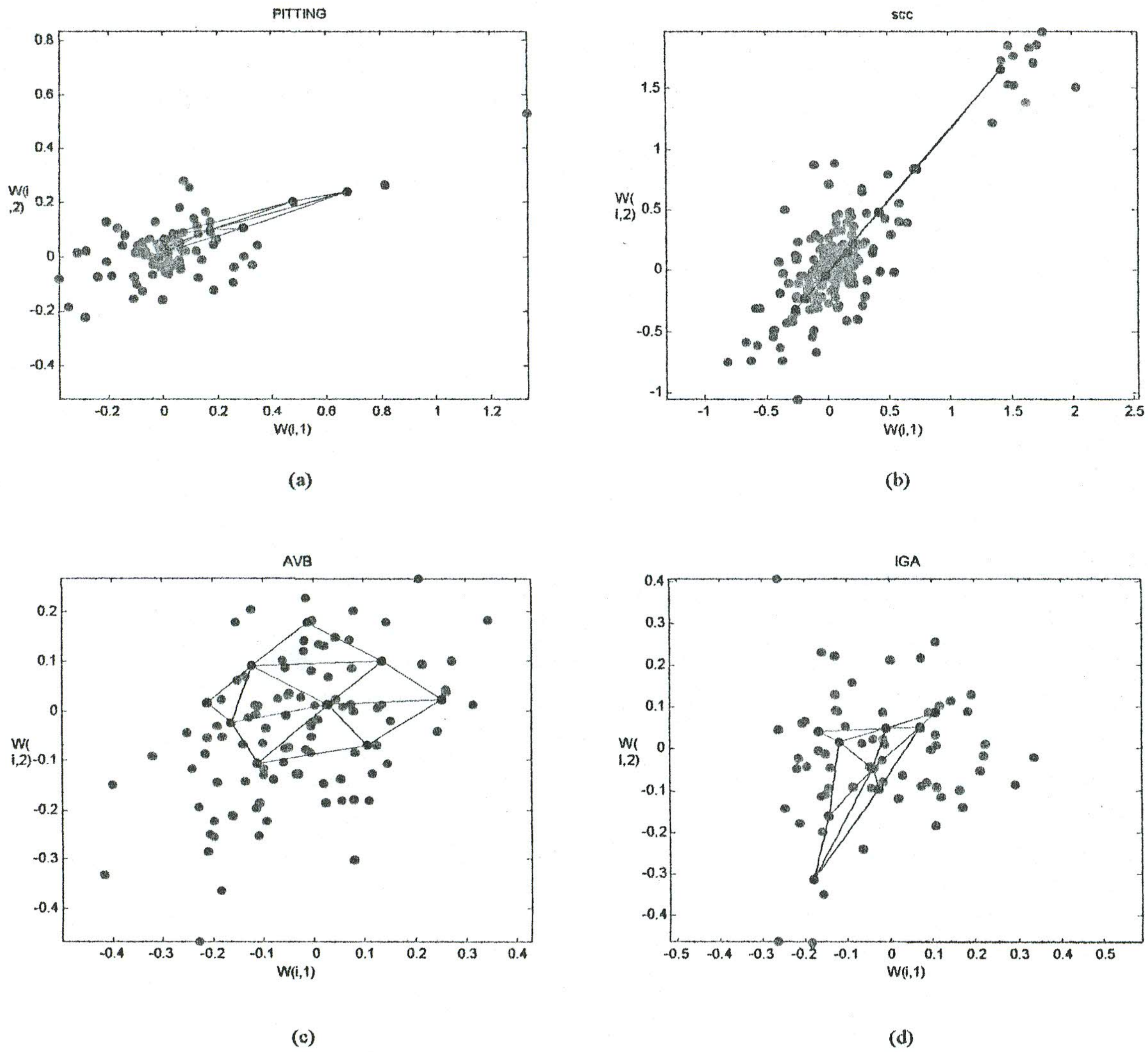

Figure 4. SOM-LPC feature maps of typical defects.

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