Quantifiable Corrosion Detection in Aging Aircraft

John R. Brence* and
United States Military Academy, West Point, NY, 10996

Donald. E. Brown†
University of Virginia, Charlottesville, VA, 22903

The ability to detect and predict corrosion damage in its early stages could lessen the chances of catastrophic failure in aging, over-extended aircraft; thereby providing a safer and more reliable transportation system for both civilian and military sectors. This is especially critical now as transportation providers attempt to meet the increased expense of repairing aging aircraft with smaller budgets. These budget constraints exemplify the importance of early corrosion detection and repair and, if necessary, the determination of the optimal time to replace corroded parts. The discovery of models that limit the possibility of a tragic accident while optimizing resource utilization would allow transportation providers to efficiently focus their maintenance efforts. While our concern in this study was with aircraft, the results will also be useful to other transportation providers. This paper provides a background on eddy current (EC) non-destructive tests (NDT), the methodology used to extract the data into a useable form and the results of our comparison of empirical models to detect corrosion damage. The NDT data were derived from EC scans of the United States Air Force's (USAF) KC-135 aircraft.

I. Introduction

MANY commercial and military aircraft have reached or exceeded their original design life and are subject to significant increases in maintenance and repair cost due to corrosion. Corrosion is now recognized to have a detrimental effect on the structural integrity of aging aircraft components, and the lack of predictive capability has prevented the operators of aging aircraft from successfully controlling corrosion. There is particular concern about potential catastrophic damage from corrosion on the structural integrity of the fuselage. Corrosion may lead to a decrease in strength as a result of a loss in skin thickness; early fatigue crack initiation caused by the formation of stress risers, and increased fatigue crack growth rates.[1]

While corrosion problems are endemic to all services and all commercial aircraft, the United States Air Force (USAF) has many old (20 to 35+ years) aircraft that are the backbone of the total operational force. The oldest are the more than 500 jet tanker aircraft, the KC-135s, which were first introduced into service more than 40 years ago. For the most part, replacements are a number of years away, and the program schedules continue to be

* Adjunct Assistant Professor, Department of Systems Engineering, Mahan Hall.
† Department Chair and Professor, Department of Systems and Information Engineering, Olsson Hall.

constrained by, and subject to, the vagaries of annual funding cycles. The KC-135s, along with many aging aircraft, have no planned replacement and are expected to stay in service for another 25 years.[2]

With varying degrees, all USAF aircraft have encountered and will continue to show signs of fatigue, stress corrosion cracking, corrosion, and wear. Historically, corrosion has caused an escalation of maintenance costs and, in many cases, has severely impacted operational readiness due to the increased time required in depot level repair.

Corrosion is life threatening and costly. More efficient, inexpensive corrosion prediction, detection, and classification tools are desperately needed to protect civilian industry and the military from catastrophic accidents and overwhelming expenses.

If done properly and proactively, corrosion control is an effective weapon to combat potential aircraft structural failures. Failure to institute an effective corrosion control program could lead to weakened structural integrity of an aircraft potentially causing fatal results. However, since detection and treatment often occurs at the microscopic level; constant vigilance, state-of-the-art technology and advanced numerical methods are often required for an effective corrosion program.[3]

Corrosion costs are extremely high. The United States spends almost $300 billion a year[3], the North American aircraft industry spends $13 billion a year[4] and the United States Air Force spends approximately $1 – 3 billion a year[2] on operations pertaining to corrosion costs. These monies for corrosion repairs and prevention programs take away from needed equipment upgrades and other operational programs. Due to budgetary constraints in both commercial and military sectors, there is a need for an efficient way to defend against the corrosion threat.

The Department of the Defense is aggressively working to defend against corrosion in order to lengthen the lifespan of its aging fleet of aircraft. Three research institutes were combined to establish the Academic Center of Aging Aircraft at a cost of $4.2 million. The center’s focus is on cost effective technologies to control and prevent corrosion, development of cutting edge methods to diagnose corrosion related problems and to improve the overall maintenance program that services these aging aircraft. Michael McCabe, director of the Institute at Dayton (one of the partner research institutes), reports that Department of Defense (DoD) aircraft maintenance expenditures have grown to $13 billion annually; climbing at a continuous rate of 7 – 12% per year.[5] Yet another indication of the seriousness of the corrosion detection, prevention, and maintenance issue.

A specific event that underscores the importance of corrosion detection accuracy was an accident involving an Aloha Airlines Flight in 1988 in which undetected metal fatigue and corrosion caused a large portion of the main fuselage to separate while the aircraft was cruising at 24,000 feet.[6] Several people were injured and one crew member was killed.

II. Issues with Corrosion Detection

Current methods of corrosion detection, mainly non-destructive tests, rely on trained operators to find corrosion and other flaws. Hence, maintenance decisions based on these tests are highly dependent on the analytical prowess of the operator. According to many human factors studies that have researched aircraft NDT inspection and evaluation procedures, there are several factors that can degrade inspector performance. One of the key deterrents to this degradation of performance is the application of advanced technologies and automation to reduce and manage the inspector's workload, thereby raising the expectation for more reliable and less cumbersome NDTs.[7] There are many factors that influence the ability of an operator to detect corrosion: training, alertness and confidence of the operator, correct application of proper NDT technique, environment of the test – laboratory or field, material homogeneity and isotropy, flaw characteristics, shape of part, calibration and capability of the system, and many other factors.

As discussed, there is a wide range of factors can degrade the operator's skills at the corrosion identification task. For example, inappropriate training, lack of sleep, or simply lack of focus can result in miscalculation of corrosion damage. Boredom is a key factor when conducting non-destructive evaluations since the likelihood of finding a flaw is typically small. Thus, the number of times actual corrosion is detected is strongly outweighed by the times it is not.[8]

The current approach to corrosion detection creates a false-color image of the measurements from the non-destructive tests (Figure 1). In Figure 1, the deeper orange-colored areas are suspected to be corrosion, while the yellowish and greenish-blue colors show no corrosion indications. In addition, the multiple blue circles show the response produced from a metal rivet. It is then up to the operator to examine the image and identify defects in the material. The difficulty in interpreting this visual display of the measurements is whether the clarity, color, and detail of the visualization are sufficient to make a determination of flawed materials. There is also the question of how the data were filtered or manipulated to create this visualization and whether that introduced additional errors.

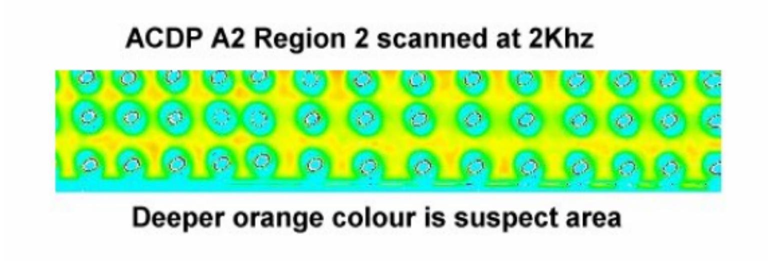

Figure 1: Visual representation of eddy current response[9]

Improper representation of data by choosing the wrong resolution of the image or an inadequate color palette can lead to a wrong conclusion. Because the eye has a non-linear response to color, the perception of color varies from person to person, thereby making the selection of an appropriate color scheme extremely difficult.[10] In the case of corrosion detection, a miscalculation of whether a surface is flawed may have a catastrophic result.

III. Linking Artificial and Natural Corrosion

In order to conduct our study to discover a relationship between NDT data and corrosion, we need precise measurement of the extent of the corrosion. Thus we have built models based on artificial corrosion, where the value of the material loss is known. With the improvement of artificial corrosion production, non-destructive tests have shown that the raw results from scans on artificial corrosion are similar to tests conducted on natural corrosion. Artificial corrosion plates are often used as controlled calibration specimens, in order to ensure proper operation of the scanning equipment.

The Institute for Aerospace Research, Canada developed an accelerated process to simulate the corrosion products and damage associated with crevice corrosion, which typically occurs in lap joints. The corrosion specimens formed during the accelerated process were very similar to those found in naturally corroded lap joints. In addition, the artificial corrosion damage had similar characteristics to that developed during the natural process.[4]

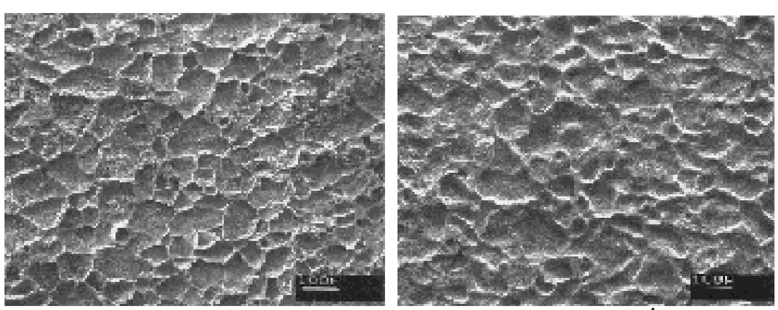

Figure 2: Artificial and Natural Corrosion at 100 microns[4]

IV. Data Acquisition

The data used for this paper were acquired from the Institute of Aerospace Research (IAR), National Research Council, Canada. The datasets and related information are from a funded study by the United States Air Force. The study, titled "Nondestructive Inspections of Calibration Specimens and KC 135 Aircraft Specimens: NRC-LTR-ST-2267," was used to test the performance of several methods of non-destructive tests with a focus on eddy and pulsed eddy current testing.

The specimens that were tested included artificial corrosion calibration specimens and retired KC-135 aircraft parts. For the eddy current tests, the specimens were scanned using a multi-frequency probe. Each specimen was scanned using four frequencies: 5.5 kHz, 8 kHz, 17 kHz, and 30 kHz for 0.04-inch panels and 2 kHz, 4 kHz, 7 kHz, and 12 kHz for 0.063-inch thick panels. These panels were scanned using both eddy current and pulsed eddy current non-destructive testing techniques. This paper will focus on the eddy current scans.

V. Non-Destructive Testing

The goal of any company is to maximize profits by minimizing expenses. For the armed forces, this means maintaining mission readiness by maximizing the service life of equipment and structures, while minimizing maintenance costs. There are many ways to achieve this goal. At one end of the spectrum, the organization performs periodic maintenance at frequent intervals so that the equipment is always in an operable, safe condition. This approach almost guarantees no failures, but at exceedingly large maintenance costs.

Non-destructive testing is the examination of an object or material with technology that does not affect its future usefulness. By allowing inspection without interfering with future use, NDT efficiently balances quality control and cost effectiveness. Non-destructive evaluation (NDE) is more quantitative in nature than NDT. NDE is used to not only locate a defect, but also to measure the properties of that defect ~ size, shape, and orientation. It is also used to determine material properties and physical characteristics. The three main reasons to conduct NDT are 1) Ensure freedom from defects likely to cause failure, 2) Ascertain the dimensions of a component or structure, and 3) Determine the physical and structural properties of any materials in a product.[11]

NDE comprises the monitoring of structural integrity, crack or defect initiation as well as tracking the growth or structural alterations caused by these imperfections. NDTs provide a means to conduct effective NDE.[11] There are several methods of NDT used for flaw detection in materials: Radiological methods: X-rays, gamma rays and neutron beams; Acoustical and vibrational methods: ultrasonic and mechanical impedance measurements;

Visual and optical methods: interferometry, holography, and dye penetrants; Thermal methods: infrared radiation and thermal paints; and Electrical and magnetic methods: eddy current, magnetic flux leakage (includes magnetic particle inspection) and microwave testing. These techniques present the advantage of leaving the components undamaged after inspection; hence, the title "non-destructive" test. Routinely, more than one NDT is used to evaluate a material for flaws, in order to compensate for the limitations of a single method.

At the other extreme is the "if it ain't broke, don't fix it" philosophy. This is a very cheap remedy, but if it introduces the potential for death, injury, or extraordinary damage, it is totally unacceptable. Clearly, we must find a middle ground. The application of non-destructive tests and evaluation, coupled with fracture mechanics, offers just that. The addition of these methodologies permits sounder, more technically justified maintenance decisions.[8]

A. Eddy Current NDT Results

The eddy current NDT has application in defect and corrosion detection, materials sorting, thickness measurements, displacement measurements, and weld detection. Advanced applications include defect sizing, hardness assessments, sub-surface temperature measurements, conductivity and permeability measurements, and multiple conducting coating thickness measurements. This method is a proven technique in these areas, but relies too heavily on the expertise of the operator to interpret the results. For more information on this technology, see [12, 13,14].

In out study, each eddy current test produced four different data files, one for each scan frequency. The scans were conducted left to right from the bottom left corner of the specimen to the top right. Each scan point produced one data point as shown in Figure 3. The data points were voltage measurements that included negative values.

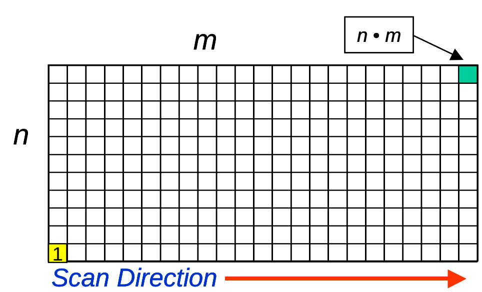

Figure 3: Scan pattern

Included with the eddy current datasets were bitmap images that visually represent the areas of material loss. These images were created from the response of the eddy current scans. When combined with calibration specimens these pictures are very useful, mainly because the corrosion areas are known and can be colorized for differentiation; it gets more difficult when the corrosion areas are not known. These bitmaps were a key element in the data-mapping phase of the training data in this study. The eddy current scan of the calibration specimen E1 is shown in Figure 4. From top left to bottom right are the 5.5 kHz, 8 kHz, 17 kHz, and 30 kHz scan results.

Analysis of the raw data from a particular scan utilizes a unique set of thresholds based on the frequency of the scan. The thresholds used in Figure 4 are not very accurate. This figure shows the results from a simultaneous multi-frequency scan of a single metallic surface. Each quadrant in the figure displays a different frequency result. Notice that even in a homogenous loss area, there are different shades of colors indicating varying degrees of loss. Since current probe technology allows for multiple scans, we assert that a better corrosion detection method would collect the raw data from the multiple scans and then, through the use of an algorithm or other mathematical model, develop and implement an additive set of thresholds based on this raw data. This would improve the overall accuracy of loss detection within and around the associate loss areas.

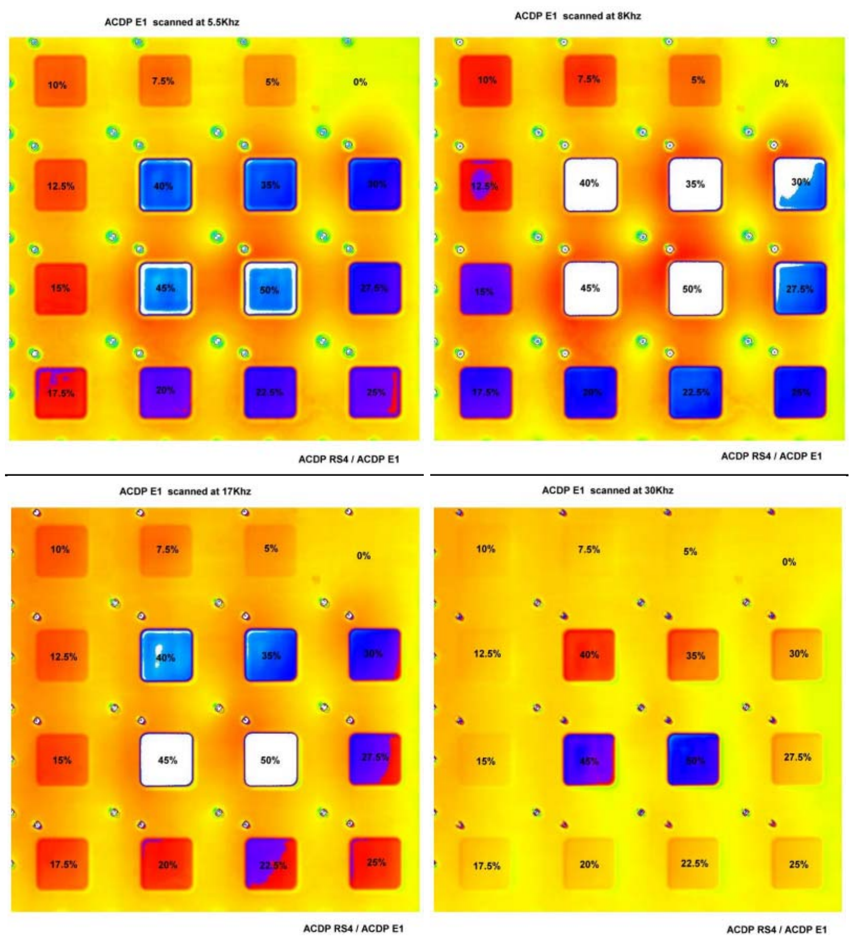

Figure 4: Calibration Specimen E1 visual results[9]

VI. Data Mapping and Consistency

The term data mapping is used to describe the action of combining four scan files (predictor or input variables) and determining the associated material loss, which was the response variable's value. We also performed consistency checks by comparing our resulting data set with the one used in the IAR study.

The first step was to decode the given files from the original data format and create new files containing a single column of $n \bullet m$ observations. These files were then combined into a single file with four columns and $n \bullet m$ rows.

The next step was to include the response variable's values – the amount of material loss at a given location. These values were found by mapping the contents of the image to the appropriate frequency observations. A C++ program (Picview) was created to read the bitmap images and apply numerical values 0 or 255 to each observation based on a user chosen threshold. The numerical values were assigned to the red, green, or blue spectrum. Different combinations of the numerical values created a different color response. Files of different thresholds were used as an added measure to ensure proper response mapping. The starred areas in Figure 5 show the material loss areas produced or generated in each image.

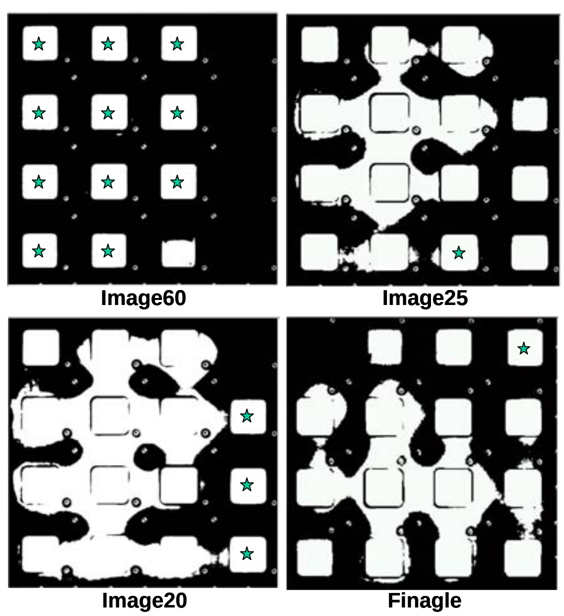

Figure 5: Picview Images

The original datasets were supposed to have the data points in a corresponding order to the bitmap images provided (Figure 4). The data mapping process would have been an easy task if this supposition were true. However, mapping the dataset quickly became a puzzle. A visual comparison of what the dataset should have looked like and the actual mapping scheme is shown as Figure 6. The labeled squares show the areas of material loss and the circles are machined holes in the material.

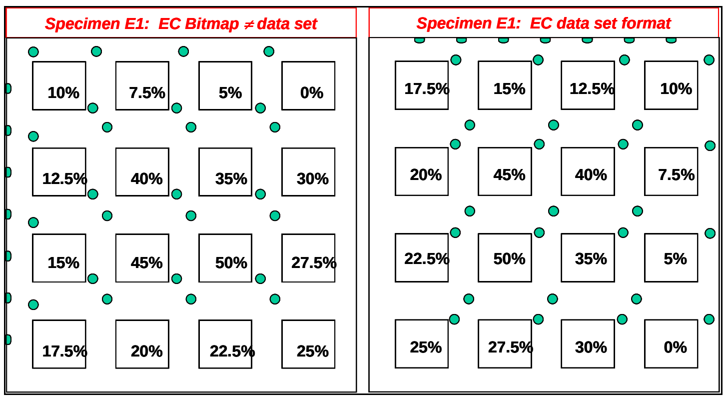

Figure 6: Bitmap image vs. actual data layout

After the above conversions of the total dataset, the training set was constructed using the actual data layout and Picview image data. Only the loss areas, represented by the labeled squares in Figure 6, were used in the final dataset; the rest of the data were deleted. The original dataset had 606,825 data points; the new dataset has 160,608 observations. Paring down this dataset deletes many noisy data elements that have no consequence on the results.

Once we had generated the dataset for the study, we validated this set. Our validation step used the graph shown in the original study by IAR and reproduced in Figure 7. Since the raw data used in the original graph were not available; we could only validate our data set by comparing our results with those shown in this graph (Figure 8). The graphs were compared by looking at the plots of the frequency response for each value of response vs. material loss since actual values were not available. All voltages used in the graphs were average values.

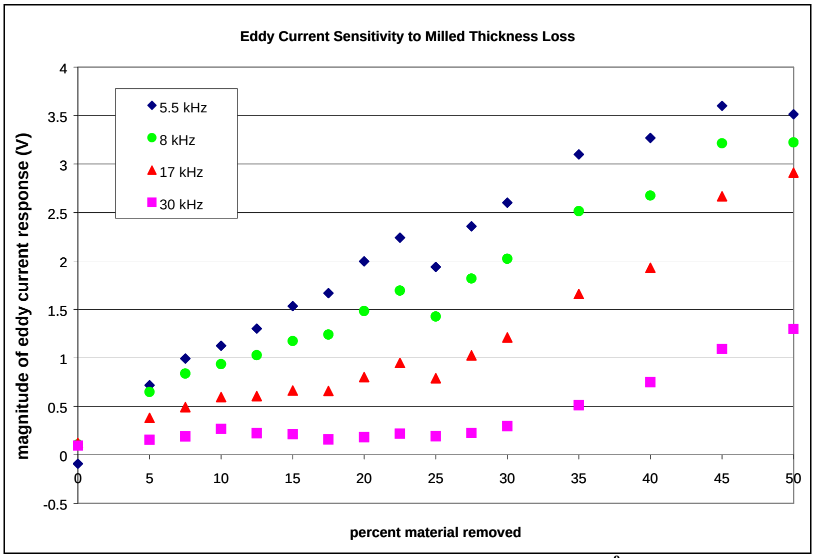

Figure 7: Original graph from LTR-ST-2267 [9]

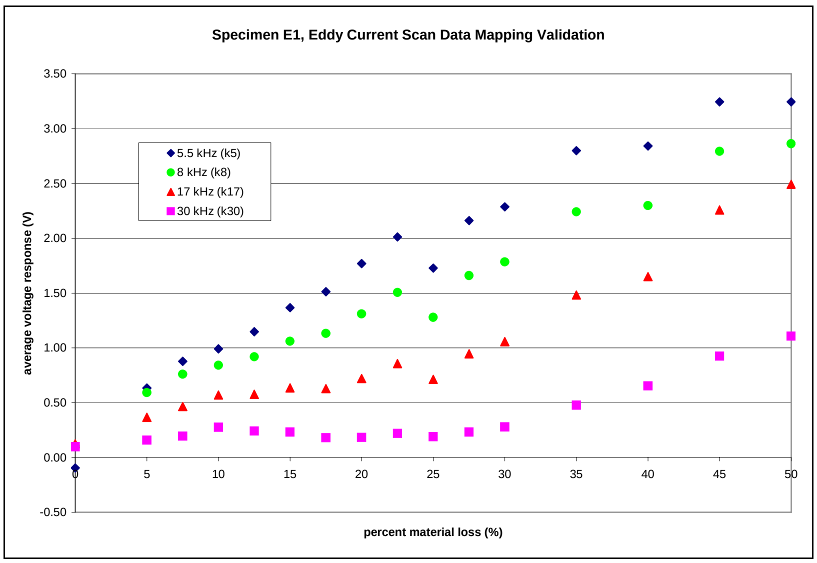

Figure 8: Graph from data mapping

The curve of each frequency scan was comparable; however, Figure 8 had smaller average values in general. The difference in magnitude between the associated graphs was considered inconsequential, since the difference was uniform throughout the responses of the various frequencies. Hence, our results would require at most only a translation of the frequency response to obtain their exact results.

VII. Model Evaluation

We sought to evaluate models from the data mining process using a test set. In particular we considered using a dataset created from scans on natural corrosion. Unfortunately, there was no way to validate the actual material loss in naturally corroded material. Additionally, the scans from the IAR study proved inconclusive in exposing material loss (Figure 9). Note the bottom fourth of these scans is unusable anyway due to the noisy response from the eddy current scans. Once again, from top left to bottom right are the 5.5 kHz, 8 kHz, 17 kHz, and 30 kHz scan results.

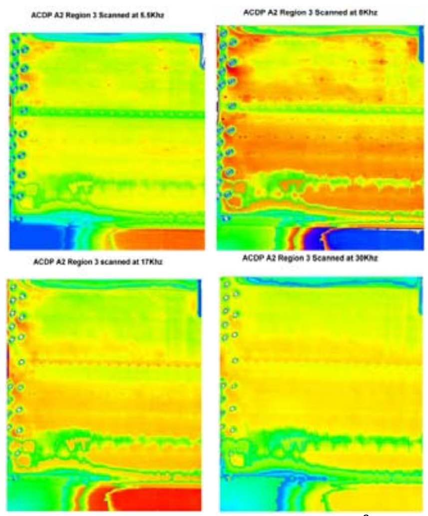

Figure 9: Specimen A2, Region 3 [9]

Without a natural corrosion test dataset, we chose to evaluate models using a random split of 75% (120,456 observations) of the specimen E1 data for training and 25% (40,152 observations) for testing. The model-building portion of the dataset needed to be sufficiently large to develop a reliable model. In order to fairly judge the accuracy of the developed model, we used a large test dataset.

VIII. Approaches used for Corrosion Detection

To search for relationships between NDT data and corrosion we had a choice from a variety of modeling techniques. Essentially the problem has ratio-scaled predictor variables and an interval-scaled response variable. Several methods have direct application and others can be applied, even though their underlying assumptions do not strictly hold. The methods we chose to examine were multiple linear regression[15], regression trees[16], polynomial networks (an extension of group method of data handling (GMDH))[17,18], ordinal logistic regression[15,19] and random forest regression[20]. These methods are commonly used in data mining for prediction and/or data exploration. Refer to the referenced publications for further information. Related methodologies are applied to aircraft performance and maintenance modeling in publications such as [21,22,23].

In general, more complex models tend to provide excellent accuracy with training data but do poorly with test data. Usually this means that a model has over-fit the data and the model will fail miserably with the application of fresh data in a real setting. One reason for this phenomenon is that complex models tend to over-fit the noise in the training data set, which then does not model the noise in the test data (or the real data). Hence, data miners tend to apply Ockham's razor, and choose simpler models if the accuracy of the result in the test data does not improve very much. Surprisingly for the data in this problem we found that complexity models performed well in both training and test sets. This shows that the corrosion process is inherently complex and not reducible to simple relationships.

B. Results

In multiple regression and ordinal logistic regression, the models were 4^{th} order polynomials with interaction terms and natural log transformed independent variables. When we evaluated the predictive performance of these models, the more parsimonious models did not perform as well. The polynomial network model (more complex still, with the equivalent of an eighth degree polynomial) performed better than both the multiple regression and ordinal logistic regression models (Table 1). However, as shown by the values of root mean square error, the improvement was slight.

Both a least squares (LS) and a least absolute deviation (LAD) regression tree splitting methods were tested. The least absolute deviation model performed slightly better than the other methodologies with 819 nodes, but a better choice is least squares tree with 1,857. A more complex extension of the LS regression tree algorithm, random forest regression, proved to be the best method to detect material loss using root-mean-squared-error (RT MSE), performing 18.37% better than its nearest competitor.

Table 1: Comparison of methods using a test dataset

Overall Model Comparision by Test Set		
Model	***RT MSE***	***Variance***
Multiple Regression	5.388	29.030
Logistic Regression	5.610	31.468
Polynomial Network	4.872	23.739
LAD Regression Tree	4.690	21.997
LS Regression Tree	3.724	13.869
Random Forest Regression	***3.040***	9.242

IX. Interpretation of Results

The complexity of the models discovered was an interesting occurrence in this study. In order to explore this phenomenon, a three-dimensional graph was developed using the three most important NDT predictor variables at values 5.5 kHz, 8 kHz, and 17 kHz, respectively. This graph shows the complex nature of the data where there are “patches” of response values strewn throughout the three-dimensional plane. The different colors on the graph show the various material loss values.

Figure 10 shows why the more complex models and tree-based models statistically performed better than the other models. These models tend to “stitch” the data together in order to estimate the material loss. Notice the several “patches” of color that could be segregated to provide better modeling accuracy.

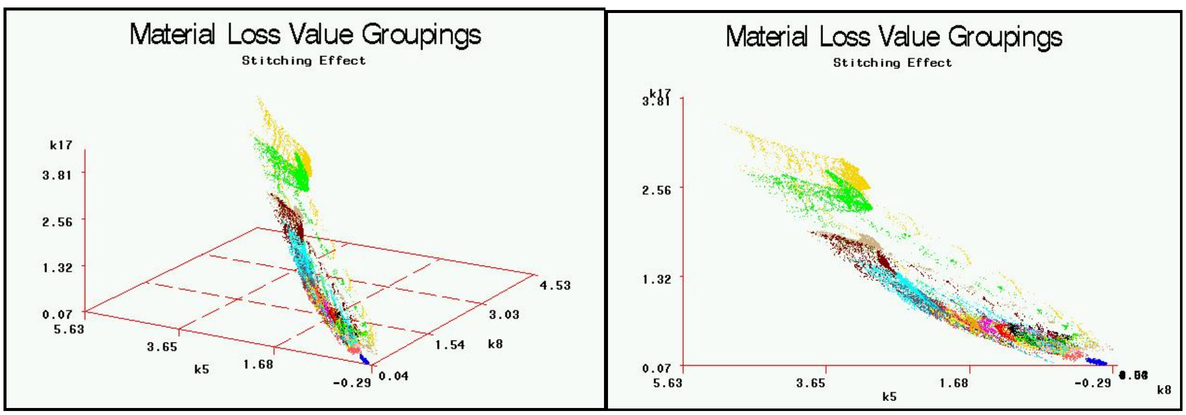

Figure 10: Two perspectives of the eddy current data

We call the attempts to model complex response patterns within small local regions, stitching; it is like the quilt maker using lots of fine stitches for many different pieces of material in a quilt. Figure 11 shows how stitching occurs in the two dimensional case. Notice that each response value, denoted by a specific shape, follows a different dispersal pattern. In this case, the graph shows the relationship between the predictor variables, X_1 and X_2, to the different shaped values of the response variable, Y. A simpler parametric model would not be able to adequately estimate these responses. Therefore, the more complex a model, the better it will perform, even with the test dataset. The test data provide a method of confirming the inherent complexity of detecting material loss from corrosion using NDT. A non-parametric local model performs well, because such models have enormous flexibility in describing the “stitched” regions, while parametric models must capture these regions with increasingly higher ordered relationships of the predictor variables. Random Forest Regression, in particular, has an advantage over parametric models because it uses cuts to split out the different values of the response.

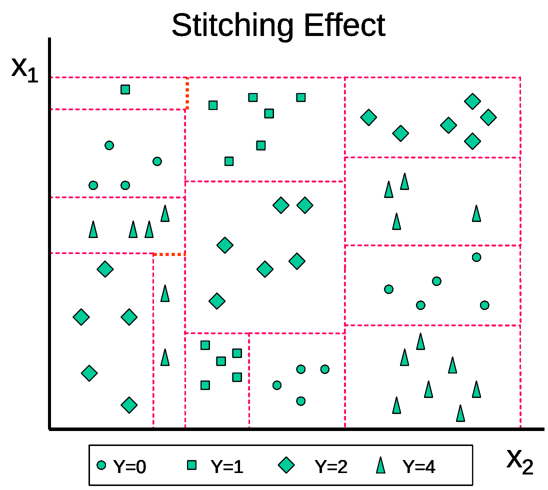

Figure 11: Example of Stitching Effect in 2D

X. Conclusion

This paper has described the use of comparative mathematical methods to discover relationships between NDT and corrosion. We have shown the potential to augment current methods of visually displaying NDT data and asking maintenance operators to find significant corrosion. In particular, we have found models that detect corrosion with average errors of about 3% of total material loss. The best models derive from random forest regression that split the NDT data into cells that correspond to the different values of material loss. Every model tested showed a surprising level of complexity that can be attributed to the nature of the corrosion and the NDT testing.

Corrosion occurs at a very fine scale, and moves through the metal in ways that are determined by a variety of factors. For example, two important factors are environmental conditions experienced by the aircraft and characteristics of the manufacturing processes that produced both the metal and the aircraft. Eddy currents are generated by moving an induction coil over local areas that are either free of corrosion or corroded, which causes non-linear jumps in their values over very small regions of space. The combinations of eddy currents at different frequencies can help to isolate corrosion in small areas but to do this requires complex models that can handle the inherent non-linearities. Random Forest Regression, which is non-linear, seems well suited to this local isolation problem. When we look at Figure 10 and Figure 11, we see that the separate small regions that contain the different values of corrosion. In empirical modeling terms, this is a multi-modal problem, where the modes for each material loss value are separated in feature space into many small regions. Hence, Random Forest Regression has effectively uncovered the complexity of the corrosion- NDT relationship.

Additional work will include analysis of data sets with other NDT measurements to augment the eddy data. We expect to obtain these data sets over the next year. The work reported here will provide a basis for modeling these sets and looking for broader relationships between NDT and corrosion. The work so far provides a good basis building systems that can support maintenance operations and significantly reduce the chances of missing corrosion that may lead to catastrophic failures.

References

[1] CC Technologies Laboratories Inc., "Mathematical Model to Predict Fatigue Crack Initiation in Corroded Lap Joints," Draft. Dublin Ohio. August 1998.

[2] The National Academy Press, "Aging of U.S. Air Force Aircraft," http://books.nap.edu/books/0309059356/html/index.html, 1977

[3] NACE International, "NACE Issue Paper: Aircraft Corrosion," http://www.nace.org/naceframes/Government/planefnl.htm, [cited APR 2001].

[4] Institute for Aerospace Research (IAR), Canada, http://iar-ira.nrc-cnrc.gc.ca/smpl/smpl_1g_e.html, [cited NOV 2005].

[5] *Aviation Week & Space Technology*, November 17, p19, 2003.

[6] Miller, D., "Corrosion Control on Aging Aircraft: What is being done?," *Materials Performance*, pp.10-11, 1990.

[7] Forsyth, D. S., "Automation of Enhanced Visual NDT Techniques," www.ndt.net/article/pacndt98/18/18.htm, 1999.

[8] Bray, Don E. & Stanley, Roderic K., *Nondestructive Evaluation: A Tool in Design, Manufacturing, and Service*. CRC Press, Boca Raton, FL, U.S.A., 1997.

[9] Forsyth, D.S., "Nondestructive Inspections of Calibration Specimens and KC 135 Aircraft Specimens," Institute for Aerospace Research, Canada, 2000.

[10] Gros, X.E., *NDT Data Fusion*, John Wiley and Sons., New York, NY, U.S.A., 2000.

[11] Blitz, Jack., "Electrical and Magnetic Methods of Non-destructive Testing," Chapman & Hall, London, 1997.

[12] Canadian General Standards Board, "Advanced Manual For: Eddy Current Test Method,"CAN/CGSB-48.14-M86, 2004.

[13] Hagemaier, Donald J., "Fundamentals of Eddy Current Testing," American Society for Nondestructive Testing, Inc., 1990.

[14] Hocking.com, http://www.hocking.com/theory.htm, [cited Feb 2004].

[15] Hastie, Trevor, Tibishirani, Robert, & Friedman, Jerome, "The Elements of Statistical Learning: Data Mining, Inference, and Prediction," Springer, New York, 2002.

[16] Breiman, L., Friedman, J., Olshen, R. A. & Stone C. J., "Classification and Regression Trees," Wadsworth and Brooks/Cole, Monterey, CA, U.S.A., 1984.

[17] Farlow, Stanley J., "Self-Organizing Methods in Modeling: GMDH Type Algorithms," Marcel Dekker, Inc., New York, NY, U.S.A., 1984.

[18] Madala, Hema R. & Ivakhnenko, Alexy G., "Inductive Learning Algorithms for Complex Systems Modeling," CRC Press Inc., Boca Raton, FL, U.S.A., 1993.

[19] Hosmer, David W. & Lemeshow, Stanley, "Applied Logistic Regression," John Wiley& Sons, Inc., New York, 2000.

[20] Breiman, L., "Random Forests," Statistics Department, University of California, ftp://ftp.stat.berkeley.edu/pub/users/breiman/, 2001.

[21] Bajwa, Anupa R. & Kulkarni, Deepak, "Engine data analysis using decision trees," *AIAA/ASME/SAE/ASEE Joint Propulsion Conference and Exhibit, 36th*, Huntsville, AL, July 2000.

[22] Jeong, S., Chiba, K., and Obayashi, S., "Data Mining for Aerodynamic Design Space,"AIAA Paper 2005-5079, *AIAA 23rd Applied Aerodynamics Conference*, Toronto, Canada, June 2005.

[23] Kim, Chwail; Wang, Semyung & Choi, Kyung K, "Efficient Response Surface Modeling by Using Moving Least-Squares Method and Sensitivity," *AIAA Journal*, vol. 43 no.11 pp. 2404-2411, 2005.