EDDY CURRENT SIGNATURE CLASSIFICATION OF STEAM GENERATOR
TUBE DEFECTS USING A LEARNING VECTOR QUANTIZATION NEURAL
NETWORK

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Acknowledgment:

This material is based upon work supported by the U S. Department of Energy under Award No. DE-FG07-02D14431.

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EXECUTIVE SUMMARY

A major cause of failure in nuclear steam generators is degradation of their tubes. Although seven primary defect categories exist, one of the principal causes of tube failure is intergranular attack/stress corrosion cracking (IGA/SCC). This type of defect usually begins on the secondary side surface of the tubes and propagates both inwards and laterally. In many cases this defect is found at or near the tube support plates.

Several different methods for non-destructive testing of the steam generator tubes exist and a new method (In-Tube Radar) is being developed at New Mexico State University in collaboration with Sandia National Laboratories. Presently, eddy current testing has emerged as the dominant testing method in industry but requires a significant amount of expertise to accurately identify and characterize tube defects. New Mexico State University received funding under the NEPO program last year to investigate automated methods for diagnosis of steam generator tube defects focusing specifically on IGA/SCC defects located at support plates. This detection approach uses an artificial neural network architecture called Learning Vector Quantization, (LVQ). The neural network is trained with EPRI data sets transformed with a newly developed algorithm.

The research plan described in this proposal uses the automated diagnosis work currently in progress at New Mexico State University as a foundation for further development, enhancement and customization of the LVQ architecture to identify and classify tube defects. Specifically, three major goals are proposed for this new effort. They are:

Refining and customizing the algorithms that govern the weight vectors or codebooks of our selected neural network architecture, the LVQ approach. This will include the application of Kohonen's algorithms, LVQ2, LVQ3, OLVQI, and a new learning algorithm developed specifically for this project to address the eddy current data.

Designing new characterization of training data for the neural network. This involves the creation of new data analysis approaches applied to the eddy current data sets using different data definition models, new data transform models and integration of defect weighing algorithms

Expanding the range of detectable defects to include free-span defects. This encompasses experimentation with the LVQ to determine its robustness in identifying and processing new defect classes.

The work outlined in this proposal is a direct complement and follow-on to work currently funded under the nuclear energy research initiative (NERI) under a Sandia National Laboratory partnership with the Department of Mechanical Engineering at New Mexico State University and a NEPO project funded last year. In addition, the scope of work is a direct interest area of the EPRI. The proposal is presented as a 12 month effort for a total cost of \$99,905.

BACKGROUND AND PROBLEM DEFINITION

The nuclear power industry would greatly benefit from technological advances that decrease the downtime of nuclear plants particularly for maintenance and repairs. Detection and mitigation of steam generator tube failures can contribute significantly to the efficiency and economy of nuclear power. The principal problems with steam generators have been reported by EPRI to include: denting and tube support corrosion, denting and tubesheet corrosion, tubing corrosion (wastage, pitting, ID cracking, OD stress corrosion cracking, intergranular attack), and mechanical damage (fretting, fatigue cracking, impingement) (MacDonald, Shah and Ellison: 1996). A significant number of the pressurized water reactors (PWRs) are operating with tubing defects near or beyond the limits established by regulatory guidelines. In a review of steam generator tube ruptures, at least ten have occurred over the past 25 years. The approximate rate of rupture is one every two years. In the US however, in recent years tube ruptures have occurred at a rate of one per year. "Five different tube degradation mechanisms caused ten rupture: three ruptures were caused by outside diameter stress corrosion cracking (ODSCC), two ruptures were caused by high-cycle fatigue, two ruptures were caused by loose part wear, two ruptures were caused by primary water stress corrosion cracking (PWSCC)." (MacDonald, Shah and Ellison: 1996).

The probability of steam generator tube failures can be reduced through timely and effective inspection, diagnosis, and appropriate acceptance (fitness-for-service) criteria. Eddy current testing has emerged as a standard procedure for inspecting thin-walled steam generator tubes because it offers high scanning speed and good accuracy. However, eddy current detection threshold is high; deep cracks can be missed and sizing and resolution are not accurate. Furthermore, eddy current methods are weak for sizing the length and depth of circumferential cracks, intergranular attack (IGA) damage, pitting, high-cycle fatigue cracking, fretting, and wear.

Ultrasonic inspections methods have had some success in sizing and resolution of ODSCC detected during an eddy-current inspection. Innovative new methods are also under development and offer the potential for significant improvements over present eddy current methods or complementing eddy current techniques. One of these improvements is a laser imaging system for inside surfaces of the tubing.

Nassersharif, et. al are researching and developing a new technique based on a continuous wave radar that offers great potential for significant improvements in non-destructive testing of steam generator tubes by providing a volumetric scan of the tube wall at higher resolution.

Eddy current as well as the continuous-wave radar technique require both calibration and personnel training for successful detection of damage in the tubes. The EPRI NDE center in Charlotte, North Carolina is a national

center of excellence for calibrations and personnel training in the use of eddy current devices. Effective and accurate use of the inspection devices requires significant personnel training with calibrated samples. While calibrated samples provide a reference frame for training personnel and comparative data points, accurate, effective, and consistent diagnosis of the defect type in the field remains a significant challenge.

Progress on Previous NEPO Funded Research

Under a previous NEPO award (DE-FG07-01ID14237) entitled "Automated Diagnosis and Classification of Steam Generator Tube Defects" we designed and developed an automated approach for identification of defects.

The overall objective of the present NEPO research project is to further develop the automated system. In addition, our goal was to integrate a method and software prototype for the automation of eddy current signal diagnosis for nuclear steam generator tubes using a neural network architecture for defect detection. The intent was to design a system that offered a more consistent and faster method for defect diagnosis based on signals generated from eddy current inspection methods. The present project has two main components, eddy current data analysis and neural network development.

Eddy Current Data Analysis

In October of 2001, Electric Power Research Institute (EPRI), in Charlotte, North Carolina provided the opportunity for a Master's Student from NMSU to visit their center, explore, collect data, and interact with eddy current testing (ET) field analysts. He also observed other non-destructive evaluation methods of steam generator tubes in nuclear power plants.

The student brought back a set of eddy current test data from EPRI. Data supplied by EPRI resulted from tests performed in early 1980s (from an MIZ-18 probe and data acquisition system). This data serves as the training and testing sets in our present efforts to automate the diagnosis process with an artificial neural network architecture.

The first step in building data training and testing sets for the neural network was to analyze exactly what type of defect and calibration data we were provided from EPRI. This involved statistical analysis at a macro level to categorize the number of data sets with corresponding documentation information by manufacturer. In addition, the various types of defects found in each data set were analyzed to better focus our team's efforts on exactly what direction we would take with regard to the design of our automated system. As a result of this effort, our decision was to pursue an automated system that could classify IGA/SCC defects at tube support locations. Our unit of analysis for network training purposes was then focused on Westinghouse steam generators and Inconel 600 tubes. Our available set of Westinghouse files with IGA/SCC defects at the tube support locations totaled 13 from the pulled tube collection.

The primary goal in the present project is the design of an automated system to detect steam generator tube defects. Fundamental to this

objective is the ability of this automated system to process large data sets, some sets with close to a half million data points. Therefore, a considerable amount of time has been spent working on the design of an automated system for mining the pulled tube data, performing transforms for identifying data patterns potentially indicating tube defects and developing algorithms that mathematically express Lissajous figures. One of the greatest challenges in this step has been to filter tube support structure signals from potential underlying failure indications. We have been working with different frequency mixes as well as mix algorithms to address this challenge. Since the objective of the project is to develop an automated system, our goal is to avoid human intervention in the reading of Lissajous figures. Furthermore, we have focused on developing mathematical models expressing eddy current data patterns. These models form the vector sets for neural network training and input data.

To develop these mathematical models we first analyzed data in the calibration files corresponding to the 100% through-wall defects. These defects were assigned a 10-volt value and a voltage curve was created similar to ones supplied by EPRI. Similarly, different parameters in the x y plot allowed us to calculate a phase curve as it related to the lower through-wall parameters. Using these two curves we have a basis measure for the anomalies in the pulled tube data. EPRI and other sources have well documented the phase angle and amplitude (voltage) for various defects. In our analysis of the raw data we have successfully determined location, magnitude, and type of defect in much the same way that an ET Analyst would.

The major portion of the work associated with this project in the data analysis stage has involved writing programs to read in and manipulate the original MIZ 18 data that has been obtained from EPRI. Then, files were generated that were used to train our neural network. All programs have been written in MATLAB. Figure 1 shows a sample of the type of signatures that we have been able to generate by developing a special filtering algorithm.

Figure 1. Sample output from signature extraction algorithm.

As a result of the work associated with this project, we developed algorithms that recognize these data patterns and perform data transforms to create the training vectors for the neural network. Our training vectors from the data analysis stage are constructed from parameterization of the anomalies observed in the x or y data at various frequencies.

Neural Network Architecture Development Progress

A select group of researchers has focused on designing systems for diagnosing defects recorded by eddy current inspection using neural network approaches. The majority of the work in this area is directed to neural architecture models that classify, in contrast to predict the occurrence or location of defects.

The challenge in the field of neural network architectures applied to classification problems is the variety of approaches and unique methodologies associated with each approach. For example, Lingvall and Stepinski (2000) report in their work, the design of a multi-layer perceptron (MLP) architecture to analyze rivet integrity on airplane wings.

They were able to isolate eddy current data segments that characterized rivet locations on aircraft wings, then using principal component analysis, extract the basis functions for the neural network. Upadhyaya et al. (1996) developed a software product called EDDYAI that implements a fuzzy neural architecture to identify and estimate defect types in eddy current data. Fuzzy architectures appear to handle eddy current data ranges well.

Another promising neural network architecture applied to the analysis of eddy current data is probabilistic neural networks (PNNs). Au-Yang and Griffith (1998) used voltage and phase angle data to train a PNN to recognize categories of wall-depth flaws in steam generator tubes. Their results were comparable to manual analysis. Ravas and Syrova (2001) discuss the use Fourier transforms of eddy current wavelets combined with a probabilistic neural network. Results of this approach were mixed. Auto-associative Hopfield networks using binary input vectors have also been designed to analyze eddy current data with good convergence properties (Barcherini et. al.; 2000). However the nature of binary input vectors in this approach required a quantization process that was overly cumbersome.

At this point of time, no single neural network architecture has emerged as a superior approach for the diagnosis of eddy current data for defect detection. A possible reason for this is the lack of real training data for the neural network. The classification ability of a neural network depends in great part on the number of training cases available for the architecture to refine its weights during the “learning” process. Only with an adequate number of exposures to defect data can a network consistently and accurately categorize sets of input data.

Therefore, our approach to the present project has involved using a neural architecture called Learning Vector Quantization (LVQ). This type of architecture consists of a competitive layer and an additional linear layer. The competitive layer very much mimics the Kohonen self-organizing map (SOM), an unsupervised neural architecture. However, the second linear layer requires supervised target goals thus ultimately classifying the LVQ as a supervised neural network. A review of the literature has not revealed any significant works using this approach in eddy current defect detection.

After studying the different research on neural network approaches to analyzing and diagnosing eddy current data, the LVQ architecture was selected for several reasons. First, an LVQ architecture is rated among the best for classification problems. It also handles noise very well in addition to accepting large vector input sets. Furthermore, it performs very well with sparse training sets. Another advantage is that an LVQ's training set can be characterized by any type of data, not just linear or other functionally defined data.

The typical LVQ neural architecture is presented in Figure 2.

Figure 2. LVQ Artificial Neural Network Architecture

(Source: Neural Network Toolbox: Mathworks Inc.)

RESEARCH OBJECTIVES

Research objectives for this project focused on three major advancements over our previous work.

OBJECTIVE 1: CHARACTERIZING THE INPUT DATA USING DIFFERENT DATA DEFINITION MODELS.

In this project we experimented with different methods for defining defect points in the eddy current data sets for each frequency. Also, we tested and analyzed the classification precision of the LVQ using different data input classification schemes as well as training schemes. The design of new data transforms and defect weighing algorithms was also developed to produce the most accurate and precise neural network model possible for steam generator tube defect detection.

OBJECTIVE 2: REFINING AND CUSTOMIZING THE ALGORITHMS THAT GOVERN THE WEIGHT VECTORS OR CODEBOOKS OF THE LVQ.

In the standard LVQ learning algorithms, a defining property of this class is the method in which weight vectors are updated. In the first competitive layer, only one weight vector is updated, the one closest to the input vector. This is in contrast to other neural network models that update a group, or all of the weight vectors. A refinement that has proven successful allowing for more precise classification is a series of algorithms proposed by Kohonen (2001 3rd edition), and Kohonen et al. (1992), commonly referred to as LVQ2, LVQ3 and OLVQ1. It was proposed that these algorithms be integrated into our approach and new LVQ architectures be developed and tested on the basis of these different types of weight vector refinements. An additional extension was to develop a new learning algorithm

approach specifically suited for the problem of defect detection and classification in nuclear steam generator tubes.

OBJECTIVE 3: EXPANDING THE RANGE OF DETECTABLE DEFECTS TO INCLUDE FREE-SPAN DEFECTS.

This objective encompassed experimentation with the automated defect detection system to determine its robustness in identifying and processing new defect classes. In summary, previous work to this point focused on building a general proof of concept model that includes an automated data preparation system feeding into an appropriate neural network architecture. Our focus for this project includes refining and customizing the network architecture to improve classification and detection properties.

TASKS UNDERTAKEN RELATED TO WORKPLAN

Several tasks were required to accomplish the proposed project objectives.

OBJECTIVE 1 CHARACTERIZING THE INPUT DATA USING DIFFERENT DATA DEFINITION MODELS.

1. Refinement of the present training data matrix to include new eddy current data transform approaches.
2. Development of new defect weighting algorithms.

OBJECTIVE 2 REFINING AND CUSTOMIZING THE ALGORITHMS THAT GOVERN THE WEIGHT VECTORS, (CODEBOOKS) OF THE LVQ.

1. Application of the LVQ2, LVQ3 and OLVQI algorithms to the existing LVQ architecture.
2. Assessment of accuracy of each learning algorithm.
3. Design of a new learning algorithm specifically suited for the problem of defect detection and classification in nuclear steam generator tubes.
4. Testing and refinement of newly developed algorithm.

OBJECTIVE 3: EXPANDING THE RANGE OF DETECTABLE DEFECTS TO INCLUDE FREE-SPAN DEFECTS.

1. Expansion of automated defect system and training data to include new defect classes and pulled tube data files.
2. Design of an assessment system to report the robustness and accuracy of the customized neural architecture for automatically diagnosing defects.

SCIENTIFIC SIGNIFICANCE

The concept for this project arose from the need to classify and “invert” the observed signal data in the case of the continuous-wave radar project which is funded under the nuclear energy research initiative (NERI) under Department of Energy Grant Number (DE-FG-3-99SF21986) [Nassersharif and Caffey, 2000 and 2001]. Additionally, after investigating the methods currently used for analysis of the eddy current generated signatures, similar issues exist in the diagnosis of damage based on an eddy current signal. This problem has led to our currently funded research on the topic of automation of the detection of damage based on a noisy signal generated by either the eddy current or continuous wave radar probe system. Several new contributions are expected as a result of this work that have scientific significance well beyond the needs of the project itself, namely:

- Collection and/or creation of calibrations data for eddy current devices. The new collection will form the basis for development of new algorithms for classification of defect and anomaly signatures (e.g., tube defects and tube support plates).
- Development of a signature classification scheme to identify various defect types. The classification scheme should also allow for characterization of the defect as to sizing of length and depth as well as type.
- Identification and inclusion of signal features that can improve the speed and accuracy of the diagnosis.
- Development of new artificial neural network architectures with customized training and learning algorithms.

OBJECTIVE 1 CHARACTERIZING THE INPUT DATA USING DIFFERENT DATA DEFINITION MODELS.

Work began with the analysis of all the IGA/SCC types of defects at the tube support plates. A MATLAB program was designed to search through the eddy current data files and extract only the portion of the signal associated with the tube support. Once the tube support signal was isolated we started analyzing the defect data to identify characteristic features in the data that constitute a defect. Here we have focused on the following forms of the data: (1) 400/10 frequency mixed data for slope data, (2) 400/10 frequency mixed data for r and θ , (3) 400/10 frequency mixed data for the slope of r and θ data, (4) 400 Hz slope data, (5) 400 Hz r and θ data, (6) 400 Hz slope of r and θ data, (7) 200/10 frequency mixed data for slope data, (8) 200/10 frequency mixed data for r and θ , (9) 200/10 frequency mixed data for the slope of r and θ data, (10) 200 Hz slope data, (11) 200 Hz r and θ data, and (12) 200 Hz slope of r and θ data. Figure 3 below shows what this data looks like for a typical defect.

Figure 3. Typical Defect

These figures have been generated for all the IGA/SCC types of defects at the tube support plates. We have analyzed these figures to identify characteristics that can be utilized in our neural network algorithm. For this data it was noticed that the defects generally occur at the following locations: (1) peak, (2) valley, (3) inflection point, or (4) situated within one-to-two points from these points. To some degree we have

been able to mathematically model these defects; however, the inconsistency of the data has limited the success of these efforts. The idea here was to identify and model features that are indicative of damage and to utilize these features in our neural network algorithms to identify actual defects using data from eddy current tests.

In addition to this work, we identified the portion of the signal generated by the tube support plate. The thought here was to take the signal for a damaged support plate and subtract out the signal generated by an undamaged support plate. Thus, the resulting signal would only contain the portion of the signal generated by the damage. This procedure was performed on a number of the data files to determine the successes of the method. After comparing the results with previous methods it was determined that the new method did not perform any better than any of the previous methods that had been investigated.

We also investigated various approaches, including a reflected energy integral to analyze the data for automation. Analysis of the data obtained from EPRI for the MIZ-18 probe proved to be difficult because of the resolution of the data particularly when the defect resides in the tube region inside the tube support plates.

During this research effort we have investigated a number of methods and algorithms to isolate the signal generated by the tube support plate in an effort to identify features that could be used to detect and localize damage. Each of these attempts has worked to some degree. It is believed that the inconsistency in the resolution of the data is the primary reason for our inability to identify a method which works for all damage cases.

After some time we finally settled on the following approach for the extraction of feature vectors. The signal resulting from the tube support plate was first extracted for each of the tubes. The differential and absolute data was then shifted such that the mean of the signal was centered along the x-axis. Next the slope of the two dimensional curve (this is the figure eight shaped curve for the differential data) was calculated for the differential and absolute data. It was determined the slope data for the 200 Hz signal for the differential and absolute data had a characteristic shape to it. As a result we used the error associated with a nonparametric curve fitting technique as feature vectors. In addition to this we also used the negative peak associated with the 100 Hz signal for the differential data. It was observed that a negative peak existed in the 100 Hz signal and that its location usually indicated the location of the defect. Figures 4 – 9 show the typical shape of the curves used to construct the three dimensional feature vectors used by the neural network to detect damage.

Figure 4. Differential Data, 200 Hz, No damage

Figure 5. Absolute Data, 200 Hz, No damage

Figure 6. Differential Data, 100 Hz, No damage

Figure 7. Differential Data, 200 Hz, Damage

Figure 8. Absolute Data, 200 Hz, Damage

Figure 9. Differential Data, 100 Hz, Damage

Training Data

One early representation of the training data included a vector representation of peak to peak width and height, positive and negative peak height and measures of half height for all of the tube data. Results of this experiment were not promising most likely due to the inconsistent representation of the data as a result of sampling approaches, tube characteristics, probe type and defect location. Figure 10 below shows an early approach to deriving training data.

Figure 10. Signature Characteristics

From these initial findings we refined our approaches to represent the tube data in a binary vector of training sets and finally ended up with training sets incorporating a binary element indicating damage as well as various error elements across sampled frequencies for each tube. Last, to attempt to refine the vectors, we applied a smoothing spline transform to the vector using three different parameters.

This final training set vector representation of the data is defined as the following. Data files are named as follows:

name.feature_#_error type.txt

name → row and column number of the tube.

feature → all files have this as part of the file name.

→ equal to a 1, 3, or 5. All files with a 1 indicate that a smoothing parameter of 0.1 was used for the smoothing spline. All files with a 3 indicate that a smoothing parameter of 0.3 was used for the smoothing spline. All files with a 5 indicate that a smoothing parameter of 0.5 was

used for the smoothing spline.

error type → this is equal to sse, rsq, adr, or rms. Sse indicates sum of squares error, rsq indicates R-square error, adr indicates adjusted R-square error, and rms indicates root mean squared error.

The data included in the vector set for each frequency is the slope of the Lissajous figure for the differential data and the slope of the absolute data. Thus for each figure there were a total of 8 curves generated; 1 slope curve for each of the 4 frequencies for the differential data and 1 slope curve for each of the 4 frequencies for the absolute data. Typically these frequencies were 400Hz, 200 Hz, 100 Hz, and 50 Hz. After studying these 8 curves it was apparent that for the second frequency, (200 Hz), the curve for the differential data and the absolute data had a characteristic shape and that the shape changed when damage was present.

The larger the damage the more the curve changed. We also noticed that the third frequency for the differential data usually contained a negative peak between the first and last peak of the curve and that the location of the peak usually corresponded to the location of the defect. In addition to this, the peak appeared to become more negative as the level of damage increased.

With this in mind a feature vector was constructed for each figure consisting of 4 elements.

The first element is a 1 or 0. A 1 indicates that the blip contained damage and a 0 was used for no damage.

To derive the second element of the feature vector a smoothing spline curve fit of the 200 Hz differential curve was undertaken. After performing the curve fit, the remaining available information was the sum of squares error, the R-square error, the adjusted R-square error, and the root mean squared error. We used these values as the 2nd element of the feature vector. At this point, not knowing which errors would present the best indicator of damage, training sets were generated using each type error.

The 3rd element of the feature vector was generated using the same method as the 2nd element of the feature vector but including a smoothing spline curve fit of the 200 Hz absolute curve.

The fourth element of the feature vector was generated by determining the y-value of the most negative peak (point) between the first and last peak in the 100 Hz differential curve. We noticed that for some figures there were negative peaks in the 100 Hz curve that didn't correspond to damage and that the peak was significantly larger (more negative) for the damaged figures for that same tube. We also noticed that for some tubes there were no negative peaks between the first and last peak in the curve for undamaged figures but a small negative peak did exist for damaged

figures.

We decided that using just the y-value as the 4th element of the feature vector would not work very well as an indicator of damage because for some tubes a small value did not indicate damage and for other tubes a small value did indicate damage.

Therefore the following approach was used. For each tube all of the y-values between the first and last peak of the 100 Hz differential curve were determined. We then determined the y-value for the largest negative peak and divided all of the y-values by that value. Thus for a tube that contained 4 figures I would have 4 feature vectors containing 4 elements each. The feature vector (blip) with a fourth element equal to one meant that that figure had the largest negative peak between the first and last peak. We did observe that the figure that had a value of 1 in the 4th element of the feature vector generally had the largest amount of damage.

With this reviewed, once again the naming convention and contents of each of the training vectors is presented as follows:

For the file DIR008C066I057.feature_1_adr.txt we have the following:

DIR008C066I057 → indicates row and column of the tube being investigated.

1 → indicates that a smoothing parameter 0.1 was used for the smoothing spline curve fit of the 200 Hz differential and absolute curves

adr → indicates that the adjusted R-square error was used for the 2nd and 3rd element of the feature vector

Note that the 4th element of the feature vector is independent of the type of error that we are using for the 2nd and 3rd element of the feature vector and is also independent of the smoothing parameter. So the value of the 4th element of the feature vector remains the same for all types of error used for the 2nd and 3rd element of the feature vector.

OBJECTIVE 2 REFINING AND CUSTOMIZING THE ALGORITHMS THAT GOVERN THE WEIGHT VECTORS, (CODEBOOKS) OF THE LVQ.

The study of pattern detection has been, and will continue to be a well-researched area. Interest in this type of problem is due to the inherent complexity associated with the various model inputs, the variety of realistic applications in industry, and the value of successful results as measured by cost, performance, reliability and maintenance.

One technique that has been used to study pattern detection problems is artificial neural networks (ANN). Researchers have shown that ANN's are

a good method for solving a range of pattern detection problems including the identification and classification of defects.

Classical approaches to pattern detection using neural networks involve a process of back-propagation. These supervised nets require providing all possible detectable patterns to the architecture for training purposes. The drawbacks of using supervised neural nets most often involve a very lengthy training time and the assumption that all defect patterns are in fact known. Furthermore, with ANN's alone, sometimes a close to optimal solution is unreachable. In other scenarios, the ANN training period may require a great deal of computing time making the technique unrealistic for dynamic industrial applications.

To overcome the challenges with classical approaches, more recent hybrid approaches involve integrating parallel techniques with the ANN implementation. These techniques include Lagrangian relaxation, simulated annealing, simulation and genetic algorithms. Hybrid approaches have demonstrated a reduction in ANN training time and/or the production of more accurate pattern detection. Although using these hybrid approaches suggests a promising area for research, they still do not guarantee that for large problems especially, training time can be reduced or that an optimal solution will be reached.

In application fields such as control or forecasting, researchers have proven that the use of fuzzy logic combined with neural networks has found better solutions than by using an ANN alone [Kuo 2001]. The use of fuzzy logic incorporated with an ANN architecture seems to improve a model's performance, especially those models with noisy input patterns. This point is particularly appropriate for pattern detection problems due to the input parameters.

ANN's utilizing fuzzy logic most often make use of a feed-forward architecture that reduces training time. This type of neural network is self-organizing resulting in an architecture that permits both supervised and unsupervised learning. In an unsupervised mode, the ANN has the ability to learn patterns. Yet the architecture also permits supervised learning for the purpose of learning and predicting patterns that fit the statistics of the input-output environment. The advantage of this type of architecture is its capability to learn complex mappings and create new pattern defect categories when new information is presented. This eliminates the need for a time consuming training process typical in ANN's with only a supervised learning process.

The initial ANN approach for this project involved using a Learning Vector Quantization architecture for training and defect detection. As discussed previously, this architecture provides some significant advantages over competing approaches. However this approach is not without drawbacks.

A drawback of LVQs is a lack of memory. Elman neural networks are many times used to predict wavelet patterns by storing past signal information over some running total of user defined time dependent points. As a classification in contrast to a prediction architecture, LVQs don't have this ability. Therefore, several different training approaches were undertaken to compensate for this drawback.

Testing and refinement of the ANN

Suffice it to say, numerous design approaches using various training sets were tested across several modifications of the ANN. Variations of neural architectures that were designed for this project included:

1. PNN – Probabilistic Neural Network
2. LVQ – Learning Vector Quantization
3. LVQ2 – includes a refinement of the decision borders between defect and non-defect
4. LVQ3 - includes a stabilizer that allows for more long-term accuracy
5. Discriminant heuristic – first pass segmentation approach incorporated
6. LVQ with corrective tuning – first pass tuning of training data using LVQ2
7. HMM – first pass at identifying Hidden Markov Models in training data
8. Binary logistic refinement – first pass process incorporating binary logistic regression into LVQ
9. Euclidian distance refinement

In addition to several different approaches to the design of the neural architecture, various refinements of the training data were used in this project to attempt to increase performance of the architecture. These refinements included:

1. Processed raw data
2. Slope data
3. Lissajous figures using peak to peak measures
4. Lissajous figures filtered
5. Binary representation of Lissajous figures
6. Lissajous figures of errors with smoothing parameter of .1
7. Lissajous figures of errors with smoothing parameter of .3
8. Lissajous figures of errors with smoothing parameter of .5

As discussed in the previous section, training data was created for each pulled tube using a smoothing parameter of .1, .3 and .5 for rms, rsq, sse and adr errors. On average each training file contained four to five damage indications for a total of approximately 500 vectors available for training and testing. Below is a representation of the training files for one pulled tube.

- DCR018C077I011.feature_1_rms.txt
- DCR018C077I011.feature_1_rsqr.txt
- DCR018C077I011.feature_1_sse.txt
- DCR018C077I011.feature_3_adr.txt
- DCR018C077I011.feature_3_rms.txt
- DCR018C077I011.feature_3_sse.txt
- DCR018C077I011.feature_3-rsq.txt
- DCR018C077I011.feature_5_adr.txt
- DCR018C077I011.feature_5_rms.txt
- DCR018C077I011.feature_5_sse.txt
- DCR018C077I011.feature_5-rsq.txt

Another approach to that was investigated is referred to as “decision theoretic” pattern recognition. In the decision theoretic model, we can accomplish pattern recognition via deterministic and statistical means. A diagram of the decision theoretic model is shown in Figure 11. For the top half of the diagram, the measurements are processed by the feature extractor to obtain feature vectors. These feature vectors serve as input to the decision function (classifier). The purpose of the feature extractor is to reduce the number of measurements (dimensionality reduction) and to render the measurements more suitable for the decision process. For example, the processing of eddy current data to obtain peak values may be thought of as feature extraction. The decision function (classifier) is used to assign a class membership to the feature vector. The bottom half of Figure 11 is the training mode of the pattern recognition model. In the training mode, we may have a separate set of measurements for which we know the class membership. These measurements are used to determine learning parameters, which, in turn, are used by the decision function to assign a class membership to the feature vector.

Figure 11 Decision Theoretic Pattern Recognition Model

In this analysis we used the deterministic approach. It is believed that the results can be further improved by utilizing the statistical approach where more complex decision functions can be used.

The deterministic approach involves classification rules which do not explicitly utilize the statistical properties of the pattern classes under consideration. We will limit our discussion to distance measures. There are many types of distance measures. For example, there are classification rules which utilize Euclidean distance, Mahalanobis distance, exponential distance, etc.. In this work, we utilized the Euclidean distance, because the Euclidean distance is a convenient measure.

The Euclidean distance for the damaged and undamaged classes is just the squared distance between the feature vector and the mean vectors for the damaged and undamaged classes. The Euclidean distances for the damaged and undamaged class are given by:

$$E_d(\{y\}) = \{y\}^T \{y\} - 2\{y\}^T \{\mu_d\} + \{\mu_d\}^T \{\mu_d\}$$

and

$$E_u(\{y\}) = \{y\}^T \{y\} - 2\{y\}^T \{\mu_u\} + \{\mu_u\}^T \{\mu_u\}$$

where μ_d and μ_u are the damaged and undamaged mean vectors, respectively, and $\{y\}$ is the feature vector.

To obtain a classification rule based on the Euclidean distance, we utilize discriminant functions. A discriminant function, g_i , classifies patterns $\{y\}$ into clusters D_i and D_j according to the classification rule:

assign $\{y\}$ to class D_i if,

$$g_i(\{y\}) > g_j(\{y\}) \quad \text{for } j \neq i \text{ Error! Switch argument not specified.}$$

The boundary between the two decision regions, D_i and D_j , defines the decision surface. We define the decision surface between D_i and D_j by all patterns $\{y\}$ such that

$$g_i(\{y\}) = g_j(\{y\})$$

Two common discriminant functions are the linear discriminant function and the quadratic discriminant function. A linear discriminant function has the form

$$g_i(\{y\}) = \{y\}^T \{v\} + v_o$$

and behaves as a separating hyperplane in the pattern space. Note the vector $\{v\}$ is a coefficient vector and v_o is the threshold value. A graphical representation of linear discrimination for a two-class, two dimensional classification space is shown in Figure 12. The simplest polynomial classifier is a quadratic classifier. The quadratic discriminant function is given by:

$$g_i(\{y\}) = \{y\}^T [A_i] \{y\} + \{v\}^T \{y\} + v_o$$

where A_i denotes an $M \times M$ coefficient matrix. The resulting decision boundary given by this equation is quadratic.

Figure 12 Discrimination of a Two-Class, Two-Dimensional Feature Space

Combining the above equations we obtain the classification rule:

assign $\{y\}$ to class D_d if,

$$\{y\}^T \{y\} - 2\{y\}^T \{\mu_d\} + \{\mu_d\}^T \{\mu_d\} > \{y\}^T \{y\} - 2\{y\}^T \{\mu_u\} + \{\mu_u\}^T \{\mu_u\}$$

for $u \neq d$

Simplifying the above equation we obtain the classification rule for the Euclidean distance:

assign $\{y\}$ to class D_d if,

$$\{y\}^T \{\mu_d\} - \frac{1}{2} \{\mu_d\}^T \{\mu_d\} > \{y\}^T \{\mu_u\} - \frac{1}{2} \{\mu_u\}^T \{\mu_u\}$$

for $u \neq d$

Note that the above equation is a linear equation and the resulting decision surface is also linear.

TEST RESULTS TO DEMONSTRATE NEURAL NETWORK PERFORMANCE

Table 1 shows the matrix of the various iterations of experiments used in this research project for the ANN defect detection component of the project as well as the “best” outcome within the experiment class for overall correct prediction of tube defect. Overall correct prediction is defined as model accuracy considering correct predictions of damage as well as false positives and negatives. As was expected, by creating an overly sensitive model, the correct predictions of damage measure would increase, but so too would the false positives.

Each one of the entries in the table may represent the “best” outcome using anywhere from 1 to 450 training vectors.

Table 2 shows the results for the pattern recognition approach using the Euclidean distance we obtained the following results. This table only shows the error type that had the highest number of correct damage predictions for the 1-dimensional and 3-dimensional feature vectors.

What is clear from this analysis is that hybrid neural architectures that include data preprocessing and tuning improve the classification power of the method. Those approaches integrating a statistical first pass tuning show better results.

Table 1 - Experiment Matrix with Best Reported Defect Detection Result

Training Sets→ ANN	Processed Raw Data	Slope Data	Lissajous Figures using Peak to Peak Measures	Lissajous Figures Filtered	Binary Representation of Lissajous Figures	Lissajous Figures with Smoothing Parameter of .1	Lissajous Figures with Smoothing Parameter of .3	Lissajous Figures with Smoothing Parameter of .5
PNN ¹	55%	60%						
LVQ ²	57%	61%	57%	64%	67%	73%	77%	85%
LVQ2 ³	59%	60%						
LVQ3 ⁴	59%	62%				74%	78%	79%
Discriminant Heuristic incorporated ⁵						72%	78%	83%
LVQ with corrective tuning ⁶								82%
HMM refinement applied to LVQ ⁷								84%
Binary Logistic Statistical refinement applied to LVQ ⁸						77%	82%	88%

Table 2- Experiment Matrix with Best Reported Defect Detection Result using Euclidean Distance

	2 nd Element of Feature Vector (1-D)			3 rd Element of Feature Vector (1-D)			4 th element of Feature Vector (1-D)			2 nd , 3 rd , and 4 th Element of Feature Vector (3-D)		
Smoothing Parameter	0.1 (sse)	0.3 (rms)	0.5 (sse)	0.1 (rms)	0.3 (rms)	0.5 (rms)	0.1	0.3	0.5	0.1 (sse)	0.3 (rms)	0.5 (sse)
Percentage of Correct Damage predictions	92	88	88	92	81	85	63	62	62	92	88	88
Percentage of Correct Undamage predictions	50	43	39	50	46	46	67	61	61	50	43	39

- 1 PNN – Probabilistic Neural Network
2. LVQ – Learning Vector Quantization
3. LVQ2 – includes a refinement of the decision borders between defect and non-defect
- 4 LVQ3 - includes a stabilizer that allows for more long-term accuracy
- 5 Discriminant heuristic – first pass segmentation approach incorporated
- 6 LVQ with corrective tuning – first pass tuning of training data using LVQ2
7. HMM – first pass at identifying Hidden Markov Models in training data
- 8 Binary logistic refinement – first pass process incorporating binary logistic regression into LVQ

OBJECTIVE 3: EXPANDING THE RANGE OF DETECTABLE DEFECTS TO INCLUDE FREE-SPAN DEFECTS.

Very early in the undertaking of this project, statistical analysis and data transforms were attempted that expanded the range of defects to include areas in the free span of the tube. However, due to the nature of the data provided by EPRI for this project and the method chosen for analysis, i.e. neural architectures, training and testing sets were not of sufficient number to produce reliable results. Therefore, our design decisions led us to concentrate on the tube support damage locations, for which we had the largest number of data points. By concentrating on these locations, we were able to apply several different types of error transforms on this data for subsequent analysis.

Under this objective we were also tasked with developing the automated data processing and transform system which was entirely successful. This system, as discussed previously, was written in Matlab and was extended to include a graphical user interface and output.

Conclusions to Technical Approach

We had success in designing the automated system for mining data, transforming that data into graphical output as well as vector sets for training neural architectures. However, we were less successful in our attempts to significantly improve on field technician diagnosis of tube damage. This is attributed to several points. First, our data set was over 20 years old and contained a significant amount of noise. This resulted in the need to create several filtering algorithms to lessen or remove the noise. In doing this, we may have also removed some signatures indicating damage. Since we were working with real field data in contrast to lab calibration data, we also observed some differences in sampling rate accuracy. We expect that today's present day extraction methods implement a technology that is more reliable in terms of noise filtration and sampling rates.

Secondly, the ultimate strength of a neural network's ability to classify and predict damage is based on the accuracy and number of training cases. The greater the exposure to training data and a variety of damage indications in that data, the greater the predictive and classification power of the architecture. Also, the limited pulled tube data also restricted our ability to present a variety of test cases to the neural architecture.

Having said this, the overall results of the project were quite promising in the advances in designing an automated system as well as in an overall understanding of the power and adequacy of neural network analysis for damage detection in steam generator tubes.

Project Management and Key Personnel

The principal investigators for this project were, Dr. Gabe Garcia, Dr. Linda Ann Riley, and Dr. Bahram Nassersharif. Dr. Garcia is a professor in the Mechanical Engineering Department at New Mexico State University who has expertise in pattern recognition as related to instrumentation and sensor data. He was also a co-investigator on the In Tube Radar project mentioned earlier. Dr. Riley is an Associate Dean and Professor of Engineering at Roger Williams University and has experience in the application of neural networks and genetic algorithms. Dr. Nassersharif, Dean of Engineering at University of Rhode Island has an extensive track record in research and publications related to steam generator tube ruptures, use of expert systems and neural networks.

John Schaub is a student in Mechanical Engineering and Engineering Physics. He performed much of the data manipulation, analysis, and laboratory testing of the software. He has also been the main project archivist and data manager.

Facilities and Resources

The computational facilities, equipment, and basic software already existed in the Mechanical Engineering and Industrial Engineering Departments at New Mexico State University. This project was leveraged with the In Tube Radar project. We collaborated with EPRI NDE center in Charlotte, North Carolina on the collection of training data and calibration and test samples with respect to eddy current testing. This relationship had already existed in the context of our In Tube Radar and the previously funded DOE NEPO projects.

Relationship to Existing Projects and Other Proposals

This project interacted closely with a collaborative NERI project between New Mexico State University (NMSU), Sandia National Laboratories, and EPRI. The NERI In-Tube Radar (ITR) project is a three year project funded by DOE under grant number DE-FG-3-99SF21986. The ITR project began in 1999 and ended in 2002.

This project is also closely related to a DOE NEPO funded program under grant number DE-FG07-01ID14237 and entitled "Automated Diagnosis and Classification of Steam Generator Tube Defects." The present project was a logical next step in advancing the state-of-the-art in non-destructive testing of steam generator tubing in nuclear power plants based on experience gained and results obtained from the other two DOE funded projects at NMSU.

Publications and Presentations

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Presentation: An Automated Testing and Classification System For Identifying Defects in Nuclear Steam Generator Tubes Using a Learning Vector Quantization Neural Architecture, 2003 Advanced Simulation Technologies Conference.

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