INSPECTION OF FERROMAGNETIC SUPPORT STRUCTURES FROM WITHIN ALLOY 800 STEAM GENERATOR TUBES USING PULSED EDDY CURRENT

by

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A thesis submitted to the Department of Physics, Engineering Physics, and Astronomy
In conformity with the requirements for
the degree of Masters of Applied Science

Queen’s University
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(September, 2015)

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Nondestructive testing is a critical aspect of component lifetime management. Nuclear steam generator (SG) tubes are the thinnest barrier between irradiated primary heat transport system and the secondary heat transport system, whose components are not rated for large radiation fields. Conventional eddy current testing (ECT) and ultrasonic testing are currently employed for inspecting SG tubes, with the former doing most inspections due to speed and reliability based on an understanding of how flaws affect coil impedance parameters when conductors are subjected to harmonically induced currents. However, when multiple degradation modes are present simultaneously near ferromagnetic materials, such as tube fretting, support structure corrosion, and magnetite fouling, ECT reliability decreases. Pulsed eddy current (PEC), which induces transient eddy currents via square wave excitation, has been considered in this thesis to simultaneously examine SG tube and support structure conditions. An array probe consisting of a central driver, coaxial with the tube, and an array of 8 sensing coils, was used in this thesis to perform laboratory measurements. The probe was delivered from the inner diameter (ID) of the SG tube, where support hole diameter, tube frets, and 2D off-centering were varied. When considering two variables simultaneously, scores obtained from a modified principal components analysis (MPCA) were sufficient for parameter extraction. In the case of hole ID variation with two dimensional tube off-centering (three parameters), multiple linear regression (MLR) of the MPCA scores provided good estimates of parameters. However, once a fourth variable, outer diameter tube frets, was introduced, MLR proved insufficient. Artificial neural networks (ANNs) were investigated in order to perform pattern recognition on the MPCA scores to simultaneously extract the four measurement parameters from the data. All models throughout this thesis were created and validated using experimental data. The final ANN models could provide estimates to within 2% of hole diameter and 3% of fret depth. Estimates of hole ID and tube position were further improved when considering fret depth as an input, which could occur if fret information was available. ANN models proved robust to measurement error, as would be encountered in real inspection settings.
Co-Authorship

The following people contributed to the development of this original thesis:

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This thesis work combines manuscripts of two separate journal publication and two conference publications. All manuscript preparations, experiments, and analysis were performed by the first author. The following provides a list of all co-authors and their contributions to respective manuscripts.

Steam Generator Pulsed Eddy Current Inspection

- Funded by:
  - Collaborative Research and Development Grant from Natural Sciences and Engineering Research Council of Canada (NSERC-CRD)
  - In-kind contributions from Canadian Nuclear Laboratories through the University Network of Excellence in Nuclear Engineering (UNENE)

- Collaborators:
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  - Steam Generator Inspection group at Ontario Power Generation: Sean Sullivan

- Contributions from collaborators:

  PEC probe was manufactured at Canadian Nuclear Laboratories for use in this thesis work. Expertise in SG inspection provided through useful discussions with Sean Sullivan and Brian Lepine.
Outcomes:


Acknowledgements

There are a number of amazing people whose invaluable support made this work possible. I would like to thank my supervisors Prof. Thomas Krause and Prof. Jordan Morelli for introducing me to the project and the field of NDT. Their extensive understanding of electromagnetics and their applications provided a cornerstone of the project’s development. Prof. Peter Ross Underhill’s knowledge of statistical analysis was the base upon which my own analyses of pulsed eddy current signals grew. I am grateful to all the members of the NDT lab at Royal Military College of Canada (RMC), particularly to Sarah Mokros who worked alongside me on her own thesis, providing extensive useful discussion throughout the whole project. Peter Snell at RMC manufactured steel samples for my work. A very special thanks to Erin Imrie, whose unconditional support for me and my work allowed me to persevere through all the hardships I encountered during the project. Finally I would like to thank my family and friends for keeping me motivated.

Financial support from National Sciences and Engineering Research Council (NSERC), University Network of Excellence in Nuclear Engineering (UNENE), and Queen’s Department of Physics, Engineering Physics, and Astronomy is gratefully acknowledged.
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<td>PWR</td>
<td>Pressurized Water Reactor</td>
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<tr>
<td>CANDU®</td>
<td>CANadian Deuterium Uranium</td>
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<td>PHTS</td>
<td>Primary Heat Transport System</td>
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<tr>
<td>SHTS</td>
<td>Secondary Heat Transport System</td>
</tr>
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<td>SG</td>
<td>Steam Generator</td>
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<tr>
<td>NDT</td>
<td>Nondestructive Testing</td>
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<td>ECT</td>
<td>Eddy Current Testing</td>
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<td>UT</td>
<td>Ultrasonic Testing</td>
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<tr>
<td>AC</td>
<td>Alternating Current</td>
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<tr>
<td>PEC</td>
<td>Pulsed Eddy Current</td>
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<td>DC</td>
<td>Direct Current</td>
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<tr>
<td>FE</td>
<td>Finite Element</td>
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<td>RFEC</td>
<td>Remote Field Eddy Current</td>
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<tr>
<td>OD</td>
<td>Outer Diameter</td>
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<tr>
<td>ID</td>
<td>Inner Diameter</td>
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<tr>
<td>IGSCC</td>
<td>Intergranular Stress Corrosion Cracking</td>
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<tr>
<td>LOI</td>
<td>Lift-Off Intersection</td>
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<tr>
<td>FFT</td>
<td>Fast Fourier Transform</td>
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<td>PCA</td>
<td>Principal Component Analysis</td>
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<td>MPCA</td>
<td>Modified Principal Component Analysis</td>
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<tr>
<td>MD</td>
<td>Mahalanobis Distance</td>
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<tr>
<td>SVM</td>
<td>Support Vector Machine</td>
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<tr>
<td>ANN</td>
<td>Artificial Neural Network</td>
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<tr>
<td>Acronym</td>
<td>Description</td>
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<tr>
<td>MLR</td>
<td>Multiple Linear Regression</td>
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<tr>
<td>410SS</td>
<td>410 grade Stainless Steel</td>
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<tr>
<td>KVL</td>
<td>Kirchoff’s Voltage Law</td>
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<tr>
<td>MLE</td>
<td>Maximum Likelihood Estimate</td>
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<tr>
<td>RMC</td>
<td>Royal Military College</td>
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<td>CNL</td>
<td>Canadian Nuclear Laboratories</td>
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<tr>
<td>AWG</td>
<td>American Wire Gauge</td>
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Chapter 1

Introduction

1.1 General

With increasing greenhouse gases present in the atmosphere due to excessive burning of fossil fuels, alternative energy sources are playing an ever expanding role as power sources for modern society. One of the most prominent, and controversial, energy sources harnessed in the 20th century is nuclear fission. Pressurized Water Reactors (PWR), and Canadian Deuterium Uranium (CANDU®) reactors, have many similarities to more traditional fossil fuel power plants. Coolant water of a Primary Heat Transport System (PHTS) is heated through nuclear fission processes, specifically by kinetic energy transfer from neutrons released during the decay of Uranium-235 isotope. The reactor core is situated in a large reservoir of water, called the moderator, which in PWRs is also the PHTS. PHTS water, in turn, heats Secondary Heat Transport System (SHTS) water through heat exchangers of Steam Generators (SGs), which subsequently power turbines to produce electricity [1].

PWRs, designed in the USA during the 1950s, burn enriched uranium fuel to achieve a self-sustaining nuclear fission, which provides an abundance of neutrons for heating PHTS water [1]. When the CANDU reactor was being developed, during the 1950s and 1960s, the cost of enriching uranium proved prohibitive, so a design based on natural uranium fuel was adopted. Naturally occurring uranium ore is primarily U-238, only containing ~0.7% U-235, and since U-235 produces the bulk of the thermal neutrons, maintaining neutron efficiency is paramount [1]. This design constraint requires the use of heavy water, where one hydrogen atom is substituted with deuterium (isotope of hydrogen in which the nucleus is a proton and a neutron), to reduce neutron absorption by the moderator and coolant, increasing neutron efficiency.
CANDU® SGs are the thinnest barrier between irradiated PHTS and the SHTS that powers
the turbines [2]. Regular exposure to radiation imposes expensive material constraints; so on top
of maintaining SG thermal efficiency, SG tube integrity is paramount to safe operation with
secondary side materials not designed for radiation fields [3]. There are many degradation modes
active in CANDU® SGs, including stress corrosion cracking, tube fretting wear, tube denting, and
support structure corrosion, to name a few [3], [4]. Life management strategies are therefore
implemented to ensure the safe operation of nuclear SGs. For CANDU® reactors, the primary
methods of inspecting SGs are the nondestructive testing (NDT) techniques called eddy current
testing (ECT) and ultrasonic testing (UT) [3]. Of these two, ECT is employed for the bulk of
inspections due to its speed when compared to UT, which is brought in to verify certain ECT flaw
identifications [3]. While ECT is an effective SG inspection method, aging reactors have
developed a suite of issues over the years that constantly challenge researchers to devise new
methods and probes for inspecting tubes, beginning with single frequency ECT bobbin probes, to
multi-frequency bobbin probes, and more recently multi-frequency array probes [2]–[5]. All of
these methods rely on sinusoidal excitation of eddy currents, and so share some of the associated
limitations that will be identified in this introduction. An emerging, alternative technique, based
on excitation of transient eddy currents is proposed in this thesis as a complimentary method to
inspect regions challenged by conventional ECT, namely ferromagnetic support structures in the
presence of overlapping degradation modes and magnetite sludge.

1.2 Eddy Current Testing

Eddy current testing (ECT) is probably the most widely used method for inspecting
conducting materials. The basis of ECT revolves around the induction of eddy currents, named as
such for their circular behaviour. These currents arise through the practical application of
Faraday’s Law, where changing electromagnetic fields produce currents which generate opposing
fields according to Lenz’s law [6]. Through the interactions of excitation and induced
electromagnetic fields, information can be inferred from conducting materials. Specifically, deviations in signals from measured impedance response can be interpreted to indicate the presence of discontinuities such as surface and subsurface cracks, thickness variations, and local conductivity changes [7]. Conventional ECT involves excitation of eddy currents via sinusoidal alternating currents (AC) through a coil that is in close proximity to the conductor of interest. Variations in sensing coil impedances are commonly displayed on an impedance plane, and resulting shapes are manually interpreted to determine their sources [7]. While conventional ECT is a powerful tool, a number of significant limitations have been identified. Response depends on the size and depth of material flaws, and other perturbations, such as the presence of magnetic materials, local permeability variations, and geometric discontinuities [7].

As a consequence of some of the issues identified above for sinusoidal ECT, an emerging inspection method, pulsed eddy current (PEC), is being investigated [8]–[10]. This technique differs primarily from conventional ECT through the use of transient electromagnetic fields to induce eddy currents, typically a square voltage pulse applied to a driving coil. In most systems, the steady-state currents produced in the sample remain for a time, and are allowed to fully decay before the excitation waveform is repeated. In a Fourier sense, the pulse waveforms are richer in frequency spectrum than their single or multi-frequency conventional ECT counterparts, and the lower frequency components penetrate deeper into materials, increasing potential inspection depth [7]. Additionally, the steady-state current provides a direct current (DC) magnetization of ferromagnetic materials, enhancing the method’s potential for inspecting magnetic steels [8], [9], [11], [12].

1.3 Research Survey

1.3.1 Analytic Models

Analytic solutions to axially symmetric eddy current problems were solved in 1968, and form the basis of modern ECT [13]. These solutions permitted highly accurate calculations of coil
impedances when excited with sinusoidal waveforms in the presence of multi-layered conducting half spaces, and when encircling conducting rods. Integrals of first-order Bessel functions solve for the vector potentials, permitting relevant electromagnetic quantities to be extracted. Small flaws were modeled in these solutions as eddy currents in the opposite direction of those excited by the driving waveform [13]. With this information in hand, the impedance plane display, in which probe reactive impedance is plotted against resistance, could be understood with respect to effects of lift-off, resistivity, operating frequency, and sample thickness [7], [13]. Solutions for bracelet arrayed X-Probe have been obtained, building off of the previous analytic solutions discussed above [5]. Analytic models are constantly being refined to address issues such as probe lift-off [14], improved by examining magnetic fields instead of impedances [15] and modified by different probe designs [16].

Finite element (FE) models are used in electromagnetics to acquire approximate solutions when closed form solutions become prohibitively complex. By breaking the region of interest into discrete nodes through a user controlled mesh, the electric and magnetic fields over the entire space are determined by calculating values at nodes and interpolating between them. FE models are also routinely employed when effects of various flaws under consideration are too complicated or expensive to reproduce in laboratory environments. Using a FE approach validated with experimental measurements, remote field eddy current (RFEC), where receive coils are located in the remote field area (more than 2 tube diameters from the transmit coil), has demonstrated the capability of sizing outer diameter (OD) flaws as accurately as inner diameter (ID) flaws [17]. A simplified impedance model was validated using FE generated and experimentally obtained results for estimating ID tube flaws and material properties for conducting nonmagnetic and ferromagnetic tubes [18]. Numerical simulations have also been employed for predicting ECT responses due to the presence of magnetite fouling [19]. An adaptive algorithm based on non-isotropic nested Gauss-Paterson formulae, which compensates
for random input variables, has been applied to unknown sludge deposits in SG quatrefoil support structures [20].

1.3.2 SG tube inspection with ECT

As mentioned in Section 1.1, sinusoidal ECT is the most widely used method for inspecting SG tubes [3], [4]. Bobbin type coaxial probes, examples of which are shown in Figure 1(a), were initially used for all SG tube inspections, operated at single frequency or multiple frequencies simultaneously [3]. They have proven fast and reliable, scanning at approximately $1 \, \text{m/s}$, for detection of volumetric flaws such as fretting wear scars [21] and pitting corrosion, as well as axial cracks along SG tubes [3], [4]. As SGs aged, they developed new issues that had previously gone undetected, demonstrating limitations to the early probes. Bobbin drive and sensing coils were coaxial with the probe, therefore eddy currents induced in tubes followed the circumference, coaxial again to the probe and making it impossible to detect circumferential cracks. Intergranular stress corrosion cracks (IGSCC) formed parallel to coil windings [4], and so were undetectable by simple bobbin probe geometry. Additionally, some flaws such as cracks at dents, and axial cracks at tube bends and support structure locations, could not be reliably detected using bobbin probes [3], [4]. Rotating pancake coil probes, such as the PlusPoint probe, were introduced to address some of these issues as they proved sensitive to both axial and circumferential cracks [3], [4], [22], [23]. A major drawback of these new probes was a significant reduction in scanning speed, by roughly two orders of magnitude [3]. In addition, surface riding probes that had spring loaded guides to maintain constant lift-off [7], would wear out after having inspected far fewer tubes than bobbin probes, and drove inspection costs up [3]. Modifications to this probe design to include a U-yoke core to improve sensitivity to permeability variations such as magnetite sludge were examined [24]. A new generation of transmit-receive probes designed in the 90s are the most advanced probes currently employed in SG tube inspections. The X-probe, a schematic of which is shown in Figure 1(b), consists of a bracelet
array of coils that can be multiplexed to use each coil as a driver or a pickup coil [3], [5], [25]. These probes retain the flaw sensitivity of rotating transmit receive probes, while improving inspection speeds to 1 m/s, similar to bobbin probes [3].

Figure 1 Photos of bobbin transmit-receive bobbin probes (a) [26] and schematic of bracelet array X-Probe (b) [3]

1.3.3 PEC Analytic Solutions

When dealing with transient electromagnetic fields, analytic solutions become far more difficult to develop. Lack of agreement between analytic and experimental results for transient fields, particularly at early times, are due to inherent feedback effects, accentuated in the presence of ferromagnetic materials [27]. Additionally, magnetization of ferromagnetic materials adds secondary fields, further complicating models [27], [28]. Solutions to the differential equations for transmit-receive probe geometries using Fourier transforms incorporate these effects for conducting rods, including ferromagnetic rods, result in good agreement at all times with experimental data [29], [30]. Difficulties extend to FE models of transient electromagnetic fields as the extremely rapid changes in magnetic flux require large numbers of elements and small time steps, particularly at early times, before steady-state fields are achieved, which significantly increases computation times. For these reasons, much of the PEC research to date has been experimental, which is the topic of this thesis.
1.3.4 Time-Domain PEC Signal Analysis

Depending on probe types, there are various existing methods for analyzing PEC signals. Most analysis involves examining sensor response features in the time domain. PEC probes either use pickup coils whose induced currents are analysed for feature identification [8]–[11], or perhaps more commonly magnetic sensors such as Hall sensors or giant magnetoresistive sensors are employed to directly measure magnetic field strengths in the probe’s vicinity [31]–[38]. In all these cases signals were subtracted either from a reference taken in air, or in a few cases differentially connected coils [8], [10], [11], [33]. Coil based probes are less expensive to manufacture, and voltages measured across coils are easier to collect and process when compared to magnetic field measurements. Some drawbacks of coil based probes include the high precision required during coil manufacturing, which will be discussed in Section 3.1. When analysis is done in the time-domain, there are a number of key signal features used for inspections. Differential peak height and arrival time are the most common features used for interpreting PEC signals. Increasing surface flaw volume has been related to increasing peak heights [31], [33], [35], [36], [39]–[41]. For tube ferromagnetic inspections, peak amplitude has also been associated with ID variations [42]. Peak arrival time has been experimentally associated with flaw depth [34], [35], [37], [40]. For differential signals the zero-crossing time, defined as the first time the response signal changes sign from positive to negative, can be related to sample thickness [37], [42], [43]. The zero-crossing time can also be associated partially with flaw depth [33]. An experimentally derived feature called the lift-off intersection point (LOI), is a point on PEC response curves that is invariant to lift-off while varying other parameters such as plate thickness [38]. In the absence of lift-off variations, rising time, defined as the point in time at which the signal rises, has been related to sample thickness [36].

It is apparent from reviewing publications that there is no uniform analysis accepted for PEC, unlike the universally accepted impedance plane interpretation of ECT signals. To improve flaw detection and material inspections using PEC, further signal analysis is required. Some
research has been done investigating the rich frequency spectrum inherent in PEC response signals. The broadband nature of square waves provides a wealth of excitation frequencies, and therefore, examining fast Fourier transforms (FFTs) of PEC signals is a logical next step. Increases in fundamental frequency amplitudes have been attributed to surface defects [37]. Characteristic frequency of flaws has been related to their axial length, once depth has been established [34]. Reconstruction of flaw signals has been attempted using odd harmonics, where at least 10 are required, two of which must have a depth of penetration larger than expected flaw depth [41].

1.3.5 PCA Applied to PEC Signals

Principal components analysis (PCA) is a multivariate statistical signal processing technique that decomposes data into a few mutually orthogonal eigenvectors (the principal components) and associated weightings, called scores. This technique provides a mechanism for extracting the most important features, in a least squares sense, from the data. Through signal decomposition, the dimensionality of data is significantly reduced, and in general only a few (less than 5) eigenvectors and scores are required to represent the information. The modified PCA (MPCA) method, a variation of PCA in which signal means are not subtracted before analysis [8]–[11], will be explained in Section 2.2. MPCA has been applied to PEC signals for feature extraction primarily for aerospace applications, when inspecting for cracks with lift-off up to 2 cm [10], [11], and when searching for cracks in single [40], [44] and multilayer conducting structures [8], [31], [32], [45]. There are some instances of PCA being applied to conventional ECT signals [46]–[49]. A comparison of time-domain feature identification against PCA demonstrated overall flaw detection improvements of 4%, with the most significant improvement of 20% for the detection of sub-surface flaws [40]. Through a comparison between first and second PCA scores, clusters could be identified indicating first or second layer cracks, and if they were top or bottom of said layer in laboratory cases [31], [45]. The capability of reliably detecting
first and second layer flaws when air gaps were present between conducting layers has also been demonstrated [32]. A combination of MPCA and Mahalanobis Distance (MD) allowed for cracks to be reliably detected in CP-140 aluminum lap-joints [8]. Metal loss, surface defects, and subsurface defects were separable using three PCA scores for a 3 hall sensor surface probe [44]. Initial applications of MPCA to PEC data collected for SG inspection has shown promise at solving 2 inspection variables simultaneously [9]. The introduction of third and fourth inspection variables proved challenging when analysing MPCA scores, as relations between 4 or 5 scores were required for proper flaw identification.

1.3.6 Further Analysis Techniques

PCA is a powerful analysis tool for examining dominant features that affect measured signals. When more than 2 or 3 scores are required for adequate reconstructions, the constraint of eigenvector orthogonality can result in desired flaw information being spread over multiple eigenvectors. More in-depth analysis of PCA scores is therefore required, in these cases, to properly identify flaws. Multiple linear regression using a stepwise technique in MATLAB was considered to provide a deterministic model relating MPCA scores to hole size, tube position, and fret depth for SG tube support structure inspection with PEC [50]. Support vectors machines (SVMs), a machine learning method that can be utilized for classification, have been applied to PEC signals after PCA processing for crack identification in multilayer aluminum structures [31], [45]. The SVMs separated flaws into first and second layer cracks, and subsequently into top or bottom cracks for the given layer [31], [45]. Normalization of signals before PCA processing was examined to improve on previous SVM results in an attempt to create an automatic defect classification system [31]. Sophisticated regression tools, specifically artificial neural networks (ANNs) for deterministic regression to flaws, have been considered for both ECT and PEC applications.
Artificial neural networks are a class of parallel processing architecture inspired by the physiological structure of neurological systems such as the brain [51]. Each node in the network takes potentially multiple inputs from a previous layer and, through an activation function, produces a single output that branches to nodes in subsequent layers. Connections between layers have associated weights that are updated iteratively through training via error backpropagation that can be either online or by batch, depending on the type of problem. In this way, networks can “learn” to regress a set of input variables to desired outputs [51]. Neural networks have been employed for selecting polynomial fits, optimizing between fit quality and polynomial order, while dealing with potentially noisy input waveforms [52]. For ECT, crack profile reconstructions have been accomplished at a single frequency with aperture shifting, combining information from scans where \( k \) measurements are obtained at different locations scanning past a crack, and compressed with PCA before inverse mapping with a neural network [48].

This method decomposed the crack region into a regular grid with three layers, solving each cell to estimate the binary crack parameter (crack or no crack) [48]. Similar approaches have been taken for crack inversion of measured SG tube ECT signals using local conductivity as a gauge of crack presence instead of a simple binary-type output, as it was found that for conductive cracks, relative crack size had lesser effect on response amplitudes when compared to conductivity [53], [54]. Crack regions were decomposed into a grid structure, assigned conductivity between 0\% – 100\% of nominal conductivity. PCA was used to compress data before inversion with ANNs [53], [54]. Depth and width of surface cracks was estimated by training an ANN on PCA scores of simulated ECT response signals, and subsequently applying the ANN to experimentally obtained data both inside and outside the training set range [55]. It was observed that the ANN could generalize to inputs outside the training range, but accuracy was reduced, suggesting the need for a complete set of training data for desired flaw inspections [55]. An iterative approach for solving three parameters, crack length, width, and depth, was
accomplished by ANN regression of simulated ECT signals for conductive flat plates [56]. Length, solved by the first network, fed to a second network solving width, and both were input to a third network solving depth. Width and depth could not be resolved to the same precision as length [56]. ANN results were validated with experimentally obtained 5 kHz ECT signals of known flaws in an aluminum plate [56].

1.4 Objective

The objective of this thesis is to examine the performance of a PEC system in the simultaneous determination of SG tube and ferromagnetic support structure degradation modes. Flaws considered were flat-bottomed, rectangular fretting wear of 15.9 mm Alloy 800 tubes, and uniform corrosion of 410SS and carbon steel baffle plate SG tube support structures. Tube off-centering within support structure holes was also investigated as an indicator of SG health, and the effects of pseudo-magnetite sludge were briefly examined. An 8 element surface pickup coil array probe was used for the investigation and results were analysed with modified principal components analysis (MPCA), which was subsequently combined with multiple linear regression (MLR) and artificial neural networks (ANNs).

1.5 Scope, Methodology, and Structure

This thesis is structured in accordance with the manuscript style thesis format, and contains six chapters and four manuscripts. Chapter 2 provides an overview of relevant theory for understanding transient electromagnetic fields, details the modified PCA (MPCA) technique used to extract dominant signal features and compress information, explains multiple linear regression, and outlines the basics of ANNs for their application to this work.

Experimental technique is covered in Chapter 3, providing a detailed description of the PEC probe, Alloy 800 tube samples, simulated baffle plate support structures, and the apparatus in which all components were secured.
Four manuscripts are presented in Chapter 4. The first paper, *Pulsed Eddy Current Inspection of Support Structures in Steam Generators*, investigates the effects of tube frets and support structure location on PEC signals, separates fret depth from support hole ID variations, and 1D tube position for hole ID variations. In the second paper, *Regression Analysis of Pulsed Eddy Current Signals for Inspection of Steam Generator Tube Support Structures*, preliminary MLR models of PCA scores were obtained to determine 2D tube positions within various support structure hole IDs. The third manuscript, *Analysis of Pulsed Eddy Current Data using Regression Models for Steam Generator Tube Support Structure Inspection*, examines the complications encountered when attempting to generalize regression models to new data and when introducing a fourth variable, frets. It also identifies exploratory factor analysis as a method of pre-screening MPCA scores to improve regression model fits to validation data. Finally in the fourth paper, *Pulsed Eddy Current Inspection of Steam Generator Tube Support Structure using Artificial Neural Networks Analysis*, PEC signals are processed by PCA before being fed to ANNs for simultaneous determination of fret depth, hole ID, and 2D tube position. Improvement due to reduction to a 3 variable problem through the addition of fret information as an input is also examined.

A short discussion on the four manuscripts is contained in Chapter 5, which explains the progression of the work for this thesis. Overall conclusions are drawn in Chapter 6. Finally, some areas of future work are identified in Chapter 7, including further measurements that would be beneficial to the advancement of the project, and additional analysis techniques to be considered for PEC signals.
Chapter 2

Theory

In this section Maxwell’s equations will be examined as they pertain to ECT, followed by an electromagnetic-based explanation of the physical principles of PEC. Changes to Maxwell’s equations for electromagnetic phenomena in conductors will be presented along with a discussion of charge dissipation in good conductors. The primary feature extraction tool used in this thesis, MPCA, will be described and a derivation presented. MLRs models, exploratory factor analysis, and ANNs will be introduced as analysis techniques for examining MPCA scores.

2.1 Electromagnetic Theory

2.1.1 Maxwell’s Equations in matter

Maxwell’s four equations, outlined below, alongside the Lorentz force law, form the basis for understanding electromagnetic fields in matter [6]. Before delving into Maxwell’s equations, the charge density in matter is examined first. Total charge density $\rho$ can be separated in two parts [6]:

$$\rho = \rho_f + \rho_b,$$  \hspace{1cm} (2-1)

where $\rho_f$ is the free charge density, and $\rho_b$ is the bound charge density defined by [6]:

$$\rho_b = -\nabla \cdot \vec{P},$$  \hspace{1cm} (2-2)

where $\vec{P}$ is material polarization as occurs in dielectric materials. Gauss’s Law for fields in matter can now be written as [6]:

$$\nabla \cdot \vec{E} = \frac{1}{\varepsilon_0} \left( \rho_f - \nabla \cdot \vec{P} \right).$$  \hspace{1cm} (2-3)

Electric displacement $\vec{D}$ can be written in terms of electric field $\vec{E}$ and polarization as [6]:

$$\vec{D} = \varepsilon_0 \vec{E} + \vec{P},$$  \hspace{1cm} (2-4)
then equation (2-3) simplifies to:

\[ \nabla \cdot \mathbf{D} = \rho_f. \]  

(2-5)

This will be valid in a simple medium, that is, one that is linear, isotropic and homogeneous. A similar approach can be applied to the total current density \( \mathbf{j} \), which has three components [6]:

\[ \mathbf{j} = \mathbf{j}_f + \mathbf{j}_p + \mathbf{j}_b, \]  

(2-6)

where

\[ \mathbf{j}_p = \frac{\partial \mathbf{P}}{\partial t}, \]  

(2-7)

and

\[ \mathbf{j}_b = \nabla \times \mathbf{M}. \]  

(2-8)

\( \mathbf{j}_p \) is the polarization current stemming from the linear motion of charges due to changes in electric polarization, which is negligible for applications considered in this thesis, and \( \mathbf{j}_b \) is the bound current associated with material magnetization \( \mathbf{M} \). Equation (2-6) can now be expressed as:

\[ \mathbf{j} = \mathbf{j}_f + \frac{\partial \mathbf{P}}{\partial t} + \nabla \times \mathbf{M}. \]  

(2-9)

Ampère’s law with Maxwell’s correction term can be written with the full current density of equation (2-9) [6]:

\[ \nabla \times \mathbf{B} = \mu_0 \left( \mathbf{j}_f + \frac{\partial \mathbf{P}}{\partial t} + \nabla \times \mathbf{M} \right) + \mu_0 \varepsilon_0 \frac{\partial \mathbf{E}}{\partial t}, \]  

(2-10)

where \( \mu_0 \) and \( \varepsilon_0 \) are, respectively, the permeability and permittivity of free space, and \( \mathbf{B} \) is the magnetic flux density. Magnetic field strength \( \mathbf{H} \) can be defined as [6]:

\[ \mathbf{H} = \frac{1}{\mu_0} \mathbf{B} - \mathbf{M}, \]  

(2-11)

which can be used to re-express equation (2-10):

\[ \nabla \times \mathbf{H} = \mathbf{j}_f + \frac{\partial \mathbf{D}}{\partial t}. \]  

(2-12)

For linear media, it is found that [6]:

\[ \nabla \cdot \mathbf{H} = 0. \]  

(2-13)
\[ \vec{P} = \varepsilon_0 \chi_e \vec{E}, \quad (2-13) \]
\[ \vec{M} = \chi_m \vec{H}. \quad (2-14) \]

where \( \chi_e \) and \( \chi_m \) are electric and magnetic susceptibility, respectively. Equations (2-4) and (2-11) can be simplified to [6]:

\[ \vec{D} = \varepsilon \vec{E}, \quad (2-15) \]
\[ \vec{H} = \frac{1}{\mu} \vec{B}. \quad (2-16) \]

where \( \varepsilon \equiv \varepsilon_0 (1 + \chi_e) \) and \( \mu \equiv (1 + \chi_m) \) are the material electric permittivity and magnetic permeability, respectively. Materials under consideration in this thesis are assumed to be linear, isotropic, and homogenous media, that is to say they have uniform and non-varying \( \mu, \varepsilon, \) and \( \sigma \)-conductivity. When this assumption holds true, the current density can be written as a linear function of electric field [6]:

\[ \vec{j} = \sigma \vec{E}, \quad (2-17) \]

which is commonly called Ohm’s Law. For the good conductors considered in this thesis the approximation \( \varepsilon = \varepsilon_0 \) can be made [57].

Maxwell’s equations in matter can now be written in terms of electric and magnetic fields, inserting expressions for \( \vec{D} \) and \( \vec{H} \) defined by equations (2-15) and (2-16) into equations (2-5) and (2-12) yielding [6]:

\[ \nabla \cdot \vec{E} = \frac{\rho_f}{\varepsilon_0}, \quad (2-18) \]
\[ \nabla \cdot \vec{B} = 0, \quad (2-19) \]
\[ \nabla \times \vec{E} = -\frac{\partial \vec{B}}{\partial t}, \quad (2-20) \]
\[ \nabla \times \vec{B} = \mu \sigma \vec{E} + \mu \varepsilon_0 \frac{\partial \vec{E}}{\partial t}, \quad (2-21) \]
Three of Maxwell’s equations have distinct names stemming from their originators. Gauss’s Law is equation (2-18), Faraday’s Law is equation (2-20), and Ampere’s Law with Maxwell’s correction is equation (2-21). Equation (2-19) reflects the lack of magnetic monopoles in nature. Unlike electric charges (such as electrons) there has been no physical evidence supporting the existence of magnetic monopoles [6], a reality reflected by equation (2-19) that results in complete magnetic flux closure.

2.1.2 Electromagnetic fields in conductors

The Law of Conservation of Charge indicates that net charge cannot be created or destroyed. The flow of charges in a conductor is described by Ohm’s Law (equation (2-17)). The continuity equation is derived from Gauss’s Law and Ampere’s Law, combined with the Law of Conservation of Charge, and is expressed as [6]:

$$\nabla \cdot \mathbf{J} = -\frac{\partial \rho_f}{\partial t}. \quad (2-22)$$

Equation (2-22) states that the divergence of free currents is equal in magnitude and opposite in sign to the rate of change of free charge density. Combining equation (2-22) with (2-17) and (2-18) yields:

$$-\frac{\partial \rho_f}{\partial t} = \sigma (\nabla \cdot \mathbf{E}) = \frac{\sigma}{\varepsilon_0} \rho_f. \quad (2-23)$$

which has solutions of the form:

$$\rho_f(t) = \rho_{f_0} e^{-\frac{\sigma t}{\varepsilon_0}}, \quad (2-24)$$

where $\rho_{f_0} = \rho_f(t = 0)$. The above equation indicates that free charges dissipate through conductors with a relaxation time $\tau \equiv \frac{\varepsilon_0}{\sigma}$, which will be considered further in Section 2.1.4. For a perfect conductor, $\sigma \to \infty$ and therefore $\tau \to 0$, which is to say free charges are expelled to the surface instantly. In the case of a good conductor like copper, the relaxation time for free charge dissipation is at least on the order of the collision time, which in copper is $\tau \sim 2 \times 10^{-14} \text{s}$ [57],
and equation (2-24) can be approximated as $\rho_f(t) = 0$ for frequencies below the GHz range [57]. Inserting this back into equation (2-18) produces the result $\nabla \cdot \vec{E} = 0$ for a good conductor at frequencies below a GHz.

### 2.1.3 Diffusion Equation Approximation for Good Conductors

Some manipulation of Faraday’s law is required to expand our understanding of how electromagnetic fields diffuse through good conductors. Applying the curl operator to both sides of equation (2-20):

$$\nabla \times (\nabla \times \vec{E}) = -\nabla \times \frac{\partial \vec{B}}{\partial t}$$  \hspace{1cm} (2-25)

allows for the use of the following vector identity [6]:

$$\nabla \times (\nabla \times \vec{A}) = \nabla (\nabla \cdot \vec{A}) - \nabla^2 \vec{A}$$  \hspace{1cm} (2-26)

where $\vec{A}$ is an arbitrary vector. Equation (2-25) can be expressed using equation (2-26) as:

$$\nabla (\nabla \cdot \vec{E}) - \nabla^2 \vec{E} = -\frac{\partial}{\partial t} (\nabla \times \vec{B})$$  \hspace{1cm} (2-27)

As identified in Section 2.1.2, for good conductors the approximation $\nabla \cdot \vec{E} = 0$ can be made and equation (2-27) simplifies to:

$$\nabla^2 \vec{E} = \frac{\partial}{\partial t} (\nabla \times \vec{B}).$$  \hspace{1cm} (2-28)

Equation (2-28) is now ready to be combined with equation (2-21) to write everything in terms of a unique vector field:

$$\nabla^2 \vec{E} = \mu \sigma \frac{\partial \vec{E}}{\partial t} + \mu \epsilon \frac{\partial^2 \vec{E}}{\partial t^2},$$  \hspace{1cm} (2-29)

which is called Maxwell’s modified wave equation. A similar expression can be derived for magnetic fields [6]:

$$\nabla^2 \vec{B} = \mu \sigma \frac{\partial \vec{B}}{\partial t} + \mu \epsilon \frac{\partial^2 \vec{B}}{\partial t^2}.$$  \hspace{1cm} (2-30)
Given a time harmonic field, the time derivative terms on the right hand side of equations (2-29) and (2-30) have coefficients proportional to $\sigma \omega$ and $\varepsilon \omega^2$ for the first and second terms, respectively. Here $\omega$ is defined as the angular frequency of the time harmonic field. The conductivity of copper is $\sigma = 5.8 \times 10^7 \, S/m$, and for a typical good conductor $\varepsilon = \varepsilon_0$, so before frequency is taken into account the first coefficient is $\sim 10^{19}$ larger than the second. For frequencies below $10^9 \, Hz$, the second terms of equations (2-29) and (2-30) are $\sim 10^{-10}$ smaller, and can be neglected, reducing the equations to:

$$\nabla^2 \vec{E} = \mu \sigma \frac{\partial \vec{E}}{\partial t}, \quad (2-31)$$

$$\nabla^2 \vec{B} = \mu \sigma \frac{\partial \vec{B}}{\partial t}, \quad (2-32)$$

which are similar in form to the well-known thermal diffusion equation.

2.1.4 Charge Dissipation in Good Conductors

The approach to steady-state condition in a good conductor when subjected to electromagnetic fields follows a three step process [57]. Free charges are first expelled to the surface. Following this, electric and magnetic fields are expelled from the volume. Finally surface currents and wave fields are damped. As discussed in Section 2.1.2 the first step of this process occurs very rapidly, and so the overall approach to equilibrium is dominated by the second and third steps. A few approximations are required to obtain a more physical interpretation of relaxation time for fields diffusing in good conductors. The left and right terms of equation (2-32) can be approximately estimated as [2]:

$$\nabla^2 \vec{B} \sim \frac{\vec{B}}{\ell^2}, \quad (2-33)$$

$$\frac{\partial \vec{B}}{\partial t} \sim \frac{\vec{B}}{\tau_D}, \quad (2-34)$$
where $\tau_D$ is the characteristic diffusion time, and $\ell$ is a characteristic length of the physical system. Combining equations (2-32) with (2-33), (2-32), and (2-34) yields a solution form to the diffusion equation:

$$\vec{B} = f \left( e^{-t/\tau_D} \right),$$  \hspace{1cm} (2-35)

where the characteristic diffusion time is given as [57], [58]:

$$\tau_D \sim \mu \sigma \ell^2.$$  \hspace{1cm} (2-36)

This expression for diffusion time of electromagnetic fields in good conductors is dependent on physical parameters that allow for an intuitive understanding of the effect. Increasing conductivity allows charges to move more freely, reducing the damping of the system, while a larger conducting volume requires more time for currents to decay. Differences in diffusion times between materials under investigation in this thesis have been linked to improved feature separation, and are discussed in Manuscript 1 [9].

### 2.1.5 Eddy Current Generation

Eddy currents are generated in conducting materials through electromagnetic induction. A changing magnetic field induces an electric field or electromotive force (emf) in surrounding conducting materials. Writing Faraday’s Law (equation (2-20)) in integral form gives an expression for the emf [1]:

$$\varepsilon = \oint \vec{E} \cdot d\vec{l} = - \int \frac{d\Phi}{dt} \cdot d\vec{a}$$  \hspace{1cm} (2-37)

where $\varepsilon$ is the emf. Integrals of equation (2-37) are over a closed loop or enclosed area, respectively. Magnetic flux $\Phi$ can be related to magnetic fields by the area integral:

$$\Phi = \int \vec{B} \cdot d\vec{a}$$  \hspace{1cm} (2-38)

Equation (2-37) can be simplified by incorporating the description of magnetic flux [1]:

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Faraday’s Law can be succinctly expressed by equation (2-39), which in addition to Lenz’s law [1], states that an emf will be induced having a polarity required to oppose any changes in magnetic flux. With regards to eddy current NDT, currents are generated in conducting materials through application of external magnetic fields, which in turn produce their own fields and interact with sensing tools, such as pick-up coils. In this thesis information is gleaned through analysis of induced currents or voltages in sensing coils resulting from the interaction of the driving and eddy current fields.

2.1.6 Simple Circuit Approximation

Pulsed eddy current testing involves the abrupt application of an emf to an excitation coil, generally taking the form of a voltage step function. Near-instantaneous change in emf causes current to flow in the coil, rising exponentially at a rate limited primarily by the resistance and the self-inductance of the coil. The single coil problem can be expressed by a simple series RL circuit with a DC supply and timed switch to cause instantaneous current changes, as shown in Figure 2.

\[
\varepsilon = -\frac{d\Phi}{dt}
\]  

(2-39)

Figure 2  RL circuit example representing a single coil with voltage \(V_0\) instantaneously applied at time \(t=0\)

For \(t \geq 0\), solving the circuit using Kirchoff’s Voltage Law (KVL) the following differential equation is obtained [1]:

...
\[ V_0 - iR - L \frac{di}{dt} = 0, \quad (2-40) \]

where \( R \) and \( L \) are the DC resistance and self-inductance of the coil, \( V_0 \) the DC source voltage, and \( i \) the current flowing through the circuit. When the switch is closed (current allowed to flow) at \( t = 0 \) a solution to equation 2.28 can be obtained as [1]:

\[ i(t) = \frac{V_0}{R} \left( 1 - e^{-\frac{R}{L}t} \right). \quad (2-41) \]

At \( t = 0 \) there is a very sharp rise in current, a rising rate that decays according to \( R/L \) as described by equation (2-40). Current increases until reaching a steady state value determined by \( V_0/R \), which is the DC current. The simple expression of driving current has been plotted in Figure 2Figure 3 by inserting parameters of the PEC probe manufactured for this thesis, which will be detailed in Section 3.1.

\[ \text{Figure 3 Drive coil current response as a function of time approaching steady state value, } V_0/R, \text{ for a simple 3 V step function.} \]

To model induced currents in secondary pickup coils the simple circuit model must be expanded to include a second coil mutually coupled to the first. To differentiate parameters of the two coils, the drive coil resistance, inductance, and current will have subscripts \( d \), whereas for the pickup coil they will have subscripts \( p \). In this coupled system the mutual inductance is denoted
by $M$. A circuit representation of the two coils, in which the drive loop is connected to the voltage source, is shown in Figure 4.

![Circuit Diagram](image)

**Figure 4 Coupled RL circuits representing drive and pickup coils**

Applying KVL to both loops the following coupled differential equations are obtained \[4\]:

\[
i_d R_d + L_d \frac{di_d}{dt} = M \frac{\partial i_p}{\partial t} + V_0 U(t), \quad (2-42)
\]

\[
i_p R_p + L_p \frac{di_p}{dt} = M \frac{\partial i_d}{\partial t}, \quad (2-43)
\]

where $U(t)$ is a heavyside step function. Pickup coil current $i_p$ can be solved by applying a Laplace transformation to Equations (2-42) and (2-43) \[59\]:

\[
i_p(t) = \frac{MV_0(e^{-\alpha_2 t} - e^{-\alpha_1 t})}{(\alpha_1 - \alpha_2)(L_d L_p - M^2)}, \quad (2-44)
\]

where the coefficients $\alpha_1$ and $\alpha_2$ are \[59\]:

\[
\alpha_1, \alpha_2 = \frac{(L_d R_p + L_p R_d) \pm \sqrt{(L_d R_p + L_p R_d)^2 - 4R_d R_p (L_d L_p - M^2)}}{2(L_d L_p - M^2)}. \quad (2-45)
\]

Current induced in the secondary loop pickup coil in this work, shown in Figure 5, is on the order of $\text{mA}$. Pickup coils have resistances on the order of $30 \, \Omega$, which results in measured voltages in
the \( mV \) range and requires amplification before analysis. Relatively small induced currents, compared to the driving current, are the result of weak mutual coupling between drive and pickup coils for the probe geometry used in this thesis.

Drive and pick-up coils were mounted with mutually orthogonal orientation and spatial separations. Probe coil arrangements are discussed in Section 3.1. This simplified circuit representation is an adequate approximation for transient current response due to step function excitation, but it does not address the true system in which there are additional coupling effects associated with the conducting sample. Graphically, this could be illustrated through the addition in Figure 4 of a third loop with mutual inductance terms linking each loop independently. This complex mutual inductance problem was not solved for in this thesis work, although complete solutions are possible in many situations [27], [29], [30].

![Figure 5](image)

**Figure 5** Current in pickup coil calculated from experimental parameters.

### 2.2 Principal Components Analysis

As discussed in Section 1.2, PCA is a statistical feature extraction method that reduces dimensionality of multivariate data by expressing it as a linear combination of vectors and associated coefficients. By compressing data with PCA, patterns in dominant features caused by raw signal variations are more easily identified.
2.2.1 Modified PCA Procedure

The purpose of PCA is to re-express multivariate data in a manner that reorients it such that the first few dimensions account for the most information possible. In a modified PCA, the mean is not subtracted from data before processing [10], and selection of representative basis vectors is a least-squares minimization process. Multiple PEC measurements can be represented by a \((n \times p)\) matrix \(\vec{Y}\) composed of \(p\) column vectors, \(\vec{Y}_i\), of length \(n\) representing a single measurement. The goal of PCA is to determine a vector \(\vec{V}\) that does the best job of representing \(\vec{Y}_i\). A vector \(\vec{U}_i\) can be used to approximate \(\vec{Y}_i\), and takes the form [10], [60]:

\[
\vec{U}_i = s_i \vec{V}
\]  

(2-46)

where the \(s_i\) is called the principal component score of \(\vec{Y}_i\), and must be calculated. The vector \(\vec{V}\) is chosen such that the sum squared residuals (SSR) between \(\vec{Y}_i\) and \(\vec{U}_i\) is minimized [10]:

\[
SSR = \sum_{j=1}^{n} \sum_{i=1}^{p} (\vec{Y}_{ji} - \vec{U}_{ji})^2 = \sum_{j=1}^{n} \sum_{i=1}^{p} (\vec{V}_{ji})^2 - 2 \sum_{j=1}^{n} \sum_{i=1}^{p} \vec{V}_{ji} \vec{V}_i \vec{V}_j + \sum_{j=1}^{n} \sum_{i=1}^{p} s_i^2 \vec{V}_j^2. 
\]  

(2-47)

In order to make \(\vec{V}\) unique, it is assumed that \(\vec{V}\) is normalized:

\[
\sum_{j=1}^{n} \vec{V}_j \vec{V}_j = \vec{V}^T \vec{V} = 1.
\]  

(2-48)

The principal component score of equation (2-46) can be obtained through the dot product of \(\vec{Y}_i\) and \(\vec{V}\):

\[
s_i = \sum_{j=1}^{n} \vec{V}_{ji} \cdot \vec{V}_j, 
\]  

(2-49)

which can be expressed as:

\[
s_i = (\vec{Y}_i^T \vec{V}). 
\]  

(2-50)

Equation (2-49) can be substituted into the middle term of equation (2-47) and summed over \(j\), simplifying it thus:
Recognizing that equation (2-51) can be further reduced by applying the normalization of equation (2-48) to the final term, SSR can be expressed as:

\[
SSR = \sum_{j=1}^{n} \sum_{i=1}^{p} (\mathbf{v}_{ji})^2 - 2 \sum_{i=1}^{p} s_i^2 + \sum_{j=1}^{n} \sum_{i=1}^{p} s_i^2 \mathbf{v}_{ji}^2.
\] (2-52)

It is evident by looking at equation (2-52) that to minimize the SSR given a data matrix \( \mathbf{Y} \), the principal component scores \( s_i \) must be maximized. Further application of equations (2-48) and (2-50) allows for an expression of PCA scores as:

\[
\sum_{i=1}^{p} s_i^2 = \mathbf{s}^T \mathbf{s} = (\mathbf{V}^T \mathbf{Y})(\mathbf{V}^T \mathbf{V}).
\] (2-53)

The problem of determining appropriate \( \mathbf{V} \) and associated scores is one of optimization that can be solved by forming the Lagrangian of equation (2-53) [60]:

\[
\Lambda = (\mathbf{V}^T \mathbf{Y})(\mathbf{V}^T \mathbf{V}) - \lambda (\mathbf{V}^T \mathbf{V} - 1),
\] (2-54)

where \( \lambda \) are Lagrange multipliers. Equation (2-54) can be minimized by taking the derivative with respect to \( \mathbf{V} \) and setting the result equal to zero [60]:

\[
\frac{d\Lambda}{d\mathbf{V}} = 2 \mathbf{V}^T \mathbf{Y} \mathbf{T} - 2 \lambda \mathbf{V} = 0,
\] (2-55)

which reduces to a standard eigenvector decomposition of \( \mathbf{Y} \mathbf{Y}^T \):

\[
\mathbf{Y} \mathbf{Y}^T \mathbf{V} = \lambda \mathbf{V}.
\] (2-56)

This demonstrates that, in a least squares sense, eigenvectors of \( \mathbf{Y} \mathbf{Y}^T \) offer the best representation of the column vectors of \( \mathbf{Y} \). It can be shown that eigenvalues of equation (2-56) correspond to the square of the desired PCA scores. The eigenvector with the largest eigenvalue will do the best job of reconstructing \( \mathbf{Y} \). Similarly, the eigenvector with second largest eigenvalue does the best job of representing residuals \( \mathbf{V} \), once the previous eigenvector has been subtracted, deflating the data as:
This procedure can be repeated until a set of \( m \) vectors are produced. These \( m \) vectors and associated scores will do the best possible job, in a least squares sense, of representing \( \bar{Y} \) [10], [60]. The resulting eigenvectors are uncorrelated, and only a few are required to capture most of the information contained in \( \bar{Y} \). As indicated earlier, the signal average is normally subtracted from the data matrix \( \bar{Y} \) before processing with PCA. The modified PCA presented in this thesis [10] has been shown to reduce sensitivity to small changes in scale due to variations in probe parameters or amplification system, thereby enhancing robustness of the analysis when considering other experimental apparatus.

2.2.2 PCA Signal Reconstruction and Data Compression

The primary benefits of PCA are feature extraction and data compression. In this thesis, through the use the first five MPCA eigenvectors and associated scores, data can be reproduced with an average reconstruction accuracy of 99.9\%, calculated from mean squared errors of the waveforms. High reproduction accuracy through the use of only five scores and associated eigenvectors illustrates the data compression with MPCA. An example signal reconstruction using 3 MPCA vectors and scores is shown in Figure 6, where the first curve is amplified experimental data, the second a reproduction using a single vector, and the third a reconstruction with all three vectors. Eigenvectors for this reproduction are shown in the inset of Figure 6. By contrast with MPCA, attempting to analyse PEC responses with Fourier transforms results in well over 50 non-negligible coefficients for similar reconstruction accuracy, reinforcing the dimensionality reduction possible with MPCA. When fewer than three MPCA scores are required for adequate data reconstruction, additional post processing is not usually required, as it is not exceedingly difficult to produce 3 dimensional plots to examine their relations to physical measurements. However once reconstructions retain four or more MPCA scores it becomes complicated and tedious to examine relation and cross-correlations of scores with measurements,
and therefore, additional data processing techniques, specifically multiple linear regression (MLR) and artificial neural networks (ANNs), have been examined for this thesis.

![Example MPCA reconstruction](image)

**Figure 6** Example MPCA reconstruction of a PEC response by 3 eigenvectors and associated scores demonstrating the reproduction quality of MPCA. Inset figure illustrates eigenvectors used for reconstruction.

### 2.3 Multiple Linear Regression

Regression is a widely used technique for the analysis of a data sets, since it can help establish a clear relation between sets of one or multiple independent variables ($X$'s) and a dependent variable $Y$. A regression model is a linear combination of independent variables that corresponds closely to the dependent variable. In general, regression analysis is employed to describe the relationship between $X$'s and a $Y$, inferring the statistical significance of each independent variable of the model, and examining predictive capabilities to observations made.
outside the sample data. Regression models can be formally stated for a set of \( n \) independent variables as [60]:

\[
y_t = \epsilon_i + b_0 + \sum_{j=1}^{n} b_j x_{ij},
\]

(2-58)

where \( y_t \) refers to a single data point of the dependent variable \( x_t \). \( \epsilon_i \) is an unobserved error term and \( b_j \) are the regression coefficients (with \( b_0 \) as a constant offset). The \( j \) index refers to a particular independent variable, and \( i \) indexes the point within a given column vector. Equation (2-58) can be compressed in matrix form as follow [60]:

\[
\hat{y} = \hat{X} \hat{b} + \hat{\epsilon},
\]

(2-59)

where \( \hat{X} \) is the matrix of independent variables with an additional column of 1s to capture the constant term \( b_0 \), and \( \hat{y} \), \( \hat{b} \), and \( \hat{\epsilon} \) are vectors of the dependent variable, regression coefficients, and unobserved error, respectively. Values for \( \hat{b} \) are chosen to minimize the sum square deviations of modeled values \( \hat{X} \hat{b} \) and actual values \( \hat{y} \). Parameter estimates \( \hat{b} \) of the coefficients of equation (2-59) are given by [60]:

\[
\hat{b} = \left( \hat{X}^T \hat{X} \right)^{-1} \hat{X}^T \hat{y}.
\]

(2-60)

Using the estimates provided by equation (2-60), fitted values \( \hat{y} \) can be determined [60]:

\[
\hat{y} = \hat{X} \hat{b},
\]

(2-61)

and residuals between the dependent variable \( \hat{y} \) and fitted values \( \hat{y} \) can be calculated:

\[
\hat{\epsilon} = \hat{y} - \hat{\hat{y}}.
\]

(2-62)

Multiple linear regression, specifically the \textit{stepwiselm} function in MATLAB, was utilized in this thesis to relate PEC responses to corresponding measurements [61]. The calculated PCA scores were selected to be independent variables for the regression models. By combining regression with PCA the dominant signal features could be employed in models, reducing their complexity
and computation time significantly. This was examined in practice in Manuscripts 2 and 3 [50], [62].

2.4 Exploratory Factor Analysis

Factor analysis is a method for investigating whether a set of observed measurements are related to a smaller number of unobserved hidden variables, called factors. The factors are not measured, and are hypothetical constructs used to represent the variables. Factor analysis has its roots in psychology, with Charles Spearman’s development of the Two-Factor Theory, where he examined factors affecting human abilities by testing how well subjects performed on various tasks pertaining to intelligence [63]. Given a set of $p$ measurement variables, it is assumed they can be described by $m$ hidden factors, along with a unique factor. In this manner, the $j^{th}$ measurement variable can be expressed by the linear combination [64]:

$$X_j = a_{j1}F_1 + a_{j2}F_2 + \cdots + a_{jm}F_m + e_j,$$

(2-63)

where $X_j$ is the measured variable, $F_m$ and $a_{jm}$ are the latent factor and factor loadings, and $e_j$ is the unique factor for the $j^{th}$ variable. Factor loadings represent the strength of correlation between the variable to that particular factor. In matrix notation, factor analysis can be expressed as [64]:

$$R - \bar{U}^2 = \bar{\Lambda} \bar{\Lambda}^T,$$

(2.64)

where $R$ is the correlation matrix of measured variables, $\bar{U}^2$ is the diagonal matrix of unique variances, or specific error variance, of each variable, and $\bar{\Lambda}$ is the matrix of factor loadings. When the unique variances are subtracted from the correlation matrix, what remains is the common variance. Factor analysis is a method of dimensionality reduction that has similarities to PCA. In PCA, the diagonal elements of correlation matrices, the self-correlation of a variable (1’s), are used for the analysis. Factor analysis replaces the diagonal elements of the matrix with prior communality estimates, which are the sum-square of the factor loadings that are adjusted
iteratively during model construction [65]. Communality is the amount of correlation that is free of specific error variance, and is common to other variables. In PCA, principal components are mutually orthogonal constructs that attempt to describe the maximum variance in the data sequentially. In contrast, factor analysis relies on optimization procedures to produce linear combinations of factors that maximize the shared portion of the variance, which is to say there is not a unique solution in factor analysis.

Taking an example from psychology, factor analysis has been applied to investigate student test scores for paragraph comprehension, sentence completion, word meaning, addition, and dot counting [65]. If a single factor model was chosen, calling it “general intelligence”, loadings associated with the five variables could be construed as a measure of students overall intelligence. A two factor model, however, could provide more insight to specific types of intelligence. If the first three variables had high loadings on a first factor, and the final two variables had high loadings on the second factor, it could be stated that the factors represented “verbal aptitude” and “quantitative aptitude” respectively [65]. Factor loadings can be obtained by solving the eigenvalues and eigenvectors of equation (2.64). MATLAB fits the factor analysis model using a maximum likelihood estimate (MLE) to determine loadings and specific variances, given a data set and number of latent factors for the model [66]. Factor analysis is invariant under orthogonal rotation [65]. The goal of applying rotation to the correlation matrix is to maximize loadings of variables to a single factor if possible. While variance described by each factor changes after rotation, the overall variance described by the factor model remains unchanged. The MATLAB algorithm also applies varimax rotation to maximize loading magnitudes between 0 and 1 [65], [66]. Exploratory factor analysis was used to refine MPCA score selections for regression models in Manuscript 3 [62].
2.5 Artificial Neural Networks

2.5.1 Artificial Neural Network Basics

Artificial neural networks (ANNs) exploit interconnectivity of processing elements, conventionally called neurons or nodes, to address potentially complex pattern recognition problems [51], [67]. It is improper to think of each node of the network as a direct analog of biological neurons, and it is better instead to imagine them as the collective activity of a group of biological neurons. Similar to biological neurons, each node has potentially many inputs, producing a single output which can branch to many other nodes in the network. The input that the \( \text{i}^{\text{th}} \) node of the network receives from the \( \text{j}^{\text{th}} \) node is denoted \( x_j \), and the output of the \( \text{i}^{\text{th}} \) node is denoted \( x_i \). Each input \( x_j \) to the \( \text{i}^{\text{th}} \) node has an associated weight or connection strength, represented by \( w_{ij} \). These connection strengths are analogous to the firing frequency of biological neurons, indicating relative strength of synaptic connections [51], [67]. Inputs for neurons considered for this thesis can be either excitatory or inhibitory, that is positive or negative outputs of neurons in the previous layer. With respect to weights, \( w_{ij} \), positive values correspond to excitatory connections whereas negative values are inhibitory. Each node produces a net input value \( \text{net}_i \) that is based on the outputs and weights of all of its input connections. This can typically be represented by a sum-product of input values and associated weights, expressed as [51]:

\[
\text{net}_i = \sum_{j=1}^{n} w_{ij} x_j \tag{2-63}
\]

where \( n \) is the total number of input connections to the \( i \)th node. Once the \( \text{net}_i \) has been calculated according to equation (2-63), the output of the \( i^{\text{th}} \) node can be determined by applying an output function [51]:

\[
x_i = f_i(\text{net}_i), \tag{2-64}
\]
where \( f_i \) is called the output function or activation function. The network is a dynamical system i.e. a system that evolves over time. In this context, for ANNs, the learning process can be understood as an updating of connection weight values. A system of differential equations for the weighting values can be written as

\[
\dot{w}_{ij} = G_i (w_{ij}, x_i, x_j, ...),
\]

(2-65)

where \( G_i \) represent the learning law of the network, such as backpropagation or Hebbian learning [51]. The learning process involves finding weights representative of the pattern the network is supposed to learn. In general, a closed-form solution to this system of equations is difficult to obtain, although techniques such as back-propagation [51], discussed in Section 2.5.3, permit acceptable approximations to be acquired.

2.5.2 Activation Functions

Two activation functions are employed for ANNs created for this thesis using the neural network pattern recognition package in MATLAB [68]. The first type is employed in hidden layer neurons, which use a sigmoid activation function. This activation function can be written as [51]:

\[
f_i(\text{net}_i) = (1 + e^{-\text{net}_i})^{-1}.
\]

(2-66)

This converts the multiple inputs to the node into output values that branch to nodes in the output layer. The second type of activation function, associated with output layer nodes, is a simple linear activation function [51]:

\[
f_i(\text{net}_i) = \text{net}_i,
\]

(2-67)

which is to say the output value of output layer nodes is directly fed forward in the network. In the two layer network under consideration, equation (2-67) indicates the final computation stage before total ANN outputs are reported to the user. Updates to output layer weights are straightforward, since during network training there are definite target values with which to compare values calculated by the ANN. The process for selecting hidden layer node weights is
less evident, as there is no way of knowing in advance what the correct outputs of these units should be [51].

2.5.3 Backpropagation

Backpropagation is a method through which error between network output values and target values is transmitted back through the network to each node in intermediate layers that contribute to the outputs [51]. Each node of intermediate layers receives a fraction of the total error, proportional to the contributions of that particular unit to the total output. Based on the error signal received by each node, weights are then updated accordingly, to cause the network to converge towards the targets. In this manner, ANNs can be trained to encode desired patterns of data. Different nodes organize themselves through this method to recognize different features of the entire input space [51]. Once training is complete, different nodes in hidden layers will respond with active outputs if they recognize patterns that resemble those upon which they were trained. Conversely if no features are identified, hidden layer neurons will inhibit their outputs. By this process reasonable outputs can be produced from noisy or partially complete patterns.

The backpropagation algorithm used for ANNs in Manuscript 4 [69] of this thesis is the Levenberg-Marquardt algorithm [70]. It is a damped least-squares minimization method, and is a powerful tool for providing iterative solutions to nonlinear problems [70]. It is a process that interpolates between ordinary least-squares methods and steepest-descent methods. The purpose of employing such an algorithm is to determine global minima of error surfaces associated with the network being trained. Levenberg-Marquardt backpropagation has proven to be less sensitive to local-minima than simple gradient-descent searches [70].
Chapter 3
Experimental Technique

3.1 Probe Design and Manufacturing

The PEC probe was designed by the NDT group at RMC [71]. The probe used for this thesis, as described in Manuscripts 1, 2, 3, and 4, [9], [50], [62], [69], was constructed by Joe Renaud at CNL as in-kind contribution to the project. The probe was 77.6 cm in length, with an OD of 13.5 mm. A photo is shown in Figure 7. A clear, smooth epoxy layer coated the probe body in order to maintain coil integrity, while measurements were being obtained. The central drive coil was wound with 127 turns of 36 AWG wire, coaxial with the probe body, with parameters located in Table 1. Sensing (pickup) coils were divided into two groups of 4, in front and behind the drive coil positioned at 90° intervals around the probe, with axes orthogonal to the drive coil as presented in the schematic of the probe in Figure 8. For spatial reference, each coil was assigned a number as indicated in Figure 8. Surface pickup coils were pancake coils, i.e. thin in the vertical direction. Additionally they had a slight curvature that followed the contour of the probe body. They were wound with 360 turns of 42 AWG wire, with measured parameters as shown in Table 2. Thinner gauge wires of drive and pickup coils were soldered to more robust 28 AWG wires at the probe head, which in turn were soldered to a standard male 41 pin ECT connector. The cable length between probe body and connector was 3 m to simulate some of the issues introduced by long cables (up to 30 m for in-reactor inspections), such as increased noise and loss of signal strength. For reactor inspections cable lengths up to 30 m could be required. Cables were protected by a malleable, but relatively hard, plastic.
Figure 7  Photograph of PEC probe manufactured at CNL.

Figure 8  Simplified "unrolled" schematic of pickup coil arrangements and numbering. Dots reflect markings on the probe and were used as reference points.

Table 1  Drive coil electrical parameters as measured by BK Precision 879 LCR meter.

<table>
<thead>
<tr>
<th>Resistance (Ω)</th>
<th>Inductance (µH)</th>
</tr>
</thead>
<tbody>
<tr>
<td>±0.1Ω</td>
<td>±0.1µH</td>
</tr>
<tr>
<td>9.0</td>
<td>179.2</td>
</tr>
</tbody>
</table>
Table 2  Pickup coil electrical parameters as measured by a BK Precision 879 LCR meter.

<table>
<thead>
<tr>
<th>Coil Number</th>
<th>Resistance (Ω) ± 0.1Ω</th>
<th>Inductance (μH) ± 0.1μH</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>26.7</td>
<td>259.2</td>
</tr>
<tr>
<td>2</td>
<td>27.0</td>
<td>260.7</td>
</tr>
<tr>
<td>3</td>
<td>26.2</td>
<td>249.5</td>
</tr>
<tr>
<td>4</td>
<td>26.2</td>
<td>249.8</td>
</tr>
<tr>
<td>5</td>
<td>26.2</td>
<td>249.2</td>
</tr>
<tr>
<td>6</td>
<td>26.5</td>
<td>254.4</td>
</tr>
<tr>
<td>7</td>
<td>26.0</td>
<td>246.7</td>
</tr>
<tr>
<td>8</td>
<td>25.9</td>
<td>247.6</td>
</tr>
</tbody>
</table>

3.2 Alloy 800 Tube Samples

Two Alloy 800 tubes were used to represent SG tubes for this thesis. The first tube, shown in Figure 9, was 46.1 cm long and had an OD of 15.9 mm and wall thickness of 1.2 mm. This tube represented as manufactured and installed SG tubes. The second Alloy-800 tube, shown in Figure 10, was similar to the first in dimensions, but had a series of 5 consecutive 25.4 mm long rectangular, flat-bottom machined frets. While not truly representative of fretting degradation of tubes pulled from SGs, these frets were useful for investigating basic effects of wall loss. Measured dimensions, and positions relative to the tube inlet, identified by the taped end in Figure 10, are indicated in Table 3. Depth of frets was determined by measuring the tube OD at the center of the fret, and subtracting it from tube OD measurements at either end of the fret. All tube dimension measurements were performed with digital readout callipers.
Alloy 800 has a resistivity $\rho = 97.8 \mu \Omega \cdot cm$, measured at 22.7 °C by a four point of contact method, and relative magnetic permeability $\mu_r = 1.0006$ [72], resulting in $\mu \sigma = 1.0 \times 10^6 S/m^2$. As indicated by (2-36), diffusion time of electromagnetic fields is proportional to $\mu \sigma$, and this value will be compared to that of ferromagnetic support structures in Section 3.3.
3.3 Simulated Support Structures

In order to simulate ferromagnetic drilled baffle plate SG support structures, two sets of four cylindrical samples were manufactured. Carbon steel and 410SS were selected for this thesis as they are the primary materials with which nuclear SG tube support structures are made. Many SG support structures are made of carbon steel [73], [74]. While carbon steel has less desirable physical properties, specifically, reduced corrosion resistance, it does not activate in the presence of radiation fields, and so is more commonly used in nuclear environments. Each sample was initially a 32 mm OD cylinder, machined from 25.4 mm thick sheets of 410SS and general purpose low-carbon steel. Holes were water-jetted through the center of each cylinder, with IDs measured with calipers, indicated in Table 4 and Table 5 for 410SS and carbon steel, respectively. These samples will be referred to as collars for the remainder of this thesis. Radial gaps were calculated by subtracting Alloy 800 tube OD from measured hole ID. The tight fit of collar 1, representing as installed support structures, was not used for measurements as meaningful tube off-centering was not possible. 410SS collars were used in Manuscripts 1, 2, and 3 [9], [50], [62].

<table>
<thead>
<tr>
<th>Collar Number</th>
<th>Hole ID (mm) ±0.1 mm</th>
<th>Radial Gap (mm) ±0.1 mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>16.5</td>
<td>0.3</td>
</tr>
<tr>
<td>2</td>
<td>17.0</td>
<td>0.6</td>
</tr>
<tr>
<td>3</td>
<td>18.8</td>
<td>1.5</td>
</tr>
<tr>
<td>4</td>
<td>20.3</td>
<td>2.2</td>
</tr>
<tr>
<td>5</td>
<td>21.8</td>
<td>3.0</td>
</tr>
</tbody>
</table>

Carbon steel collars were manufactured with slightly different ID values than 410SS collars. A slight tapering was observed in the 410SS collars due to the water-jetting procedure.
Results of Manuscript 1 were found to be invariant to this effect as measurements were taken primarily at the center of the collars. To ensure future measurements would not be affected, an additional step was performed during the manufacturing process for the carbon steel collars. Holes were water-jetted at a slightly reduced ID, and subsequently machined until circular with drill bits of appropriate dimensions. As a result of this process, hole IDs for carbon steel collars were incremented by 1.59 mm (1/16”), as shown in Table 5 in accordance with availability of drill bit sizes. Carbon steel collars were used in Manuscript 4 [69].

Table 5 Hole ID measured with digital readout calipers, and radial gap with centered Alloy 800 tube, for carbon steel collars. Higher precision measurements attributed to uniformity introduced by additional machining.

<table>
<thead>
<tr>
<th>Collar Number</th>
<th>Hole ID (mm)</th>
<th>Radial Gap (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>±0.05 mm</td>
<td>±0.05 mm</td>
</tr>
<tr>
<td>1</td>
<td>16.50</td>
<td>0.3</td>
</tr>
<tr>
<td>2</td>
<td>17.48</td>
<td>0.79</td>
</tr>
<tr>
<td>3</td>
<td>19.05</td>
<td>1.58</td>
</tr>
<tr>
<td>4</td>
<td>20.65</td>
<td>2.38</td>
</tr>
<tr>
<td>5</td>
<td>22.22</td>
<td>3.16</td>
</tr>
</tbody>
</table>

410SS values for $\mu\sigma$ were taken as a range from $\mu\sigma = 1.2 \times 10^9 \, S/m^2$ to $\mu\sigma = 1.8 \times 10^9 \, S/m^2$ determined from [75], [76]. Carbon steel is characterized by a range from $\mu\sigma = 3 \times 10^9 \, S/m^2$ to $\mu\sigma = 7 \times 10^9 \, S/m^2$ [76], [77]. When comparing diffusion times according to equation (2-36), electromagnetic fields take $\sim10^3$ times longer to decay in the ferromagnetic steels when compared to Alloy 800. Consequences of this will be examined in Manuscript 1 [9].
3.4 Experimental Apparatus

A custom apparatus was designed and created for this thesis by Dr. P. R. Underhill. The bulk of the apparatus was machined aluminum. Two main sections, shown in Figure 11, are the collar housing and tube housing. The collar was fixed in place by a steel screw. A pair of steel screws clamped the tube between two aluminum blocks with appropriate curvature in tube housing. The horizontal and vertical position of the entire tube housing could be positioned by adjusting the corresponding micrometers, and provided position repeatability within 0.02 mm of targets. Due to relatively low depth of penetration of electromagnetic fields in the ferromagnetic collars, whose minimum thickness was greater than 5 mm, the collar’s aluminum housing was not anticipated to have an effect on measured PEC responses.

Figure 11  Micrometer apparatus providing horizontal x and vertical y tube position within collar holes of various IDs. Bulk of the apparatus is aluminum.
Chapter 4

Manuscripts


Chapter 5

Discussion

Initial investigations into the effectiveness of PEC for SG tube and support structure inspections were limited to examining two variables simultaneously. During preliminary tests with the PEC probe, it was determined that coils 3, 4, 7, and 8 produced more closely matched signals when compared the other four (see Section 3.1 for coil layout). This matching led to only 1D horizontal off-centering of the probe to be considered in Manuscript 1 [9], along with support structure hole ID variations and fret depth variations, in a pairwise fashion. While time-domain signal analysis proved impractical, MPCA proved useful in identifying overlapping collars and frets during probe translation. The relative ease of identifying ferromagnetic materials from OD frets of the Alloy 800 tube was attributed primarily to large differences in electromagnetic diffusion times. The fourth MPCA eigenvector, whose score was related to fret depth, had a peak much earlier in time when compared to the first eigenvector, which reflected the mean measured signal. Eddy current amplification effects of ferromagnetic 410SS lead hole size to be linked with the magnitude of the first MPCA score. Relative proximity of probe and collar was captured by the second MPCA eigenvector, similar in shape and peak location to the first, but asymmetric for the pseudo-differential pair. Simple relations were found between MPCA scores and inspection variables when only two parameters were varied simultaneously [9]. Following the initial success of MPCA analysis for PEC signals, full 2D off-centering was considered while varying hole ID in Manuscript 2 [50]. The full array of 8 pickup coils was now in use and, along with the inclusion of a third variable to be solved simultaneously, increased the problem’s complexity which made correlations between MPCA scores and measurement variables far less evident. This lead to the use of multiple linear regression to relate data and measurements in a statistical manner [50].

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Multiple linear regression was performed on MPCA scores generated from data collected by all 8 coils of the PEC probe in Manuscript 2 [50]. Regression coefficients were obtained via the `stepwiselm` function of MATLAB [61]. For each variable being regressed upon, the most correlated score was determined, and subsequently removed. Following this the next highest correlation was determined from the newly reduced data, iterating until no more scores were statistically significant. Linear terms and quadratic terms (both interaction and pure quadratic) were selected as potential candidates for the regression models. Models generated using a single set of data and validated on two nominally identical repeat sets. While automated coefficient generation through MATLAB proved powerful, models over-fit to the training data due to an overwhelming amount of scores input with redundant information. For collar ID models, scores from the front coils or back coils were regressed upon separately. Similarly horizontal and vertical off-centering models were generated with coil arrays aligned with the respective planes of probe off-centering. This improved model fits to the two validation sets [50].

Following the success of multiple linear regression models at determining hole ID, horizontal, and vertical off-centering, a fourth variable, fret depth, was included during data collection for Manuscript 3 [62]. When the same procedure was repeated to generate models describing the now four different variables, overall fit qualities were drastically reduced. Fret depth models produced the best fits, again attributed to diffusion time differences between ferromagnetic 410SS and Alloy 800. An iterative solution, in which modelled fret depth was added as an additional input along with MPCA scores for regression models targeting hole ID, horizontal, and vertical tube off-centering [62]. This effort was met with moderate success, but did not improve model fits enough for reliable measurement of target variables. Exploratory factor analysis was employed in Manuscript 3 to pre-screen MPCA scores by examining correlations to a latent factor identified as either associated with ferromagnetic material (for hole models), or OD wall loss (for fret depth models) [62]. By removing nonessential MPCA scores
regression models were further refined. While fit quality was improved, the large number of outliers did not provide enough confidence in the models. At this point, ANNs were considered for regression of MPCA scores to targets as it was postulated they would prove superior at dealing with the nonlinear fitting encountered, producing models with fewer significant outliers.

Carbon steel collars were obtained in order to more accurately represent SG tube drilled support structures, and new data was collected for ANN models of Manuscript 4 using the PEC probe [69]. During pairwise MPCA five eigenvectors were retained for signal reconstructions as further vectors did not account for significant amounts of signal information. By limiting the selection of MPCA scores to the first five eigenvectors, ANNs could be rapidly generated using the neural network pattern recognition package in MATLAB [68]. Three repeat data sets were collected, denoted A, B, and C, from which ANNs were trained. Sets A and B were appended to provide a large amount of data for the generation of ANN models. Collar hole ID, fret depth, horizontal, and vertical tube off-centering were targeted simultaneously. Models were optimized by varying the breakdown of training, testing, and validation data in the graphic user interface (GUI) in MATLAB [68]. The amount of measurements randomly selected as training data was varied from 40% to 80% of the 1044 available data points from sets A and B, with the remainder divided evenly between testing and validation. Single hidden layer ANNs are generally sufficient for basic pattern recognition applications, and was the architecture provided in the MATLAB package [68]. The number of hidden layer neurons was varied from four to twelve to examine the effect on model creation time and convergence. Once created, all ANNs were applied to the final repeat set C to test their effectiveness on nominally identical data. It was observed during this optimization procedure that the inclusion of temperature as an input variable improved model fits across the board. Temperature affects measurement properties, including probe resistance, and material conductivity and permeability, significantly enough to play a role in generating accurate models in this laboratory setting. Between collection of different data sets, temperature was
observed to vary by up to 3°C. Once all desired iterations of ANNs were obtained, optimized model parameters were determined by examining standard deviations of predicted values compared to measured values. A breakdown of 50%/25%/25% for training, testing, and validation data for model generation, and 6 hidden layer neurons, produced good models with minimal over-fitting to data with which they were trained when visually observing fits. As a final validation of the ANN, a final set \( D \) of data was collected for which new off-centering positions were considered [69]. Application of the ANN to set \( D \) yielded good fits averaging approximately 2% error relative to targets, demonstrating the ANN’s capability of generalizing within the scope of training data. To further improve fit qualities, fret depths were once again considered as input variables, reducing the problem to solving three variables simultaneously. Similar to multiple linear regression models, there was an improvement of fit quality by providing this additional information to the ANN, and reducing the complexity of the problem [69]. In practice, this information could be obtained from complimentary NDT techniques such as conventional ECT or UT. Alternatively the problem could be addressed iteratively from PEC data, first determining fret depth before solving hole ID and tube position. In Manuscript 4, the combination of MPCA and ANNs have been demonstrated to be robust when considering noise in experimentally obtained signals, and able to accurately relate PEC signals to measurement variables [69]. By correctly identifying support structure locations, measurements can be focused on regions where overlapping flaws are likely to appear, complementing the speed with which ECT can inspect SG tubes themselves.
Chapter 6

Conclusions

Inspection of SG tube and ferromagnetic support structures has been performed using an array PEC probe. Due to difficulties of separating flaw responses in time-voltage waveforms, signal decomposition to extract dominant features was performed using a modified principal components analysis. Significant differences between electromagnetic diffusion times of Alloy 800 and ferromagnetic 410SS allowed for fret signal separation from hole ID variations using MPCA scores. Horizontal off-centering and hole ID were determined simultaneously from MPCA scores using a calibration surface. Expanding measurements to a second off-centering direction, multiple linear regression models were generated, in a stepwise fashion, to relate MPCA scores directly to measurements. PEC data was collected using the full 8 coil array for 95 randomly generated tube positions spanning four 410SS hole IDs. To improve regression fits, redundant information was removed by selecting a subset of scores for models. For hole ID, the front and rear array was selected, and for horizontal and vertical tube off-centering the plane of coils aligned with probe motion was selected. This also was required as the number of statistically significant regression coefficients was becoming unwieldy, which increased over-fitting to training data, demonstrated by the very low $R^2$ when attempting to validate the model. Models applied to secondary and tertiary sets of repeat measurements were moderately successful. The extension of models to regress on a fourth variable, fret depth, was less successful. Although fret depth could be reliably determined, spread in the remaining variable predictions increased. Fret depth was considered as an input, attempting an iterative model solution, with modest fit improvements that were not enough to reliably relate to measurements. Exploratory factor analysis was used to refine MPCA score selection for regression models, removing nonessential information. This method further improved fit quality, but model $R^2$ were still unsatisfactory for
potential implementation, and would require further improvement. A single hidden layer back propagation ANN was considered as a replacement for multiple linear regression models for simultaneously determining the four measurement variables. Including temperature as an input variable, along with MPCA scores, was found to improve ANN models noticeably. Carbon steel collars replaced the 410SS collars as being more representative of common SG support structures, and new data was collected before ANN model parameters were optimized. Good fits were obtained when applying the ANN to a secondary repeat set for all four parameters, with average errors under 2% relative to targets. A separate, smaller set of randomly generated tube positions was used for independent validation of the model, with similar observed fit qualities. Further improvement to all fit qualities was accomplished by using fret depth as an input variable, reducing the ANN to target three parameters and providing relevant information with which to improve fits. Generated using experimental data, ANNs proved robust when considering actual noise in measured signals as well as variations in nominally identical measurements. The combination of MPCA and ANNs has been demonstrated to be an effective method of inspecting ferromagnetic support structures from within Alloy 800 SG tubes using a PEC array probe. This work complements existing SG inspection technologies and, as shown for tube frets, can provide independent validation of flaws flagged by ECT, improving confidence in both techniques for the end user.
Chapter 7

Future Work

Several areas of improvement have been identified in order to extend the capabilities of PEC inspections of SG tube support structures. Effects of magnetite sludge on PEC response in conjunction with hole ID variations and frets could be examined in more depth to increase the number of overlapping degradation modes under consideration. The detection of loose parts of a variety of materials, including brass and carbon steel, above ferromagnetic tube sheets is an area currently being investigated. More extensive flaw geometries should be considered moving forward that more closely represent observed degradation modes of nuclear SG support structures. A variety of fret lengths, triangular and tear shaped frets, and tapered frets could be examined and classified before depth sizing. General corrosion mechanisms for support structures should be examined including oval and egg-shaped holes, and tapering along the length of the support structure. By expanding the ANN training measurement space to be more representative of true flaw geometries, models could be validated on measurements obtained in real SGs to determine the viability of implementing PEC alongside existing SG inspection techniques.

A variety of modifications to the analysis of PEC signals should be investigated. With regards to MPCA, secondary sets of scores could be obtained by performing a second MPCA procedure after normalization of input signals, which would have the effect of accentuating variations in signal shapes, while reducing information of relative coil proximity to ferromagnetic materials, which tend to be correlated with amplitude. Stepwise regression models could be improved through automated selection of interaction terms and polynomial order via the stepwise generalized linear model recently added in MATLAB.
References


[72] “Alloy 800/800H/800AT Data Sheet.”


Pulsed Eddy Current Inspection of Support Structures in Steam Generators

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Abstract—Degradation and fouling of support structures in nuclear steam generators (SGs) can lead to SG tube damage and loss of SG efficiency. Inspection and monitoring of support structures combined with preventative maintenance programs can alleviate these effects and extend SG life. Conventional eddy current inspection technologies are extensively used for detecting and sizing indications from wall loss, frets at supports, cracks and other degradation modes in the tubes, as well as assessing the condition of support structures. However, these methods have limited capabilities when more than one degradation mode is present simultaneously, or when combined with fouling. Pulsed eddy current combined with principal components analysis (PCA) was examined for inspection of 12.9 mm (5/8”) Alloy-800 tubes and surrounding stainless steel (SS410) support structures. Clear separation of PCA scores associated with tubes from those associated with ferromagnetic SS410 supports permitted measurement of tube-to-support gaps, in either the presence of tube fretting or variation of relative position of the tube within SS410 supports. For concentric tubes, frets could be sized independently of SS410 hole diameter variations, which in other materials could represent support corrosion. Capability to clearly separate scores was attributed to large differences in relaxation times for diffusion of transient fields through the tube compared with diffusion into the ferromagnetic support structure.

Index Terms—Alloy 800, nondestructive testing, principal components analysis, pulsed eddy current, SS410, steam generator tube.

I. INTRODUCTION

STEAM generators (SGs) are critical components for most thermal power reactors. In nuclear reactors such as PWR and CANDU the SG tubes are the thinnest barrier [1] between the irradiated, primary heat transport system and the secondary heat transport system. To ensure continuing safe operation of nuclear reactors, life management strategies are implemented. These strategies involve regular inspections of SG tubes to detect and monitor flaws such as tube fretting wear, corrosion of support structures, and stress corrosion cracking, to name a few [2]. Eddy current testing (ET) and ultrasonic testing (UT) are used to detect and size flaw indications, and are important for providing the necessary information for condition assessments, predicting flaw growth and determining how long components can operate safely. Fretting wear occurs primarily at support structure locations in the pre-heater and U-bend of the SG [3], [4]. Degradation of SG tube supports leads to enhanced flow induced vibration causing further fretting at these and other locations [3], [4]. Currently, ET is used to inspect SG tubes and to characterize both the type and size of tube frets [5]. However, ET has difficulty characterizing support structure degradation in the presence of flaws, such as frets, and the presence of magnetite fouling negatively impacts ET inspection quality [5]. Accurate detection and characterization of frets is important for the life management of the SG, since tubes are ‘plugged’ once 40% through-wall frets are detected, reducing SG and subsequently, plant efficiency [4].

Pulsed Eddy Current (PEC) is a novel NDT technique that provides some advantages over conventional ET with applications most recently identified in aerospace [6]–[8]. A large lift-off problem was overcome in the inspection of stress corrosion cracking in the inner wing spar of F/A-18 jets [6] and second layer cracks in a thick multi-layer aluminum structure were investigated for CP-140 Aurora [7] using PEC in combination with principal component analysis (PCA). These two techniques have been shown to be effective in detecting surface and subsurface manufactured defects, isolating the effect of lift-off and gap within multi-layer aluminum aircraft riveted structures [9], [10]. PEC has shown potential to identify position and depth of subsurface volumetric flaws in aluminum using an array of Hall sensors [11]. Signals were analysed with PCA, improving on time-domain feature extraction analyses such as peak height and rise time [11]. PEC combined with PCA and support vector machines (SVMs) have shown the potential for automated defect classification in multi-layer aluminum structures [12], [13]. Independent component analysis (ICA) is an alternative analysis technique similar to PCA in that it reduces dimensionality of multivariate data, and is
beneficial when dealing with noisy, non-gaussian signals using higher-order statistics to generate independent components [13], [14]. Eddy current pulsed thermography, a thermographic inspection technique employing transient eddy current for induction heating, has been shown to produce improved results when subject to PCA and ICA [15].

PEC differs from conventional ET by utilizing a square voltage pulse as opposed to sinusoidal continuous excitation. The pickup coil transient voltage responses can be considered as a series of discrete frequencies, while the approach to direct current (DC) excitation in the pulse provides magnetization of ferromagnetic materials, enhancing pickup coil responses [16], [17]. PEC has also been shown to be sensitive at higher liftoff when compared to conventional ET [18], indicating potential for the inspection of SG support structures from within tubes.

Conventional ET is sensitive to multiple parameters, and the 2D impedance plane view does not permit examination of multidimensional interactions [8], whereas in PEC, sets of time-voltage data are the focus of analysis. PEC pickup coil responses have been analyzed using Principal Components Analysis (PCA) to reduce the dimensionality of the data [6], [7] and to improve flaw discrimination, when compared to simple time-domain analysis [8].

Results presented here examine a modification of a previously developed PEC probe [19] for its potential to inspect support structures in the presence of frets. Theory, including eddy current diffusion and modified PCA, is examined first in Section II followed by a description of experimental set up and measurement technique in Section III. Results and discussion, presented in Section IV, consider SG tube fret measurements at support structure locations, hole size variations with frets present, and tube position within simple support structure holes of various size without frets, analysed using PCA of PEC signals. The ability to clearly separate SG tube and support structure condition demonstrates the potential of PEC combined with PCA as a novel tool for SG inspection.

II. THEORY

A. Eddy Current Diffusion

The use of a square voltage pulse induces transient eddy currents in conductive media surrounding the drive coil via Faraday’s law of electromagnetic induction [20], which in turn may be sensed by pickup coils. In addition there is a strong magnetization effect in the presence of ferromagnetic materials. This acts as a secondary change in flux as the magnetic field within the material increases with time, therefore amplifying the resulting emf induced in the pickup coils. Eddy currents decay according to the diffusion equation. A square wave pulse can be decomposed into fundamental and harmonic frequency components and therefore, the response contains additional useful information in the frequency domain, when compared to harmonic excitation ET. The frequency spectrum of the PEC response has also been examined with PCA to improve feature extraction [21]. Diffusion of magnetic flux, $B$ as described by Maxwell’s equations at low frequencies ($<10^8$ Hz) can be written as [20]:

$$\nabla^2 \bar{B} = \mu \sigma \frac{\partial \bar{B}}{\partial t}. \quad (1)$$

The general solution to the diffusion equation of magnetic fields (1) in conducting media is of the form [22]:

$$\bar{B} = f \left( e^{-t/\tau_D} \right) \quad (2)$$

where the solution can often be expressed as a series of relaxation times, which have a reasonable dependence on the conductivity and permeability. The characteristic diffusion time $\tau_D$ for these transient eddy currents in a given material can be described by [20], [22]:

$$\tau_D \sim \mu \sigma l^2, \quad (3)$$

where $\sigma$ and $\mu$ are the conductivity and permeability of the medium, respectively, and $l$ is a characteristic length of the system. The complete transient response can be understood as a series of relaxation times described by (3), with longer times providing greater depth of penetration by eddy currents. With reference to (3), characteristic lengths, $l$, between the tube and support structures are not greatly different and as such, the eddy current diffusion time is governed primarily by the $\mu \sigma$ component. The two materials of interest here are Alloy-800 with a $\mu \sigma$ product of $1.0 \times 10^8$ S/m² [23] and ferromagnetic stainless steel (SS410) with a $\mu \sigma$ product between $1.2 \times 10^8$ S/m² and $1.8 \times 10^8$ S/m² [24]. From (3), the diffusion time for eddy currents in SS410 is 3 orders of magnitude longer than in Alloy-800, and is therefore expected to affect the PEC pickup coil response at later times. While it is possible that differences in material diffusion times could be used to analyse rise times of raw signals [8], [9] the focus here is the inspection of support structures and not tube flaws. Rise time information is contained in principal components with earlier time peaks. It should be noted that SS410 supports do not corrode in steam generators; however, these samples, with a $\mu \sigma$ on the same order as that of carbon steel (between $3 \times 10^9$ S/m² and $7 \times 10^9$ S/m² [25], [26]), were available to demonstrate the potential of using PEC for inspection of ferromagnetic supports in the presence of SG tube fretting. True corrosion introduces local conductivity and permeability changes that have yet to be investigated in relation to this work, but has been shown to have a quantifiable response on PEC signals in combination with PCA [27], [28].

B. Modified PCA

Principal components analysis (PCA) is a statistical method of separating large highly correlated data sets into a combination of linearly uncorrelated principal components and associated scores. The data is assumed to be represented by a sum of a small number of eigenvectors (principal components) such that a column vector $Y$ can be written as [6], [29]:

$$Y = \sum s_i V_i \quad (4)$$

where $V_i$ are the eigenvectors and $s_i$ are the principal component scores. In modified PCA the mean has not been subtracted
TABLE I
IDs of SS410 Collar Holes Used to Simulate Varying Gap
Within Ferromagnetic Drilled and Baffle
SG Tube Support Structures

<table>
<thead>
<tr>
<th>Collar Number</th>
<th>Hole ID [mm]</th>
<th>Radial Gap [mm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>16.5</td>
<td>0.3</td>
</tr>
<tr>
<td>2</td>
<td>17.0</td>
<td>0.6</td>
</tr>
<tr>
<td>3</td>
<td>18.8</td>
<td>1.5</td>
</tr>
<tr>
<td>4</td>
<td>20.3</td>
<td>2.2</td>
</tr>
<tr>
<td>5</td>
<td>21.8</td>
<td>3.0</td>
</tr>
</tbody>
</table>

TABLE II
Fret Depths in Alloy-800 Tube

<table>
<thead>
<tr>
<th>Fret Number</th>
<th>Fret Depth [mm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.65</td>
</tr>
<tr>
<td>2</td>
<td>0.74</td>
</tr>
<tr>
<td>3</td>
<td>0.87</td>
</tr>
<tr>
<td>4</td>
<td>1.00</td>
</tr>
<tr>
<td>5</td>
<td>1.11</td>
</tr>
</tbody>
</table>

from the original data [6]. In this case the eigenvector with the largest eigenvalue is the best possible choice of basis vector (in a least squares sense), accounting for the largest amount of variation in the original data. The second largest eigenvalue indicates the vector that accounts for the largest variation in the remaining data once the first has been removed, and so on. This method effectively allows for a complete reproduction of the original signal, while significantly reducing its dimensionality. This is accomplished through determination of the scores $s_j$, for each data set, reducing the amount of data from potentially hundreds of points for each measurement to 3-5 scores. By retaining the data mean, the results are less susceptible to instrumentation changes that could result in systematic offsets, which would occur if the average signals were not the same. The modified PCA presents a minimization of the sum square residuals interpretation of the results, instead of a variance minimization interpretation [6].

III. EXPERIMENTAL SETUP

A. Apparatus

Four 25 mm long SS410 samples, simulating ferromagnetic drilled supports or baffle plates, with hole inner diameters (IDs) as shown in Table I, were used to simulate uniform tube-to-support gaps, which in other materials such as carbon steel can represent corrosion of the SG tube support structure. All of the samples were cylindrical and had an outer diameter (OD) of 32 mm and will be referred to simply as collars for the remainder of this work. Two 15.9 mm (5/8”) OD, 46.1 cm long Alloy-800 tubes, with a wall thickness of 1.2 mm (0.05”), were used in this investigation. One of the tubes was as manufactured and the other contained 5 flat frets of successively increasing depth as shown in Table II. The tube frets were 25 mm in length, the same as the length of the SS410 collars used during testing and are shown schematically in Figure 1. Note that this arrangement was selected to demonstrate the capabilities of PEC in a complex flaw/support combination. Only the 4 largest hole IDs, representing increase in ID from the as-installed condition (collar 1) were considered in this study.

A micrometer apparatus, a schematic of which is shown in Figure 2, was used to hold the Alloy-800 tube within the hole of the SS410 collar. The apparatus held the SS410 collar fixed, but permitted independent control of horizontal (x) and vertical (y) positions of the tube within the hole.

B. Probe

The probe design, based on previous work [19], was modified to include an additional array of 4 pickup coils rotated 90° from the original and is shown schematically in Figure 3. The length and outer diameter of the probe were 77.6 mm and 13.5 mm, respectively. A central drive coil was wound coaxially on the probe body with 127 turns of 36 AWG wire. The two arrays of 4 pickup coils were located in front and behind the drive coil, each wound with 360 turns of 42 AWG wire. The pickup coils were arranged at 90° intervals around the probe in their respective arrays, with all of the axes perpendicular to the drive coil. The signals from the pickup coils were carried by shielded twisted pair wire to a purpose-built amplification circuit. Pickup coil responses were collected separately and were amplified 100 times. Signals were then digitized at 1 MHz using a NI6356 USB DAQ, which was connected to a desktop computer. Opposing coils, at 180°, were matched as closely as possible for signal response in order to enhance sensitivity to the presence of single-sided frets and relative distance from collar ID.
TABLE III
SUMMARY OF MEASUREMENTS PERFORMED FOR THE PRESENTED RESULTS

<table>
<thead>
<tr>
<th>Test</th>
<th>Number of measurements</th>
<th>Probe motion per measurement relative to collar center [mm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Translation</td>
<td>142</td>
<td>2</td>
</tr>
<tr>
<td>Centered fret</td>
<td>24</td>
<td>0</td>
</tr>
<tr>
<td>Tube off-centering</td>
<td>63</td>
<td>0.25</td>
</tr>
</tbody>
</table>

The excitation pulse was generated by the NI6356 USB DAQ at 1000 Hz and 50% duty cycle ratio, with subsequent current amplification resulting in a 2.5 V square wave pulse, 0.5 ms in duration, and carried to the drive coil with a coaxial cable.

PCA requires inputs spanning all possible flaw arrangements and types such that there is sufficient data for statistical analysis and so that resulting eigenvectors are not restricted to a particular set of measurements. A summary of the measurements obtained for each experiment is presented in Table III.

Translational measurements along tube axis were performed by positioning the probe axially at 2 mm increments within the Alloy-800 SG tube, while a timed LabView program generated excitation pulses and collected pickup coil voltage responses. Each experiment translated the probe by 80 mm, through the tube, past collar and fret location.

Stationary measurements were performed by centering the drive coil of the probe within the SS410 collar. For measurements examining probe response with fret depth, data was collected for frets aligned with the collar and the probe center. To examine the effect of tube movement away from the hole center, the nominal Alloy-800 tube was shifted horizontally across the full hole ID in 0.25 mm increments, with the drive coil centered vertically within the collar, as shown in Figure 3. The latter set of measurements was performed with no fret present.

IV. RESULTS AND DISCUSSION

A. Probe Response

The transient response of the probe demonstrated sensitivity to both the presence of ferromagnetic materials and volumetric tube flaws such as frets, as shown in Figure 4. The amplification of the eddy currents due to magnetization in the presence of a ferromagnetic SS410 collar, made it relatively easy to distinguish it from the signal obtained with only the as-manufactured tube present. However, the free span fret had a subtler impact on the transient response, which could not be as easily identified without a more sophisticated analysis.

The variation in pickup coil response caused by effects in either tube or support structure material, due to the differences in relaxation times as discussed in Sect. II.A, is expected to be readily separable through a signal decomposition technique such as PCA [29] (see Sect. II.B).

B. PCA

PCA was applied to the complete data set once all measurements had been performed. The first four principal components were selected for signal reproductions (using equation 4) resulting in an average reproduction error of the as-measured signal of 0.15%. Higher order principal components were not considered as the reproduction was considered sufficiently accurate for analysis. As appended data sets contained different types of measurements (probe translation, tube translation, and variable fret depth and hole ID) different combinations of generated principal components were used to extract desired information from the results.

Sample normalized eigenvectors for PCA reproduction of the translational data are shown in Figure 5. The shape of the vectors provides some insight as to the physical effects individual vectors are expected to be associated with. The first principal component ($V_1$) has a shape very similar to the original data, and represents average response of the data. The scores associated with this vector tend to be two orders of magnitude larger than any other score, indicating that it accounts for the largest amount of variation [29]. Voltage amplification due to production of a secondary magnetic field in ferromagnetic materials is expected to have
an amplification effect on first principal component scores. The second principal component ($V_2$) peaks later in time and rises more slowly when compared to $V_1$, suggesting a representation of long relaxation time transients associated with the ferromagnetic collar (see Sect. II.A). The fourth principal component ($V_4$) has two peaks of opposite sign initially rising much faster than $V_2$. It represents a shift of intensity from later times to much earlier times. Hence, it is associated with the shorter diffusion times within the Alloy-800 tube (see Sect. II.A). The third principal component ($V_3$) is not shown as its scores were not used in the analysis. Although the vectors are not generally utilized in the end-state analysis of PCA results, they are useful for providing an insight into physical parameters associated with the resultant principal component scores.

C. Fret Signal Separation and Sizing

The effect of the presence of a fret on principal component scores was investigated. Figure 6 shows three scores as a function of translational position in the tube a) with a fret present, followed further down the tube by a ferromagnetic support structure (collar 2 in Table I) and b) with support structure aligned with the fret. The scores associated with the first principal component ($s_1$), which multiply $V_1$ to produce the general trend of the data, are observed to remain constant, while the probe translates through the Alloy-800 tube and fret, only decreasing in the presence of the collar. In both cases the magnitude of change in $s_1$ appears independent of the presence of tube flaws (frets). The second principal component score ($s_2$) appears to have a slight dependence on the fret and a stronger opposing dependence on the support structure as shown in Figure 6(a). The opposing response of $s_2$ is evident as a reduced signal response to the fret and collar at the same location as shown in Figure 6(b). Finally, the fourth principal component score ($s_4$) is only sensitive to position of the 43% through-wall rectangular fret, displaying the same characteristic shape and peak-to-peak magnitude of 0.9 in Figures 6(a) and b). The clear independence of $s_1$ from the effect of frets and independence of $s_4$ from the effect of the ferromagnetic collar may be related to relative dependencies arising at later and earlier times, of eigenvectors $V_1$ and $V_4$, respectively, as discussed in Sect. IV.B.

![Fig. 5. Eigenvectors $V_1$ ($V_1$), $V_2$ ($V_2$), and $V_4$ ($V_4$) generated from a global data set for the reproduction of signals collected for this work.](image1)

![Fig. 6. First three principal component scores along an Alloy-800 SG tube, $s_1$ ($S_1$) on right vertical axis, $s_2$ ($S_2$) and $s_4$ ($S_4$) on left: a) for 43% through-wall fret and SS410 collar at different positions and b) fret and collar at the same position.](image2)

![Fig. 7. Relation of $s_4$ ($S_4$) and fret depth for various ferromagnetic collar hole IDs, best fit with a quadratic polynomial.](image3)

To further investigate the effect of tube frets on the PEC response, measurements with a stationary probe were conducted, while both through-wall fret depth as well as collar hole ID were varied. The tube was centered within the hole for this experiment. A clear trend is observed in Figure 7, for $s_4$ with fret depth largely independent of collar ID. Data has been best fit with a quadratic polynomial. Clearly, PCA provides good separation of tube fret response from ferromagnetic support structures, facilitated by the large relative difference in characteristic diffusion times (see (3) in Sect. II.A).
As the depth of a fret increases for a given collar hole ID, there is an increase in magnitude of $s_1$, as shown in Figure 8. This can be attributed to less material at the fret, which reduces the shielding effect of SG tube and thereby increases probe response to the collar. The increase in magnitude is a consistent trend between collar sizes and therefore, once fret depth is known, the collar can be sized by comparing $s_1$ to the appropriate curve shown in Figure 8.

Relative independence between hole ID and fret response in the PCA scores $s_1$ and $s_4$, respectively, was associated with the 3 order magnitude smaller diffusion time through the SG tube wall compared with diffusion into surrounding support structure as estimated in Sect. II.A. These independent effects were also reflected in the difference between orthogonal eigenvector $V_1$, associated with the large signal response due to support structure and variations therein, and $V_4$, which exhibited an early time peak associated with the short diffusion time penetration of fields through the SG tube wall and thereby, sensitivity to the presence of fret depth variations. With increasing fret depth these diffusion times become shorter in amplitude along with the removal of shielding effect of the SG tube on support structure electromagnetic field interactions.

D. Tube Shift and Collar Hole ID Sizing

Proximity of PEC probe pickup coils to the ferromagnetic samples being inspected has a significant effect on response signals. By combining data from two coils on opposite sides of the probe differentially, this proximity effect becomes apparent in the peak response voltages as seen in Figure 9 for coil pairs 4 and 8. This is consistent with previous FE model results obtained over a wider range of tube position within the SS410 hole [19]. Although the results of Figure 9 show a consistent trend for tube shift quantification, the peak height varies with collar hole ID. PCA has been used here to extract tube off-centering and collar hole ID, simultaneously. The first two principal components should contain enough information within them to reproduce signals in the presence of tube shift and hole ID variation.

Figure 10 illustrates a calibration surface that is constructed by plotting $s_1$, $s_2$ and collar ID demonstrating use of PCA scores to determine both horizontal tube position and SS410 support structure hole ID, simultaneously.

collar hole ID. By generating $s_1$ and $s_2$ from acquired data and comparing it to the calibration surface, collar hole ID can be determined. A best fit surface created for Figure 10 provides a relation between $s_1$, $s_2$ and collar ID in the form of:

$$ID = A(s_2)^2 - B(s_2) + C(s_1)^2 - D(s_1) + E(s_1)(s_2) + F$$

(5)

where A, B, C, D, E, and F are best fit parameters, and $s_1$ and $s_2$ are generated from PCA on data using existing calibration eigenvectors.

The results presented here are limited to the horizontal plane, but it is postulated that a similar trend as seen in Figure 10 would appear in $s_2$ for the vertical plane of coils. By utilizing the full 8 coils of the probe the true position of the tube within the collar could be determined in conjunction with hole ID.

This work has not considered the combination of fret sizing and horizontal shift of the tube, under conditions of varying SS410 hole ID. Magnetic sludge and ID magnetite fouling are encountered in nuclear reactor SGs and their effects on the PEC results also require examination.

V. CONCLUSION

This paper described the development of a pulsed eddy current inspection method, utilizing principal components...
analysis (PCA), for the simultaneous determination of tube position and ferromagnetic SS410 support structure hole inner diameter (ID), simulating corrosion, in Alloy-800 SG tube. Depth sizing of rectangular frets was demonstrated as being independent of variations in SS410 hole IDs. PCA was shown to be a robust analysis technique that provided good separation of tube and support structure effects on PEC signals. This independence was associated with the difference in diffusion times through the SG tube wall, compared with diffusion of electromagnetic fields into the surrounding support structure.

ACKNOWLEDGMENT

The first author would like to thank Dr. S. Sullivan from Ontario Power Generation for useful discussion.

REFERENCES


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Joe Renaud received the bachelor’s degree in mechanical engineering from Queen’s University. Since 2006, he has held positions at Westinghouse, Eddytech, R/D Tech, Zetec, and Atomic Energy of Canada, Ltd. He is currently the Director of Steam Generator Inspection Technologies, Eddyfi.

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Appendix B
**Regression Analysis of Pulsed Eddy Current Signals for Inspection of Steam Generator Tube Support Structures**

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**Summary**

Nuclear steam generator (SG) support structure degradation and fouling can result in damage to SG tubes and loss of SG efficiency. Conventional eddy current technology is extensively used to detect cracks, frets at supports and other flaws, but has limited capabilities in the presence of multiple degradation modes or fouling. Pulsed eddy current (PEC) combined with principal components analysis (PCA) and multiple linear regression models was examined for the inspection of support structure degradation and SG tube off-centering with the goal of extending results to include additional degradation modes.

1. **Introduction**

Nuclear power reactor the steam generator (SG) tubes are the thinnest barrier between the secondary and radioactive primary heat transport systems [1]. Regular inspections of the SGs search for tube flaw using non-destructive evaluation (NDE) techniques [2]. Ultrasonic testing (UT) and conventional eddy current testing (ET) are used to accurately detect and size flaws, with ET being the more commonly employed method, due to its rapid volumetric inspection capability. While ET is capable at dealing with single degradation modes it has reduced functionality when multiple degradation modes overlap or tube fouling is present [3]. Degradation of SG tube supports can lead to enhanced flow-induced vibrations [4] causing fretting wear, and the position of the tube within the support structure changes the local water flow, which results in additional degradation modes.

Pulsed eddy current (PEC) is a novel NDE technique that uses a square wave excitation to induce eddy currents. PEC can more readily inspect ferromagnetic materials in which the approach to a DC current results in magnetization of the sample [5]. PEC signals are commonly analysed using a technique called principal components analysis (PCA), which is a statistical method that reduces large amounts of data to a series of discrete scores at each measurement location [6-8]. In order to relate the obtained PCA scores to physical measurements, a multiple linear regression model was considered. As a first step toward independent feature extraction, the effect of varying the inner diameter (ID) of holes in a simple drilled support structure (simulating uniform corrosion) and varying SG tube position within the holes was examined. This examination is a necessary first step towards including additional parameters such as tube fretting wear and, more importantly, fouling in the vicinity of support plates.
2. Theory

In PEC a square voltage excitation of a drive coil is used to generate electromagnetic field interactions in surrounding conducting and ferromagnetic media [9]. Pickup coils can be used to investigate the local electromagnetic field interactions that decay according to the diffusion equation [9]. In addition, ferromagnetic materials are magnetized with the approach to the DC level of the pulse. Sensitivity to these combined effects gives PEC a unique capability unavailable in conventional ET [10].

Principal components analysis (PCA) is a statistical tool that separates large highly correlated data sets into combinations of linearly uncorrelated principle components and associated scores. Using PCA the data can be written as a linear combination of eigenvectors (principal components) and associated scores $s_i$ [6]. In this modified PCA the mean is not subtracted from the original signal [6]. This method allows for incremental reproduction of the original signal while significantly reducing the dimensionality of the data.

3. Experimental Setup

Four 25 mm long SS410 samples, simulating ferromagnetic drilled supports or baffle plates, with hole IDs as shown in Table I, were used to simulate uniform tube-to-support gaps. The sample SG tube was a nominal 15.9 mm (5/8”) OD, 46.1 cm long Alloy 800 tube, with wall thickness of 1.2 mm. Although SGs are vertical structures in this experiment the tube was horizontal. A custom apparatus permitted accurate horizontal and vertical positioning of the tube within the hole of the simulated support structure using micrometers. While both horizontal and vertical variation in position was examined, for conciseness only horizontal position results are presented here.

<table>
<thead>
<tr>
<th>Support hole ID [mm]</th>
<th>Radial gap [mm]</th>
<th>Number of unique tube positions measured</th>
</tr>
</thead>
<tbody>
<tr>
<td>17.1</td>
<td>0.6</td>
<td>9</td>
</tr>
<tr>
<td>18.7</td>
<td>1.4</td>
<td>19</td>
</tr>
<tr>
<td>20.1</td>
<td>2.1</td>
<td>24</td>
</tr>
<tr>
<td>21.8</td>
<td>3.0</td>
<td>43</td>
</tr>
</tbody>
</table>

Table I  Number of unique tube positions within each hole for which measurements were taken.

The PEC probe [10] consists of a 127 turn, 36 AWG, excitation coil wound coaxially with the probe body, and 2 arrays of 4 360 turn, 42 AWG, pickup coils placed at 90° intervals around the surface of the probe both before and after the excitation coil as shown in Figure 1. Excitation pulses were generated in LabView and output from a NI6356 USB DAQ at 1000 Hz and 50% duty cycle resulting in a 2.5 V pulse after current amplification. Pickup coil responses were carried by shielded twisted wire pairs to a custom amplification system before being digitized by a NI6356 USB DAQ at 1 MHz. The resistance, inductance and positions of the surface pickup coils were matched for opposite pairs such that the residual between them was minimized while subject to nominally identical sensing conditions.

- 2 of total 5 pages -
Figure 1  Schematic of the PEC probe inside an Alloy 800 SG tube and drilled support structure viewed horizontally. 4 of the vertically aligned coils can be seen side-on and 2 of the horizontal coils face-on.

4. Results and Discussion

To examine the effect of varying both hole ID and position of tube within the hole a map of points was randomly generated for tube positions given a particular radial gap. Table I shows, for each hole ID, radial gap between tube OD and hole ID and the number of discrete tube positions for which measurements were obtained. Once data was collected at all positions for each hole it was aggregated into a single data set for a PCA performed in LabView. Scores output from PCA were then used as inputs for a multiple linear regression model created in MATLAB, targeting either the support structure hole ID or the horizontal position of the SG tube. Six principal components were retained for each differential coil pair (diametrically opposed coils) resulting in 24 predictor variables for every measurement. A stepwise linear model was created in MATLAB, with a different subset of input PCA scores for each model. PCA score subsets were chosen, exploiting the probe geometry, to remove inputs that were either redundant or lacking information. The fitting equation of the multiple linear regression models can be described as:

\[ y \sim A + \sum_{i=1}^{n} B_i s_i + C_i s_i^2 + \sum_{j=1}^{n} D_{ij} s_i s_j \]  

(1)

where \( A \) is a constant, \( s_i \) are the PCA score inputs, \( B_i, C_i \) and \( D_{ij} \) are their regression coefficients and \( n \) is the number of predictor PCA scores chosen for the particular model.

It is important from an inspection perspective to accurately indicate the amount of support structure degradation that has occurred. The model created to determine the SS410 hole ID was generated from the PCA scores of only the front array of 4 coils as the back pair would add redundant predictors. Only linear and purely quadratic terms of Eqn. (1) were retained in this model as an excellent fit was obtained without interaction terms of Eqn. (1). A comparison of the predicted to measured hole IDs is shown in Figure 2. The best fit line has a slope of 1 with \( R^2 = 0.9994 \), demonstrating the predictive capability of the regression model. These results demonstrate that PEC, in combination with PCA and linear multiple regression, can be used to determine the hole size of a ferromagnetic SG support structure independently of the position of tube inside that support.
The position of SG tubes relative to sides of support structure holes can be used as an early indicator of flaws that may stem from changes in water flow through the support. Locations within the support hole can be mapped to horizontal and vertical positions relative to a nominally centered tube. Exploiting the orthogonal arrangement of coils, only coils aligned with the plane of interest (horizontal in the experimental configuration) were retained for analysis. Horizontal location for 95 tube positions has been compared directly to micrometer measurements in Figure 3, such that data sets with different positions within the hole could be plotted together. The best fit line with slope of 1 and $R^2 = 0.9987$ again demonstrates the predictive capability of the regression model. Vertical model results demonstrate the same trend as seen in Figure 3, but with a slightly larger spread attributed to more unbalanced coils of the vertical array ($R^2 = 0.9784$). Determination of position has been shown to be independent of hole ID in this unflawed case.
5. Conclusion

A PEC probe was examined for the inspection of support structures from within Alloy 800 SG tubes. The time-voltage responses of the pickup coils at 95 different random tube locations spanning the 4 hole IDs were subjected to a PCA. The obtained PCA scores were used as inputs to a set of multiple linear regression models created to independently determine the horizontal and vertical positions of a SG tube within a simulated support structure hole as well as measure the size of that hole. Following this work, models will be applied to secondary and tertiary data sets to examine if a generalized model can be created and used as a basis for a SG tube support structure inspection. These preliminary results demonstrate the power of PEC combined with PCA to inspect ferromagnetic materials from within conducting tubes.

6. Acknowledgements

The authors would like to thank Vijay Babbar and Brian Lepine at Canadian Nuclear Laboratories (CNL) for useful discussions. This work has been supported by University Network of Excellence in Nuclear Engineering (UNENE) and Natural Sciences and Engineering Research Council (NSERC).

7. References


Appendix C
Analysis of Pulsed Eddy Current Data using Regression Models for Steam Generator Tube Support Structure Inspection

J. A. Buck\textsuperscript{1}, P. R. Underhill\textsuperscript{2}, J. Morelli\textsuperscript{1}, and T. W. Krause\textsuperscript{2,a)}

\textsuperscript{1}Department of Physics, Engineering Physics, and Astronomy, Queen's University
\textsuperscript{2}Department of Physics, Royal Military College of Canada
\textsuperscript{a)}Corresponding author: Thomas.Krause@rmc.ca

Abstract. Nuclear steam generators (SGs) are a critical component for ensuring safe and efficient operation of a reactor. Life management strategies are implemented in which SG tubes are regularly inspected by conventional eddy current testing (ECT) and ultrasonic testing (UT) technologies to size flaws, and safe operating life of SGs is predicted based on growth models. ECT, the more commonly used technique, due to the rapidity with which full SG tube wall inspection can be performed, is challenged when inspecting ferromagnetic support structure materials in the presence of magnetite sludge and multiple overlapping degradation modes. In this work, an emerging inspection method, pulsed eddy current (PEC), is being investigated to address some of these particular inspection conditions. Time-domain signals were collected by an 8 coil array PEC probe in which ferromagnetic drilled support hole diameter, depth of rectangular tube frets and 2D tube off-centering were varied. Data sets were analyzed with a modified principal components analysis (MPCA) to extract dominant signal features. Multiple linear regression models were applied to MPCA scores to size hole diameter as well as size rectangular outer diameter tube frets. Models were improved through exploratory factor analysis, which was applied to MPCA scores to refine selection for regression models inputs by removing nonessential information.

INTRODUCTION

Nuclear power plant steam generator (SG) tubes present the thinnest material barrier between irradiated and non-irradiated regions of the reactor [1]. They are routinely inspected for flaws by nondestructive testing methods including conventional eddy current testing (ECT) and ultrasonic testing (UT) as part of reactor lifetime management strategies. Of the two, ECT is more commonly used due to its rapid volumetric inspection capabilities [2]. However, when dealing with multiple overlapping degradation modes or tube fouling, ECT sensitivity is reduced [3]. Degradation of SG tube supports can result in enhanced flow-induced vibrations causing fretting wear, and tube off-centering within support structures alters local water flow, which can induce further degradation such as pitting [4]. Accurate measurements of support structure corrosion and tube position can be used proactively to enhance lifetime management strategies by addressing problems before further degradation of SG tubes occurs.

Pulsed eddy current (PEC) is a novel NDT technique that uses square wave voltage excitations to induce transient eddy currents in conducting materials. Inspection of ferromagnetic structures can be enhanced by the pulse excitation’s approach to a direct current (DC) generated field, which results in greater magnetization of ferromagnetic materials than can be achieved by time-harmonic methods [5, 8].

PEC has been combined with modified principal components analysis (MPCA) in order to extract dominant features of observed transient response signals, when strict time-domain analysis has proved challenging [5–7]. To relate MPCA results to physical measurements, multiple linear regression models have been considered when the variation of support structure hole inner diameter (ID), simulating uniform corrosion of ferromagnetic drilled support plates, and 2D tube position were investigated [8]. Extending this problem to include outer diameter (OD) tube fretting creates a four variable problem akin to what might be observed in a real inspection when overlapping degradation modes are present.

Factor analysis is a method of investigating relations between variables of interest, and can be used to refine MPCA score selections, before the generation of regression models, in order to reduce over-fitting [9]. Factor analysis was initially developed in psychology to understand relations between observable variables such as test...
scores and reading comprehension, but has also been used in behavioural sciences to examine the trait of perfectionism [10], structural health monitoring through the removal of environmental factors [11], and fields where it is expected that correlations between a large number of observed variables can be explained by fewer unobserved latent variables [9].

In this work, regression models targeting hole ID were initially generated from the full range of available MPCA scores, but resulted in over-fitting to training data. To improve model fits to validation data, potentially redundant information was reduced by selecting MPCA scores from a subset of the PEC probe array. Furthermore, fret depth was included as an additional input variable, further improving model fits. Finally, for models targeting hole ID or fret depth, MPCA score selection was refined through factor analysis to select those scores which were most correlated with the variables of interest.

**THEORY**

In PEC, rapid changes in local magnetic field induce eddy currents in nearby conducting materials according to Faraday’s Law, which oppose the perturbing field according to Lenz’s Law [12]. Pickup coils can be used as sensors to investigate local electromagnetic fields that decay, to a first order approximation, according to a diffusion law [5]. Differences in characteristic diffusion times of materials allow for improved flaw discrimination between ferromagnetic and purely conductive materials [5]. Furthermore, ferromagnetic materials are magnetized by the approach to DC of the pulse [5], [13]. Combined, these sensitivities give PEC a unique capability when compared with sinusoidal ECT [5].

Principal components analysis (PCA) is a statistical tool with which large, highly correlated data sets can be decomposed into a set of linearly uncorrelated principal component eigenvectors and associated scores, described by:

\[ Y = \sum s_i V_i \]

where \( Y \) is a column vector of data, and \( V_i \) and \( s_i \) are the associated eigenvectors and principal component scores, respectively, used in the reconstruction. The modified principal components analysis (MPCA) used for this work differs from conventional PCA in that it retains the signal mean, producing a least squares interpretation instead of variance minimization [6]. This technique allows for incremental reproduction of signals through linear combinations of principal components and their scores, resulting in significant dimensionality reduction, while retaining most information originally contained in the data [5].

Regression is a widely used data analysis technique that provides a statistical relation between sets of independent variables and a dependent variable through a series of coefficients [14]. In this work, multiple linear regression models were considered to regress MPCA scores to inspection variables. Hole ID, fret depth, and 2D tube off-centering were varied simultaneously, and regression models were constructed in order to determine hole ID and fret depth. The general fitting equation for regression models considered in this work can be described as:

\[ y = A + \sum_{i=1}^{n} (B_i s_i + C_i s_i^2) \]

where \( A \) is a constant, \( s_i \) are the MPCA score inputs, \( B_i \) and \( C_i \) (purely quadratic) are their regression coefficients, and \( n \) is the number of predictor MPCA scores chosen for the particular model. Regression coefficients were obtained in a stepwise manner using the `stepwiselm` function of MATLAB [15]. This algorithm selected the most statistically significant variable, generated a regression coefficient, and subsequently reduced the data by removing that coefficient-variable combination. Subsequent coefficients were obtained by regressing to residuals of reduced data sets iteratively [15].

To reduce the number of MPCA scores retained for models, factor analysis was considered. Factor analysis is a method for investigating if observed variables of interest are related to some unobserved source variables called factors [9]. The parameters of the linear functions are called loadings. If we assume there are \( m \) underlying factors that can be used to describe the data, a mathematical model can be written that tries to reproduce the maximum correlations between factors and variables [9]:

\[ X_j = a_{j1}F_1 + a_{j2}F_2 + \cdots + a_{jm}F_m + e_j \]

where the factors, \( F_m \), and factor loadings, \( a_{jm} \), combined with a unique error factor \( e_j \), attempt to fit to a number of variables \( X_j \). Loadings describe the correlation between observed variables and latent factors [16]. Investigating the
loadings of an exploratory factor analysis model with two or more factors can provide insight to the relation between observed variables and latent factors [16]. In this work, factor analysis was used to “quiz” MPCA scores with respect to an observed variable, either hole ID or fret depth, as opposed to creating models directly from the data. The factor with highest loading with respect to the variable of interest was examined. MPCA scores with high loadings (magnitudes greater than 0.4) were considered to be correlated with said variable [9]. This method was employed to refine MPCA score selections before creating regression models in order to reduce over-fitting by removing potentially nonessential information. Factor analysis was performed using the factoran function in MATLAB [17].

**EXPERIMENTAL PROCEDURE**

Four 25 mm long 410SS samples, with hole IDs shown in Table 1, were used to simulate different states of uniform ferromagnetic drilled support structure corrosion. The sample Alloy 800 tube was a 15.9 mm OD with a nominal wall thickness of 1.2 mm. Five 25 mm long rectangular, flat bottom frets were machined at regular intervals along the tube. Their depths, characterized as the difference between nominal tube OD and measured OD at the frets’ centers using callipers, are indicated in Table 2. A micrometer apparatus holding the SG tube within the hole allowed for accurate tube positioning within the hole ID. The focus of models for this work were primarily hole ID, as well as fret depth.

**Table 1** 410SS hole dimensions, along radial gap between Alloy 800 and support structure, and number of unique positions for which measurements were collected.

<table>
<thead>
<tr>
<th>Support hole ID [mm]</th>
<th>Radial gap [mm]</th>
<th>Number of unique tube positions measured</th>
</tr>
</thead>
<tbody>
<tr>
<td>17.1</td>
<td>0.6</td>
<td>9</td>
</tr>
<tr>
<td>18.7</td>
<td>1.4</td>
<td>19</td>
</tr>
<tr>
<td>20.1</td>
<td>2.1</td>
<td>24</td>
</tr>
<tr>
<td>21.8</td>
<td>3.0</td>
<td>43</td>
</tr>
</tbody>
</table>

**Table 2** Depth of rectangular flat bottom frets.

<table>
<thead>
<tr>
<th>Fret Number</th>
<th>Depth [mm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.65</td>
</tr>
<tr>
<td>2</td>
<td>0.74</td>
</tr>
<tr>
<td>3</td>
<td>0.87</td>
</tr>
<tr>
<td>4</td>
<td>1.00</td>
</tr>
<tr>
<td>5</td>
<td>1.11</td>
</tr>
</tbody>
</table>

The PEC probe [5], [8] consisted of a 127 turn 36 AWG excitation coil wound coaxially with the probe body, and 2 arrays of four 360 turn 42 AWG pickup coils, placed at 90° intervals around the surface of the probe both in front and behind the excitation coil, as shown in Figure 1. Excitation pulses were generated digitally in LabView and output through a NI6356 DAQ at 1000 Hz and 50% duty cycle resulting in 2.5 V pulses after current amplification. Pickup coil responses were carried through shielded twisted pairs to custom amplification circuitry before being digitized by the NI6356 DAQ at 1 MHz per input channel. Pickup coil parameters of resistance and inductance were matched across the probe as much as possible during manufacturing to ensure coil responses to nominally identical flaws were similar.

95 unique randomly generated tube positions (XY variables) were measured spanning the four hole IDs (ID variable), as indicated in Table 1. These measurements were repeated for each fret depth indicated in Table 2 and no fret (Fret variable), bringing the total number of unique measurements to 570 (95 x 6) for measurement Set A.
All measurements were repeated a second time to produce a nominally identical Set B to provide independent validation of regression models. MPCA eigenvectors generated to produce scores from Set A, considered to be the inspection vectors, were applied to Set B for score generation as might be done for real inspections. MPCA score sets, exclusively from the front array of pickup coils of Sets A and B, are referred to as Sets FA (Front A) and FB (Front B), respectively.

RESULTS AND DISCUSSION

A list of the various regression models for determining Hole ID are shown in Table 3 in terms of the experimental variables used to generate the data and the data set (A or B) used. Table 3 also gives the $R^2$ values for the fits obtained. These models are now discussed in detail.

<table>
<thead>
<tr>
<th>Model</th>
<th>Applied to data set</th>
<th>Measurement variables</th>
<th>Number of terms in model</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>A</td>
<td>ID, XY</td>
<td>29</td>
<td>1.00</td>
</tr>
<tr>
<td>Model 2</td>
<td>A</td>
<td>ID, XY, Fret</td>
<td>38</td>
<td>0.99</td>
</tr>
<tr>
<td>Model 2</td>
<td>B</td>
<td>ID, XY, Fret</td>
<td>38</td>
<td>0.05</td>
</tr>
<tr>
<td>Model 3</td>
<td>FA</td>
<td>ID, XY, Fret</td>
<td>21</td>
<td>0.97</td>
</tr>
<tr>
<td>Model 4</td>
<td>FA</td>
<td>ID, XY, Fret</td>
<td>22</td>
<td>0.97</td>
</tr>
<tr>
<td>Model 5</td>
<td>FA</td>
<td>ID, XY, Fret</td>
<td>17</td>
<td>0.96</td>
</tr>
<tr>
<td>Model 3</td>
<td>FB</td>
<td>ID, XY, Fret</td>
<td>21</td>
<td>0.14</td>
</tr>
<tr>
<td>Model 4</td>
<td>FB</td>
<td>ID, XY, Fret</td>
<td>22</td>
<td>0.44</td>
</tr>
<tr>
<td>Model 5</td>
<td>FB</td>
<td>ID, XY, Fret</td>
<td>17</td>
<td>0.71</td>
</tr>
</tbody>
</table>

STANDARD REGRESSION ON HOLE ID

In the initial regression model (Model 1) hole ID was regressed on data obtained from just the no fret case. After some preliminary work, it was decided to exclude the interaction terms as they rapidly caused models to become unwieldy. In this initial work, well over 50 statistically significant terms were retained by the stepwise linear model algorithm, resulting in significant over-fitting. Regression fit of Model 1 is shown in Figure 2, demonstrating the high quality fit that can be obtained from a single data set without frets.

With frets included as a fourth measurement variable a new MPCA was performed. The new MPCA scores (Set A) were calculated and the procedure that produced Model 1 was repeated to give Model 2. The fit of Model 2 is shown in Figure 3, and, while the spread is larger than Model 1, it is still a good fit to measured values. In order to validate Model 2, the regression coefficients were applied to a second, nominally identical set of measurements (Set B). The result can be seen in Figure 4 and shows a complete loss of predictability. This was attributed to over-fitting of the original data set due to the large number of regression terms kept for Model 2. Consequently, small variations in MPCA scores were amplified by the model when applied to a second set of data, causing the model to breakdown.
In order to reduce the amount of over-fitting, a new model, Model 3, was created after truncating the MPCA scores to only include those from the front array of pickup coils (data set FA). This removed some redundancies in the data as both arrays were expected to contain very similar information. The results for this model are shown in Figure 5. Model 3 was slightly more successful when applied to the secondary validation Set FB compared to Model 2 ($R^2$ of 0.14 versus 0.05 as shown in Table 3). The model was still over-fitting, retaining terms that, while correlated with remaining error, were minute variations in measurement condition due to uncontrolled variables, such as temperature or ambient electrical noise.
In order to improve the models fret depth was added as an input variable. While ideally fret depth would be determined through analysis of PEC signals, ECT can reliably provide this information [2]. For in-reactor inspections, PEC would be a secondary inspection technique and ECT measurements would have already been performed on tubes being inspected by PEC. Model 4 was created by regressing scores similar to those in Model 3, with the addition of fret depth, on Set FA. While little change was observed in Figure 7, where Model 4 was applied to Set FA, large improvements could be seen when Model 4 was applied to Set FB, shown in Figure 8, for validation ($R^2$ of 0.44 versus 0.14 as shown in Table 3).
In order to reduce over-fitting, Factor Analysis was applied to a data matrix containing the scores from the front of the probe and the hole ID. The factor with the highest loading with respect to hole ID was then selected. MPCA scores with loadings above 0.4 on this factor were selected for the reduced model (Model 5). Coefficients for model 5 were obtained by regressing this reduced set of MPCA scores, along with fret depth, on hole ID. The fit to data Set FA, used to determine the coefficients, was similar to that achieved in earlier models as shown in Figure 9. Applying Model 5 to the validation Set, FB, however, showed significant improvement when compared to Model 4 ($R^2$ of 0.71 versus 0.44 as shown in Table 3).

**EXPLORATORY FACTOR ANALYSIS ON HOLE ID**

Basic factor analysis suggested that the number of scores associated with fret depth was limited and that over-fitting was unlikely to be an issue. Consequently, fret depth was regressed on Set A with the full set of MPCA. The results of the fit to Set A and the application of that fit to Set B are shown in Figures 11 and 12, respectively.
Figure 9 Collar ID fit of Model 5 applied to Set FA.

Figure 10 Collar ID fit of Model 5 applied to Set FB for validation.

A summary of fret models can be seen in Table 4. In these cases, the fits are good. The model produced clustered points when applied to Set B for validation, but tended to undershoot targets by 10%-20%, as shown in Figure 12. The potential for under-predicting flaw size is non-conservative and would be a factor in evaluating this technique for application as a steam generator inspection technology.

Table 4 Summary of fret depth model $R^2$ fit qualities when applied to Sets A and B, along with the number of terms retained and measurement parameters being varied simultaneously.

<table>
<thead>
<tr>
<th>Model</th>
<th>Applied to set</th>
<th>Measurement parameters varied</th>
<th>Number of terms in model</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model F</td>
<td>A</td>
<td>ID, XY, Fret</td>
<td>16</td>
<td>0.99</td>
</tr>
<tr>
<td>Model F</td>
<td>B</td>
<td>ID, XY, Fret</td>
<td>16</td>
<td>0.95</td>
</tr>
</tbody>
</table>
CONCLUSIONS

A PEC probe was examined for the inspection of ferromagnetic support structures from within Alloy 800 SG tubes. Time-voltage pickup coil responses for 95 unique tube positions within four hole IDs, and five fret depths as well as a nominal tube, were examined. Scores generated from MPCA were used as inputs to a set of multiple linear regression models targeting fret depth and hole ID. To improve model fits to validation data, fret depths were considered as inputs along with MPCA scores, as they could be obtained from complimentary inspection techniques such as ECT or UT. Models were further improved through factor analysis, identifying which MPCA scores correlated well with either hole ID or fret depth. This made it possible to reduce over-fitting by limiting the independent variables to be used. While the models obtained for fret depth worked well on both the training and validation data sets, the performance of models to determine the hole ID performed substantially less well on the validation set than on the training set. Further work on this parameter is warranted.

REFERENCES


Appendix D
Simultaneous Multi-Parameter Measurement in Pulsed Eddy Current Steam Generator Data using Artificial Neural Networks

Jeremy A. Buck, Peter Ross Underhill, Jordan Morelli, and Thomas W. Krause

Abstract—In-service inspection of complex systems, such as nuclear steam generator (SG) tubes and their surrounding support structures, is challenged by overlapping degradation modes. In these complex systems the simultaneous and accurate measurement of more than two interdependent parameters is difficult using standard statistical regression analysis tools. Recently, artificial neural networks (ANNs) have been investigated for dealing with the complex relation between inspection data and defect properties. In this work pulsed eddy current (PEC) data was obtained using a single driver with an array of 8 pick-up coils configured for inspection of Alloy-800 SG tube fretting, accompanied by tube off-set within a simulated corroding ferromagnetic support structure. Time-voltage data was processed by a modified principal component analysis (MPCA) to reduce data dimensionality, and MPCA scores were input into an ANN that simultaneously targeted four parameters associated with; support structure hole size, tube off-centering in two dimensions and fret depth. The neural network was trained, tested, and validated on experimental data and provided estimates to within 2% of hole inner diameter (ID) and 3% of fret depth targets. Estimates of hole ID and tube position were further improved when fret depth was used as an input, as might occur if fret depth inspection results are available.

Index Terms— Arrays, Artificial neural networks, Eddy current testing, Ferromagnetic materials, Nondestructive testing, Principal component analysis, Signal processing algorithms

I. INTRODUCTION

Steam generators (SGs) are critical components in nuclear power plants (NPPs), transferring energy from the irradiated primary heat transport system to the secondary heat transport system. In CANDU® and PWR reactor designs, the SG tubes are the thinnest barrier between irradiated and non-irradiated systems [1]. There are many potential degradation modes present in nuclear SGs such as tube fretting wear, denting, stress corrosion cracking, and support structure corrosion [2]. Life management strategies are implemented to maintain barrier integrity and ensure high SG thermal efficiency. SG tubes are regularly inspected with a suite of NDT techniques including conventional eddy current testing (ECT) and ultrasonic testing (UT) to detect and size flaws so that safe operating lifetime of components can be determined [3]. When multiple degradation modes overlap, such as tube fretting at a corroding support structure, these inspection techniques may have reduced capabilities. If tubes cannot be repaired (usually through installation of a sleeve) they are plugged, reducing reactor thermal efficiency. In the case of fretting wear, tubes are plugged once 40% through-wall frets are detected [4]. Therefore, reliable simultaneous measurement of multiple parameters is an important goal for inspection service providers and as structures age with increased overlapping degradation modes, such solutions become increasingly desirable [5]–[8].

Pulsed eddy current (PEC) is an emerging NDT technique with recently identified applications in aerospace [9]–[12] and SG nonferromagnetic tube inspection [8] and ferromagnetic tube inspection [13], that offers some advantages over ECT. PEC differs from ECT, namely by excitation waveform and probe design. A square wave voltage excitation of the drive coil results in magnetic flux changes that induce eddy currents in surrounding conducting materials via Faraday’s law of electromagnetic induction [14]. Following the leading edge of a square voltage pulse, current in the drive coil moves toward direct current (DC) levels. The resulting induced electromagnetic fields exponentially (to a first order approximation) approach zero as driver magnetic flux is no longer changing. The opposite trend is observed when excitation falls from near-DC to zero. Signal variations due to proximity to bulk ferromagnetic materials are identifiable at long times of the transient response, while tube flaws and small variations in proximity to ferromagnetic materials have a secondary effect, but at earlier times [8]. Combined with principal components analysis (PCA) [21], PEC has been used to address measurements at large lift-off [9] and identify second layer cracks in multi-layered aluminum structures [10]. PEC combined with PCA has been effective at detecting surface and sub-surface manufactured defects, and isolating effects of lift-off and multi-layer gaps in aluminum riveted structures [15], [16]. Analysis with PCA is an improvement over simple time-domain feature identification (response peak height, rise time and zero-crossing) for flaw detection [17].

This work was supported by University Network of Excellence in Nuclear Engineering (UNENE) and the Natural Sciences and Engineering Research Council of Canada (NSERC).

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Solving inverse problems, that is mapping measured signals to flaws, is an ongoing area of development for ECT and PEC [7], [13], [18]. Multiple linear regression models have been considered for deterministic mapping of experimental PEC signals and form the basis for this work [19].

Artificial neural networks (ANNs) attempt to simulate neuron interconnections observed in nature, in order to solve complex problems and are, therefore, powerful tools for pattern recognition [20], [21]. ANNs have been examined for tackling inverse eddy current problems for SG tubes [18], [22]. Error reduction for experimentally modeled ECT sensors has been achieved using ANNs by means of a pair of sensors to correct for nonlinear influences of target material (stainless steel, mild steel, and aluminum), as well as sample size [23]. Reconstruction of crack profiles from ECT data has been achieved with ANNs using binary regression outputs [18], and deterministic length and depth outputs after pre-processing [5], [24]. Numerically simulated data has been processed manually to train ANNs to identify impedance plane features for SG tubes [24], or processed with PCA to extract relevant signal features and compress ECT data, with at most two parameters simultaneously [5], [18], [20], [22], [25]. Four signal processing techniques, wavelet transforms, Fourier analysis, block mean values, and PCA, were compared with experimental ECT data for riveted lap-joints before flaw classification via ANN, demonstrating that PCA produced high quality results with the highest compression capability [25]. PCA was also determined to increase smoothness of ANN error surfaces, resulting in fewer local minima [18]. A comparison of tabu search (a metaheuristic search algorithm), simulated annealing, genetic algorithm, and PCA with ANN, was performed for simulated PEC responses to stress corrosion cracking [26]. Effects of training and testing ANNs with noise added to finite element modeling results, in order to simulate real inspection conditions, have been investigated [18], [22], [24], [26], [27]. It has also been shown that ANNs can interpolate results for bounded input data, but do not extrapolate well when data falls outside training bounds [5].

In this work PEC responses were experimentally obtained from a custom probe and processed with a modified PCA, which utilizes a minimization of sum square residuals interpretation of results instead of a variance minimization interpretation as in conventional PCA for feature extraction [9]. An ANN was trained on a set of experimental data in which ferromagnetic support structure hole inner diameter, Alloy 800 OD tube fret depths, and horizontal and vertical tube positions were varied simultaneously. A subset, bounded by the range of training data, was collected for validation of the deterministic, multi-target ANN. It is often difficult to reduce real inspection problems to one or two variables, highlighting the benefit of simultaneous feature identification and measurement. Results presented here show that this is feasible with up to four parameters using PCA combined with ANN analysis of PEC signals.

II. EXPERIMENTAL APPARATUS

A. Apparatus

Four 25 mm long carbon steel samples, termed collars, were manufactured. The collars simulated drilled ferromagnetic baffle support structures. A variety of hole inner diameters (IDs), as shown in Table I, were used to represent uniform corrosion. Collars were made cylindrical with an outer diameter (OD) of 32 mm resulting in a range of wall thicknesses from a minimum of 5 mm to a maximum of 8.7 mm, far thicker than the anticipated penetration of electromagnetic fields.

An Alloy-800 steam generator tube with 15.9 mm (5/8”) OD, 461 mm length and wall thickness of 1.2 mm was used during this investigation. The sample Alloy-800 tube had rectangular, flat-bottom OD frets, 25 mm in length and increasing in depth as shown in Table II, located at 38 mm increments along the tube.

This study investigated tube off-centering within a collar hole and therefore, the as-manufactured support structure hole ID (collar 1) was not considered as a test case, as meaningful tube off-centering was not possible. Similar length of frets and collars permitted spatial overlap. Tubes were held horizontally in the apparatus with a pair of orthogonally mounted micrometers to control horizontal (x) and vertical (y) positions of the tube within a collar as described in previous work [8]. Micrometers permitted positioning precision to within 0.01 mm.

<table>
<thead>
<tr>
<th>Collar Number</th>
<th>Hole ID [mm] ±0.05</th>
<th>Radial Gap [mm] ±0.05</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>16.50</td>
<td>0.30</td>
</tr>
<tr>
<td>2</td>
<td>17.48</td>
<td>0.79</td>
</tr>
<tr>
<td>3</td>
<td>19.05</td>
<td>1.58</td>
</tr>
<tr>
<td>4</td>
<td>20.65</td>
<td>2.38</td>
</tr>
<tr>
<td>5</td>
<td>22.22</td>
<td>3.16</td>
</tr>
</tbody>
</table>

B. Probe

The PEC probe, which was used in previous work [8], consisted of 8 surface pickup coils, placed in arrays of 4 coils before and after a central drive coil, with 90° separation between pickup coil axes and with axes perpendicular to the central drive coil. Coil arrangement is shown schematically in Figure 1 (a).

Pickup coils were 360 turns of 42 AWG wire, while the drive coil was 127 turns of 36 AWG wire. Length and OD of the probe were 77.6 mm and 13.5 mm, respectively. A 50% duty cycle ratio, 3.0 V square wave pulse, 0.5 ms in duration was generated by a NI6356 USB DAQ and current was subsequently amplified before being carried to the drive coil with a coaxial cable.

Manual triggering of the pulses was used to accommodate the requirement of repositioning the tube for every measurement. Response signals for each pickup coil were collected on dedicated analog input channels after a 100 times
voltage amplification and digitized by the NI6356 USB DAQ at a sampling rate of 1 MHz concurrently with 16 bit resolution per channel. Communication to the DAQ was accomplished through a custom LabView program running on a 3.0 GHz quad-core personal computer with 8GB of RAM.

C. Measurements

Data was collected with variation over the four parameters: collar hole ID, rectangular fret depth, horizontal tube position (dx) and vertical tube position (dy) as indicated by the schematic Figure 1 (b). A randomly generated point map was chosen over a full grid to reduce acquisition time, while maintaining enough variations to characterize the measurement space.

Horizontal and vertical tube offsets within each hole size were generated with the condition of constant point density per unit area, while being randomly distributed azimuthally. Azimuthal coordinates were generated through the random number function in Excel for each radial position. Four distinct data sets were collected with three following the same number function in Excel for each radial position. The fourth set (D) followed a separate, smaller point map in order to provide an independent validation set. Measurements were repeated for collars 2-5 and frets 1-5 including a case without frets (see Tables I and II for dimensions). Data covering a complete set of flaw inputs is required for PCA to produce sufficiently representative eigenvectors. Table III summarizes the measurements that were performed. Data was collected while the probe was stationary with all 8 pickup coils inside the ferromagnetic region of interest. Temperature was recorded using a standard digital thermometer during data collection as temperature variations between 21 and 24 °C had a measurable effect on PEC signals.

<table>
<thead>
<tr>
<th>Collar Number</th>
<th>Measurements for each A, B, and C</th>
<th>Measurements for D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>60</td>
<td>30</td>
</tr>
<tr>
<td>3</td>
<td>90</td>
<td>48</td>
</tr>
<tr>
<td>4</td>
<td>156</td>
<td>78</td>
</tr>
<tr>
<td>5</td>
<td>216</td>
<td>96</td>
</tr>
<tr>
<td>Total</td>
<td>522</td>
<td>252</td>
</tr>
</tbody>
</table>

III. Analysis

A. Pulsed Eddy Current

Example PEC signals are shown in Figure 2 for the case where coil 6 is in close proximity to both the ferromagnetic support structure and a 92% through-wall fret, and for coil 2, which is opposite coil 6 and therefore, far from the support structure and tube flaw. These two extreme cases demonstrate the similarities in PEC time-domain responses, which require a more in-depth analysis to extract reliable information from the signals. In order to identify signal variations data was decomposed using MPCA [9].

B. Modified Principal Components Analysis

PCA is a statistical technique that is generally used for feature extraction or data compression. Data can be represented by a set of linearly uncorrelated principal component eigenvectors and associated scores. It is assumed that a column vector of data \( Y \) can be written as a sum of a small number of eigenvectors [28]:

\[
Y = \sum s_i V_i
\]

where \( V_i \) are the principal components and \( s_i \) the principal component scores. The mean signal has not been subtracted in (1) in this modified principal component analysis (MPCA) in order to retain information related to signal strength and reduce susceptibility to probe or amplification circuitry replacements, thereby increasing the overall robustness of the analysis [9]. The eigenvector accounting for the largest variation in the data is statistically the best choice of basis vector for reconstructing the data and, therefore, will have the largest principal component score [28]. Subsequent eigenvectors account for successively smaller variations in the data. This method reduces data sets from thousands of points to a smaller set of eigenvectors, which are common to the entire set, and associated scores that multiply eigenvectors. Their sum reconstructs each measurement waveform as expressed by (1).

Absolute signals of diametrically opposed coils on the probe were concatenated within the same data set before processing by MPCA [10]. This produced pseudo-differential results, via concatenation instead of subtraction, while maintaining full individual coil information. A set of 5 eigenvectors and associated scores were found to represent
data for this work. Each coil pair therefore output 5 scores per measurement, compressing data from all 8 coils from a total of 8000 points to 20 (4 coil pairs). Previous work demonstrated sensitivity of MPCA scores to collar hole ID and horizontal tube position [8], but a more complex analysis is required to simultaneously extract 4 parameters from the data.

C. Artificial Neural Networks

Artificial neural networks emulate the manner in which brains process information, accomplishing this through an interconnected network of neurons [20], [21]. Each neuron has a single output activated via a dependence on a large number of inputs. Networks of neurons in nature have the potential to learn from past experience by developing synaptic connections between neurons and are fault tolerant due to the vast number of interconnections between neurons [20], [21]. ANNs are a scaled down version, reducing neuron numbers and connections significantly, while still retaining the core features including weighted connections and activation functions [20], [21]. Neurons in ANNs are organized in layers, including an input and output layer. Neurons from different layers are interconnected, with associated weights. Multiple inputs may be combined to produce a single output by using an activation threshold function [20], [21].

ANNs were employed to examine patterns in the large number of dependent variables obtained from MPCA scores of PEC data. To this end, a simple, single hidden-layer ANN architecture was selected along with an input and output layer. A single hidden layer is often enough for basic pattern recognition applications, as results in Section IV demonstrate. PCA scores from all pickup coils were input to generate ANNs in order to effectively average out coil imbalances inherent in the PEC probe. Temperature was added as a variable to ANN models in order to compensate for associated changes in measurement conditions, such as probe resistance, and material resistivity and permeability, which would further affect probe response. It was observed that inclusion of temperature at which measurements were performed, improved overall ANN model quality. The ANN input layer had 21 neurons (5 PCA scores per coil pair, and temperature), and the output layer had 4 neurons, one corresponding to each parameter of interest (collar hole ID, fret depth, horizontal and vertical off-centering). The hidden layer was chosen to have 6 neurons, which was empirically determined to strike an appropriate balance between reducing over-fitting and retaining network simplicity, while producing good fits relative to targets. A sigmoid activation function [21] was used for hidden-layer neurons, while a linear activation function [21] was used for the output layer. Analysis procedure and ANN neuron structure is shown schematically in Figure 3.

The ANN was trained by inputting data and comparing network outputs to target values. Errors in results were used to update neuron connection weightings via a Levenberg-Marquardt back-propagation algorithm [29]. Iterations of the model, termed epochs, iteratively updated weights as training data was fed again into the ANN. Batch training, using offline measurements with known targets, was used to create ANNs for this work. Sets A and B were selected to train the network, and data from them was randomly divided into subsets to generate the ANN in MATLAB: 50% training, 25% testing, and 25% validation. The training set was used to update connection weights, while validation data was checked for model over-fitting. When validation performance failed to decrease after 6 successive epochs, the training was stopped. The model was then applied to testing data as a final independent assessment of quality. Following this procedure the ANN was applied to a third repeat set C as external manual validation. Finally, to examine model generalization ability, the ANN was applied to a new data set D, as described in Section III C.

Fig. 3 Tree diagram of data analysis procedure.

IV. RESULTS

Data was processed using the ANN structure described in Section III and applied to the data. The training set consisted of two repeat sets, A and B, defined as having the same x-y point map, as described in Section II. Once an appropriate ANN was trained it was applied to a third repeat set C to test the ANN robustness against variations between nominally identical measurements. A final, smaller, data set D was processed with the ANN to validate it on a new set of tube positions. In all cases, ANN outputs were directly compared to dimensions (collar hole ID and rectangular fret depth) or target micrometer positions (horizontal x and vertical y off-centering). Figures 4(a)-(c) plot ANN as applied to set C. More data points were obtained in the case of larger hole diameters, since a larger number of off-centered positions were available for testing. When combined, these two effects explain increasing standard deviations with increasing hole size as indicated in Table IV. Table IV also shows increased error that arises when temperature (between 21 and 24 °C) is not included as an input in the ANN training set.

Applying the ANN to the entirety of training sets, A and B, produced excellent agreement with measured hole diameter, which is to be expected. When applied to testing set C, mean values were still in excellent agreement with measurement, but standard deviations of data with respect to calculated means increased. A similar trend is observed when applying the ANN to validation set D, although standard deviations of the mean increased further. Errors were determined to be less than 2% of actual hole size (to one standard deviation), highlighting the accuracy and precision of the analysis. Figure 4(d) illustrates the magnitude of the error relative to target values of ANN hole sizing results for all data set. Since sets have different numbers of measurements, histogram centroid positions and
TABLE IV
HOLE ID MEANS AND STANDARD DEVIATIONS FROM ANN RESULTS WITH % ERROR COMPARISONS FOR MODELS WITH AND WITHOUT TEMPERATURE INPUTS

<table>
<thead>
<tr>
<th>Target (mm)</th>
<th>Sets A and B (mm)</th>
<th>Set C (mm)</th>
<th>Set D (mm)</th>
<th>% Error</th>
<th>% Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>σ</td>
<td>Mean</td>
<td>σ</td>
<td>Mean</td>
</tr>
<tr>
<td>17.48</td>
<td>17.50</td>
<td>0.04</td>
<td>17.50</td>
<td>0.06</td>
<td>17.43</td>
</tr>
<tr>
<td>19.05</td>
<td>19.03</td>
<td>0.08</td>
<td>19.00</td>
<td>0.12</td>
<td>18.95</td>
</tr>
<tr>
<td>20.65</td>
<td>20.67</td>
<td>0.12</td>
<td>20.66</td>
<td>0.20</td>
<td>20.69</td>
</tr>
<tr>
<td>22.22</td>
<td>22.20</td>
<td>0.13</td>
<td>22.35</td>
<td>0.32</td>
<td>22.23</td>
</tr>
</tbody>
</table>

Figure 4 Comparison of targets and ANN results when applied to test set C for collar hole ID (a), horizontal off-centering (b), and rectangular fret depth (c). Histograms (d), (e), and (f) illustrate deviations of results from their targets when the ANN was applied to training (A and B), testing (C), and validation (D) sets.
width are indicators of model quality. Error in validation results of Figure 4(d) do not possess an evident centroid, suggesting a systematic error in either the measurement or in the ANN, but agreement between model results and targets is still quite good as identified in Table IV.

Horizontal and vertical tube positions, as predicted by ANN results, were compared to tube off-centering dx and dy targets associated with 129 unique micrometer positions. Horizontal ANN position errors relative to collar hole ID were less than 1% for one standard deviation. When calculated for vertical position, the mean had a 2% offset and standard deviation from targets relative to hole ID were less than 4%. Larger deviations were attributed to reduced probe sensitivity due to increased distance to wall when larger hole IDs were present. Figure 4(b) compares target micrometer dx off-centering to ANN predictions for testing set C, indicating excellent reproduction. Similar results were observed when comparing vertical off-centering dy predictions relative to targets. Model quality was examined as shown in Figure 4(e), comparing deviations of ANN predictions to their targets. A slight shift in centroid location was observed in testing and validation results when compared to training. This will be discussed below in the context of frets and their effects on PEC signals.

Final targets of the ANN models were the depth of flat bottom rectangular frets. While not a true representation of all fretting wear in nuclear SGs, they provide a basic understanding of wall loss effects and how they relate to PEC responses. Depth of a fret was characterized as the maximum variation between nominal tube OD and flat-bottomed fret. Comparison between ANN predictions and measurements for fret depth demonstrate high sensitivity of PEC combined with PCA and ANNs. Data clusters are easily separable due to small standard deviations as indicated in Table V. Note that % error decreases with increasing fret depth. This correlates with the observation of an amplified signal response for deeper frets [8]. This is reflected by decreasing standard deviations for larger fret depths as shown in Table V. A small shift in error centroids is apparent in Figure 4(f) for testing and validation results. However, results agree within 3% of their target wall thickness for most data and still provide excellent estimates of fret depth for SG tubes with 1.2 mm wall thickness.

ECT or UT inspection results can provide good estimates of fret depth [3]. Therefore, selecting fret depth as an additional input to an ANN is feasible if other inspection results are available. Incorporating fret depth reduced ANN targets to three, while the same neuron structure and data breakdown was maintained. This did not have a significant effect on hole ID results when compared to Figure 4(d), however error profile spread and centroid location for position results were improved from 4% and 2%, respectively, without fret depth inputs, to 2% and 1% for vertical off-centering predictions, as shown in Figure 5(a) and (b). Horizontal position error distributions were not significantly affected.

### Table V

<table>
<thead>
<tr>
<th>Depth (mm)</th>
<th>Set A and B (mm)</th>
<th>Set C (mm)</th>
<th>Set D (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>σ</td>
<td>Mean</td>
</tr>
<tr>
<td>0.00</td>
<td>0.01</td>
<td>0.02</td>
<td>-0.06</td>
</tr>
<tr>
<td>0.65</td>
<td>0.64</td>
<td>0.01</td>
<td>0.59</td>
</tr>
<tr>
<td>0.74</td>
<td>0.74</td>
<td>0.02</td>
<td>0.72</td>
</tr>
<tr>
<td>0.87</td>
<td>0.88</td>
<td>0.01</td>
<td>0.86</td>
</tr>
<tr>
<td>1.00</td>
<td>1.01</td>
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<td>1.01</td>
</tr>
<tr>
<td>1.11</td>
<td>1.10</td>
<td>0.01</td>
<td>1.08</td>
</tr>
</tbody>
</table>

Fig. 5 Error relative to target vertical position when ANN targets 4 parameters (a) and when ANN targets 3 parameters (b), using fret depth information as an additional input term.

### V. DISCUSSION

One advantage of PEC over ECT in this application is the ability to exploit differences in the characteristic diffusion times of electromagnetic fields between different materials and the use of an array to produce pseudo-differential signals. Shorter diffusion times associated with Alloy-800 SG tube material, when compared to the carbon steel support structure, results in early-time effects in transient signals being dominated by tube flaws [8]. Here the separation in respective diffusion times is anticipated to contribute to the accurate rectangular fret depth sizing by PCA combined with an ANN analysis as the measurements are less dependent on hole size and tube position, as shown in Figure 4(c). Frets used in this work were not truly representative of the large variety of fretting wear scars that occur in nuclear SGs, but were considered to be an appropriate simplification to examine the effect of SG tube wall loss on PEC signals. A larger measurement set, spanning frets more characteristic of what is observed in nuclear SGs, would be required to properly train an ANN for real inspections.
Systematic error identified in Figure 5(a) was attributed to increased sensitivity to support structure in the presence of wall loss, whereas the ANN model assumed uniform wall thickness. Including the alignment of flaws relative to sensing coils improved systematic error, as shown in Figure 5(b), by reducing the number of variables required as outputs of the ANN. It was anticipated that reducing ANN targets to 3, simplified the model allowing more effective use of neuron interconnections and hence, the overall accuracy of remaining parameter outputs was improved.

Balancing of pickup coil parameters during probe manufacturing is essential to achieve accurate evaluation of hole condition. This was demonstrated by the observation that hole ID fit qualities varied when analysis was restricted to either the front or rear array of coils. An average weighted error improvement of 1.4% for hole ID sizing with the rear array was attributed to better matching of pick-up coil response in air. Mismatch of front and back coil sets is averaged out when using data from all 8 coils, as required for the characterization of uniform corrosion. In the case of non-uniform corrosion of support structures, such as tapering or egg shaped holes, additional analysis, utilizing absolute signals, would need to be considered to properly profile the component.

Inclusion of temperature as an ANN input improved results significantly. This effect was observed during data collection as complete temperature control was not feasible. In lieu of a full study, local temperature was recorded with a digital thermometer. Collar ID results for set D improved from 2.1% weighted standard error to 1.3%. Further investigation to the effects of real SG inspection temperatures on PEC signals is warranted.

As shown in Figure 4, PCA combined with ANNs simultaneously determined the 4 overlapping parameters of cylindrical hole size, rectangular fret depth, and two-dimensional tube position. Improvements to ANN results shown in Figure 5 can be achieved by including UT or ECT measured fret depths thereby reducing the total number of target parameters, which facilitates association of inputs with measurements in ANNs. ANNs demonstrated good generalization for data within the training range, so future work will investigate expanding this range and refining ANN architecture.

VI. CONCLUSION

PCA feature extraction and deterministic ANNs have been combined to estimate four separate experimental parameters: ferromagnetic hole ID, rectangular fret depth, and horizontal and vertical tube positions, simultaneously, from sets of PEC data. The ANN was trained on experimentally obtained data and validated on independently acquired data. Excellent fits were observed for modeling hole ID and fret depth, achieving in general less than 2% and 3% relative error, respectively. Tube positions could be determined within 4% standard error relative to hole ID. Inclusion of fret depths as ANN inputs, which simplified the model to three targets, reduced tube position standard error relative to hole ID to 2%. Higher accuracy in this case was attributed to ANN model simplification.

ACKNOWLEDGMENTS

The first author would like to thank Sarah Mokros and Ken Fauurschou for useful discussions and Brian Lepine in Inspection Monitoring and Dynamics Branch at Canadian Nuclear Laboratories (CNL) for use of samples and probe. This work has been supported by University Network of Excellence in Nuclear Engineering (UNENE) and Natural Sciences and Engineering Research Council (NSERC).

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