Quantitative Non-Destructive Evaluation of Fatigue Damage Based on Multi-Sensor Fusion

Final Report for REMADE Project: 18-01-RM-12

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June 2021

Acknowledgment: "This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Advanced Manufacturing Office Award Number DE-EE0007897."

The REMADE Institute Statement

This report documents research that was conducted by University of Illinois at Urbana-Champaign under a cost-shared subrecipient contract with the REMADE Institute.

The objective of this project is to develop a non-destructive evaluation (NDE) methodology for the quantification and prediction of accumulated fatigue damage in used metallic components using multi-sensor fusion approaches.

Principal Investigator: Chenhui Shao, University of Illinois at Urbana-Champaign

REMADE Project Manager: Michael Haselkorn

The REMADE Institute project number is 18-01-RM-12

The REMADE Institute—a $140 million Manufacturing USA Institute co-funded by the U.S. Department of Energy—was launched in January 2017.

In partnership with industry, academia, trade associations, and national laboratories, REMADE will enable early-stage applied research and development of technologies that could dramatically reduce the embodied energy and carbon emissions associated with industrial-scale materials production and processing. The REMADE Institute is particularly focused on increasing the recovery, reuse, remanufacturing, and recycling (collectively referred to as Re-X) of metals, fibers, polymers, and electronic waste (e-waste).

By focusing our efforts on addressing knowledge gaps that will eliminate and/or mitigate the technical and economic barriers that prevent greater material recycling, recovery, remanufacturing and reuse, REMADE seeks to motivate the subsequent industry investments required to advance technology development that will support the U.S. manufacturing eco-system.

The REMADE Institute is committed to accelerating the adoption of sustainable innovations that will expand the circular economy.

The REMADE Institute - Accelerating the Circular Economy

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University of Illinois at Urbana-Champaign Statement

The University of Illinois at Urbana-Champaign conducted cost-shared research to develop a non-destructive evaluation (NDE) methodology for the quantification and prediction of accumulated fatigue damage in recycled metal materials using multi-sensor fusion approaches.

The Principal Investigator for the project is: Chenhui Shao, University of Illinois at Urbana-Champaign

The Project Team included: Kathryn Matlack, University of Illinois at Urbana-Champaign and Jingjing Li, Penn State University

Funding for this project was provided by the REMADE Institute with cost-share provided by University of Illinois at Urbana-Champaign and Penn State University

We do not have an industrial partner.

Acknowledgement:

We would like to acknowledge the financial support from the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE). We also thank Dr. Michael Haselkorn, Dr. Kristi Sisak, Dr. Brian Riise, and Dr. Michael Thurston for their valuable and constructive feedback.

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Acronyms, Abbreviations, and Definitions

Acoustic emission (AE)

Full width at half maximum (FWHM)

Linear ultrasonic (LU)

Micro X-ray computed tomography (micro-XCT)

Non-destructive evaluation (NDE)

Nonlinear ultrasonic (NLU)

Remaining useful life (RUL)

Scanning electron microscope (SEM)

X-ray diffraction (XRD)

Executive Summary

This exploratory project develops an innovative non-destructive evaluation (NDE) methodology for the quantification and prediction of accumulated fatigue damage in used metallic components using multi-sensor fusion approaches. NDE for the condition of incoming used materials is essential to maximize the benefits of utilizing such materials for remanufacturing. Accurate estimation and prognostics of fatigue damage in incoming materials will not only enable effective materials screening to determine if a component can be reused but will also provide valuable information for the process optimization and control of downstream remanufacturing processes.

In this project, we develop a machine learning based NDE technology by combining the strengths of linear ultrasonic (LU) and nonlinear ultrasonic (NLU) methods to predict loading conditions and fatigue levels. A remaining useful life (RUL) estimation framework with hierarchical classifiers and S-N curves for identifying fatigue damage levels and inferring RUL is developed. In addition, regression models are developed to non-destructively estimate residual stress and full width at half maximum (FWHM) based on LU and NLU measurements. The effectiveness of the proposed methods is demonstrated by using life cycle fatigue testing data for 5052-H32 aluminum alloy.

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Introduction

Project Objectives and Benefits

This exploratory project developed an innovative non-destructive evaluation (NDE) methodology for the quantification and prediction of accumulated fatigue damage in used metallic components using multi-sensor fusion approaches. Understanding the condition of incoming used materials is essential to maximize the benefits of utilizing such materials for remanufacturing. Accurate estimation and prognostics of fatigue damage in used components will not only enable effective materials screening to determine if a component can be reused, but also provide valuable information for the process optimization and control of downstream remanufacturing processes. The proposed methodology will be useful in classifying the fatigue condition of metal components, predicting their remaining useful life (RUL), and guiding reuse of such materials for remanufacturing.

The developed NDE technology is able to accurately predict both loading conditions and fatigue levels using only intermittent linear ultrasonic (LU) and nonlinear ultrasonic (NLU) measurements. This capability is further integrated with S-N curve to facilitate RUL prediction. We stress that existing NDE methods in the literature rely on continuous measurements over the entire use life, which are sometimes not available in industrial applications. As such, the developed NDE technology addresses a critical gap. In addition, we developed regression models for prediction of residual stresses and full width at half maximum (FWHM), which can provide essential information on material properties of used metal components.

Project Approach

The primary goal of this work is to develop a new NDE system (hardware) and associated data analytics methods (software) based on multi-sensor fusion. The team developed a new NDE methodology by combining the strengths of LU and NLU methods. X-ray diffraction (XRD) was used to measure residual stress and FWHM, which are important material properties. While each NDE technology is sensitive to specific fatigue conditions, the integration of multiple sensors and multiple measurements has the potential of estimating different fatigue/crack conditions simultaneously.

Four tasks were completed in 20 months. In Task 1, we established the testbed design for fatigue testing and obtained a database for fatigue development under cyclic loading. Task 1was led by co-PI Li and conducted at the Pennsylvania State University (PSU). Task 2 was focused on the refinement of the NLU method and the enhancement of its technology readiness level. This task was led by co-PI Matlack and performed at University of Illinois at Urbana-Champaign (UIUC). In Task 3, we developed a new NDE technology based on sensor fusion and data analytics. This task was led by PI Shao and conducted at UIUC. In Task 4, industry outreach was performed to maximize the impact of the proposed work on industry. This task was led by PI Shao and conducted at both UIUC and PSU. The industry participation in the project was promoted through different channels. First, John Deere worked with the team by providing input on materials of interest and discussing on the direction of interest to industry. Second, the PIs presented their methodology and results in two REMADE-hosted webinars and multiple Technology Summit and Peer Review events.

Project Accomplishments

The project successfully developed a NDE methodology based on multi-sensor fusion and machine learning. Features were extracted from *ex-situ* LU and NLU measurements and subsequently selected to form a feature pool that could indicate the loading condition and fatigue level. An RUL estimation framework that consists of hierarchical classifiers and S-N curves was developed. In addition, regression models were developed to estimate materials properties including residual stress and FWHM based on the LU and NLU measurements. The effectiveness of the proposed methodology was demonstrated using life cycle fatigue testing data for 5052-H32 aluminum alloy. It was shown that our methodology could distinguish new and fatigue specimens with an accuracy of 97.53%. Also, the methodology performed very well for specimens that were tested under a lower loading condition.

Predicting residual stress and FWHM was not included in the original project goals and objectives. This added capability is expected to be very helpful for determining important material properties in remanufacturing applications. In addition, we were not able to find baseline methods for RUL prediction from literature, because state-of-the-art methods cannot predict RUL using intermediate measurements. However, the developed methodology was thoroughly tested using cross-validation and satisfactory performance was demonstrated.

Project Results

Task 1. Life Cycle Fatigue Testing

The objective of this task was to design and install a system for fatigue testing with the ability to collect *in-situ* acoustic emission (AE) signals during testing. The signals were used to quantify the fatigue development, e.g., pores, cracks, or dislocations. The specimen preparation and testing followed ASTM standard E466 (standard practice for conducting force controlled constant amplitude axial fatigue tests of metallic materials). The standard used as well as other details of the testing protocol was selected based on feedback from REMADE members in the remanufacturing industry. To examine the internal damage of the specimen, fatigue testing was stopped at 3 increments of time and the specimen will be taken from the fatigue machine for XRD testing to measure the residual stress and FWHM. The fatigue tests were also performed on the specimens until their failure to generate the S-N curves. Additional data, such as stress, strain, number of cycles (N), NDE signals (e.g., pulse) was also collected during fatigue testing. All experimental data was then used to establish an SQL database for fatigue development.

Task 1. Results

(a)

(b)

Figure 1 (a) MTS 100KN Landmark fatigue testing system, and (b) AE sensor setup on the fatigue sample.

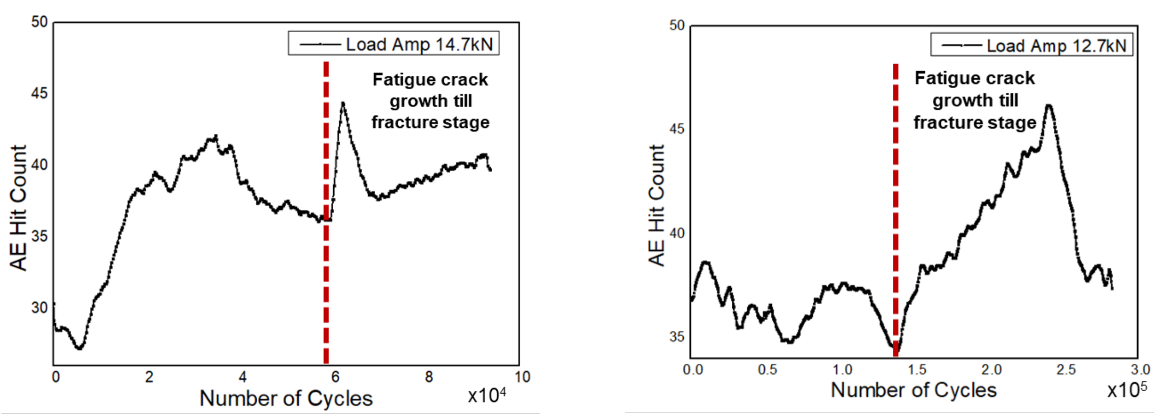
Task 1 developed a fatigue testing system that is equipped with an AE sensor. Figure 1a shows the fatigue testing system and Figure 1b presents a magnified image of the marked region in Figure 1a (blue rectangle) to display the AE sensor setup on the fatigue sample. The AE sensor is used to monitor the fatigue development.

The developed testing system was used to apply load-controlled cyclic loading to un-notched Al5052 series samples. Table 1 summarizes the experimental design.

Table 1. Summary of testing conditions

	Load amplitude	Fatigue cycles applied (N/N_f)	Max. Stress applied (MPa)
Sample 1-2	12.7kN	1/3	195MPa
Sample 3-4	12.7kN	2/3	195MPa
Sample 5,7	14.7kN	1/3	221-226MPa
Sample 6,8	14.7kN	2/3	221-226MPa
Sample 9-10	11.7kN	1/3	176MPa
Sample 11-12	11.7kN	2/3	176MPa
Ref 1-3	-	-	

Figures 2 (a, b) present the AE hit count plots for the load amplitude of 14.7 kN and 12.7 kN, respectively. From the AE hit count data in Figures 2 (a, b), a similar trend is identified (marked with red line) and regarded as the start of the fatigue crack growth. Further analysis of the AE hit count data reveals that albeit, both the loading conditions exhibit a similar rising trend to distinguish the last stage, the rising trend of AE hit signals for the higher load amplitude (i.e., 14.7 kN case) follows a steeper trend than the low load amplitude (i.e., 12.7 kN case).



(a) (b)

Figure 2 AE hit count plots for (a) load amplitude of 14.7 kN, and (b) load amplitude of 12.7 kN.

We developed an interactive database to store and share the data generated in this project. Figure 3 illustrates the structure of the database. Figures 4 and 5 display the screenshots of the database web app.

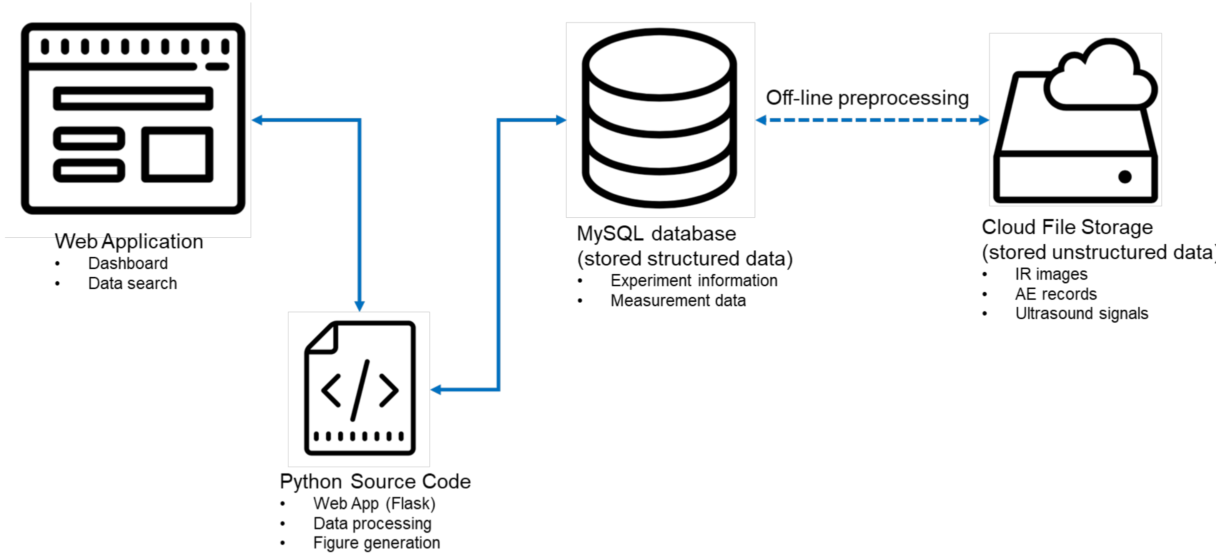


Figure 3 Structure of the database web app

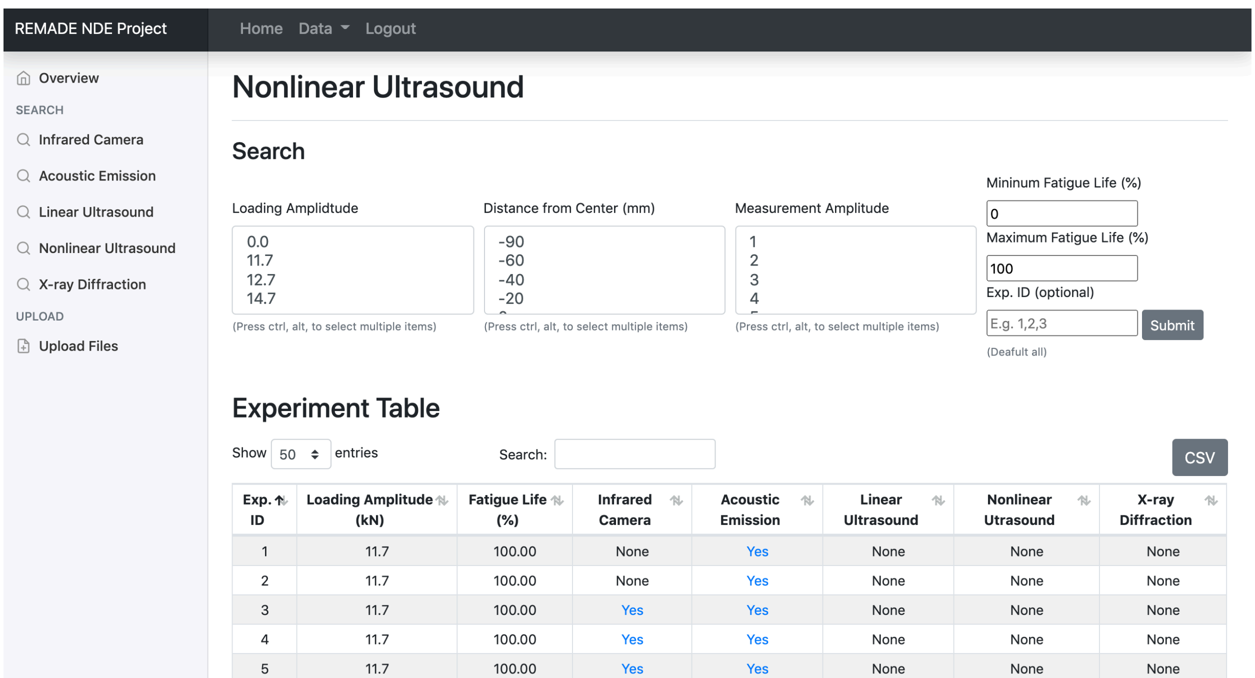


Figure 4 Screenshot of the database web app: search function

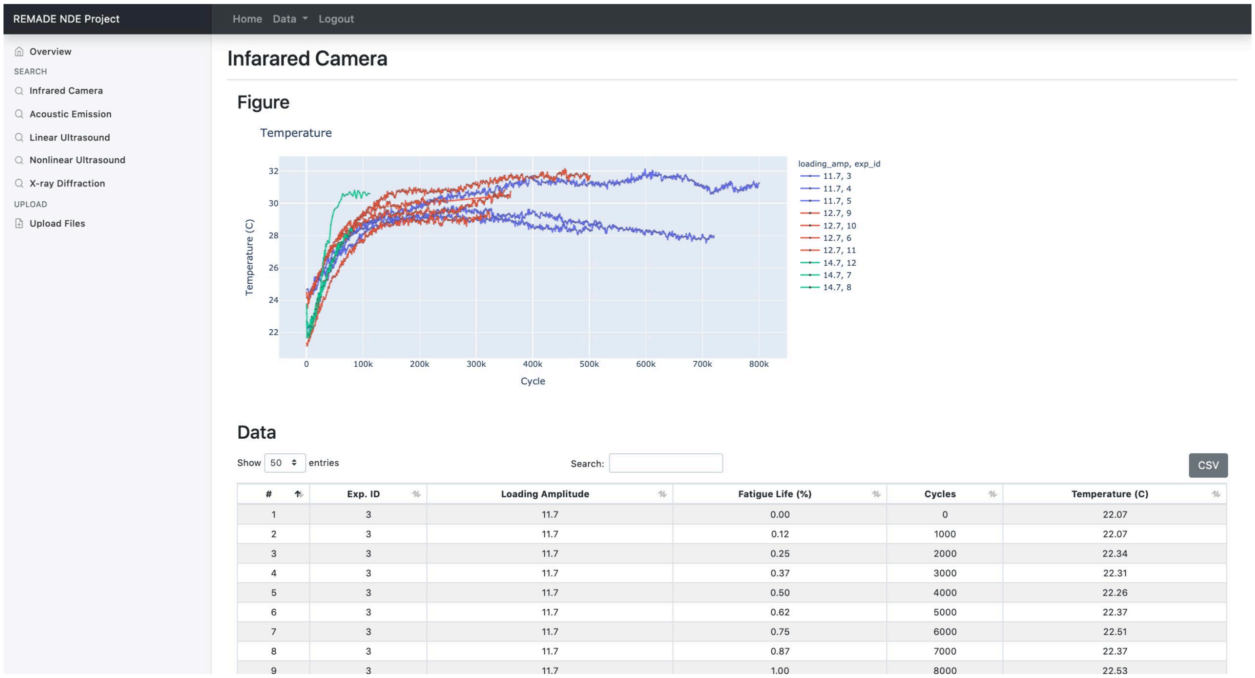


Figure 5 Screenshot of the database web app: temperature profiles are shown

Departure from the planned SOPO.

1. We originally planned to produce 40 or more fatigued samples using 4 or 5 loading conditions. However, due to limited resources available in the project, we were able to acquire 15 samples using 3 loading conditions. The impact of this departure was not significant, because our developed classification algorithms could be trained with a small amount of data. The validation results demonstrated the effectiveness of the developed methodology.
2. We originally planned to characterize samples using XCT and SEM. During the project, we found that the measurement range of these techniques was very limited and would not provide enough useful insights into fatigue development. Therefore, we used X-ray diffraction (XRD) to measure residual stress and FWHM, which are important material properties.

Summary and Significance

In Task 1, we successfully developed a fatigue testing system that is equipped with *in-situ* AE measurement capability. Using the fatigue testing system, we tested 5052-H32 aluminum alloy specimens using three loading amplitudes. The experimental data were then used to establish S-N curves for this material. We designed and implemented an interactive database to store and publicly share all experimental data generated in this project. The data and results obtained in this task are expected to be useful for industrial practitioners who use 5000 series aluminum alloy materials (e.g., automotive body). The experimental data were also used in Tasks 3 for methodology validation.

Task 2. Linear and Nonlinear Ultrasonic Testing

The objective of this task is to integrate LU and NLU methods by modifying the measurement setup to simultaneously extract the linear (information about cracks) and nonlinear (information about dislocations) parameters. This was accomplished by measuring linear ultrasonic parameters (ultrasonic velocity) and nonlinear ultrasonic parameters (the acoustic nonlinearity, β) on fatigued samples from Task 1.2. All samples that were measured with AE and XRD from Task 1 were measured. Output of this task was data of measured β and ultrasonic velocity at different locations on samples that have increasing number of fatigue cycles. This data was used in the data analytics models developed in Task 3. Discussions with John Deere were held to collect their feedback on the system integration.

Task 2. Results

We measured all samples produced in Task 1 at nine locations as shown by Figure 6, and each location was measured three times to ensure the measurement repeatability. Figures 7 and 8 present ultrasonic velocity (extracted from LU measurement) and the acoustic nonlinearity β (extracted from NLU measurement) at different fatigue levels from all loading conditions. Differences were observed in both wave speed (Figure 7) and β parameter (Figure 8) between different fatigue levels and between different loading conditions.

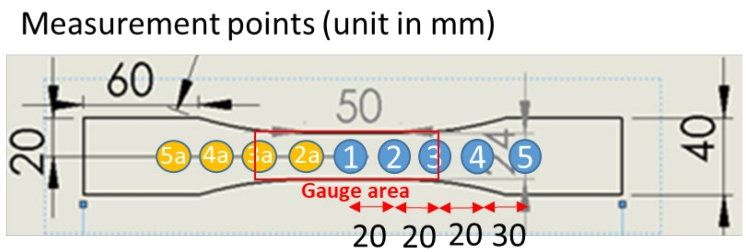


Figure 6 Measurement locations for linear and nonlinear ultrasonic testing

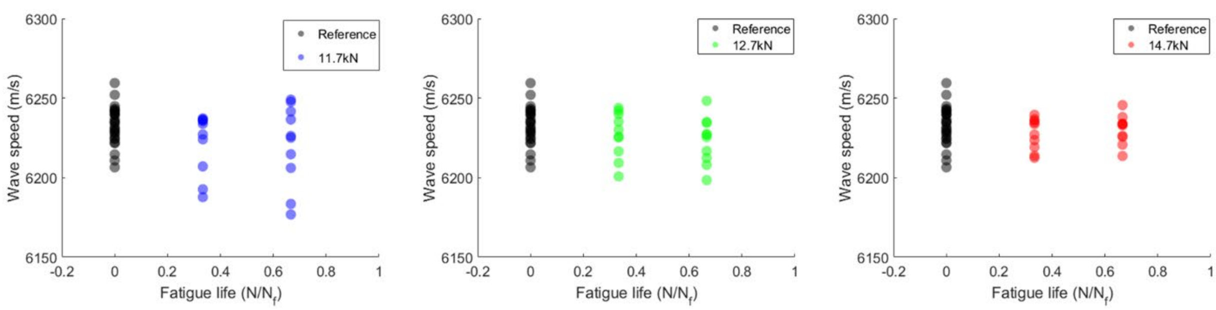


Figure 7 Wave speed vs. fatigue cycle

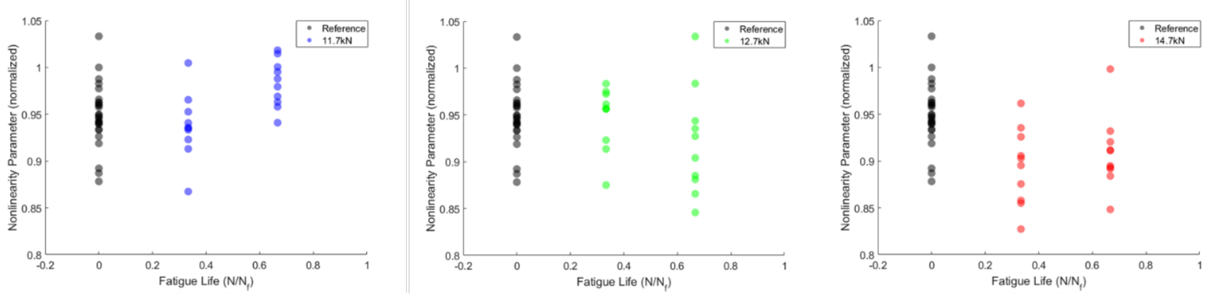


Figure 8 Nonlinear ultrasonic testing: β vs. fatigue cycle

Summary and Significance

In Task 2, we measured all samples generated in Task 1 using both LU and NLU techniques. Each sample was measured at nine locations to allow for the investigation on the spatial variations. Preliminary analysis showed that LU and NLU measurements could distinguish between fatigue levels, demonstrating the feasibility of using LU and NLU methods for RUL prediction. The measurement data were later used in Task 3 for methodology development, refinement, and validation. The LU and NLU testing systems developed here provide an essential foundation for extending the methods to industrial applications.

Task 3. Develop a RUL Prediction Model Based on Sensor Fusion

The output of this task was an RUL prediction framework that can predict RUL simultaneously using data collected from LU and NLU measurements. We also developed regression models to predict residual stress and FWHM. Specific achievements in this task include the following:

- Quantified the linear correlation between each NDE method and the RUL in terms of number of fatigue cycles,
- Develop a framework to predict RUL using NDE data, and
- Created regression models to predict residual stress and FWHM.

All models developed in this task were thoroughly validated using experimental data collected in Tasks 1 and 2.

Task 3. Results

Our developed RUL prediction framework is illustrated by Figure 9. The NDE measurements from LU and NLU were first processed and critical features were extracted to reduce the data dimensionality. Then, hierarchical classifiers were developed to predict the loading condition and fatigue level using these features. Finally, we use S-N curve developed in Task 1 to calculate RUL.

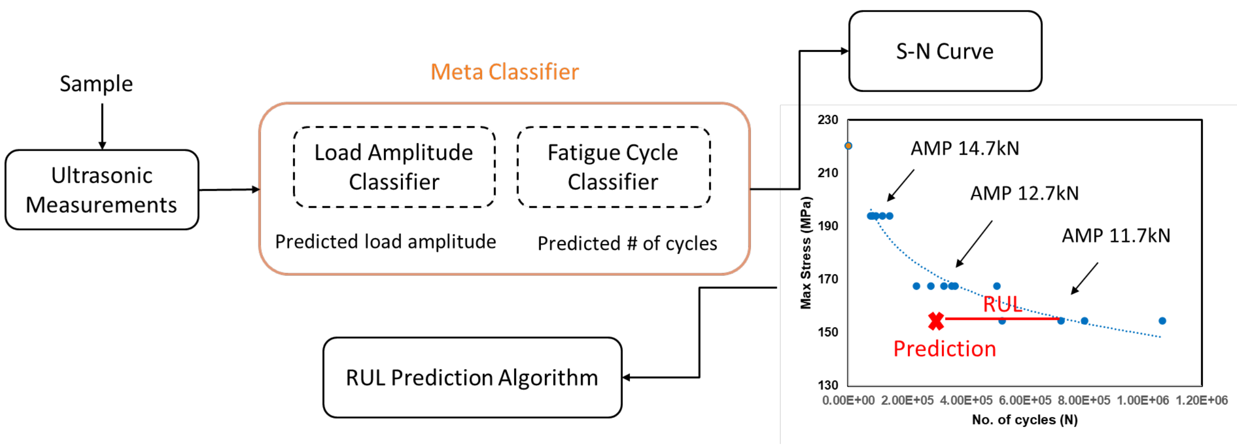


Figure 9 RUL prediction framework

Figure 10 shows the classification performance. It is observed that class 0 has 100% recall rate and only 2 measurements in class 5 are wrongly classified into class 0, **implying that healthy samples are distinguishable from damaged samples.** Similarly, both class 1 and class 2 have 96.3% recall rate and few measurements are wrongly predicted as these two classes, **showing that the classifier can reliably identify the samples that had undergone the low-amplitude fatigue testing**. Table 2 provides an example for RUL calculation using S-N curve.

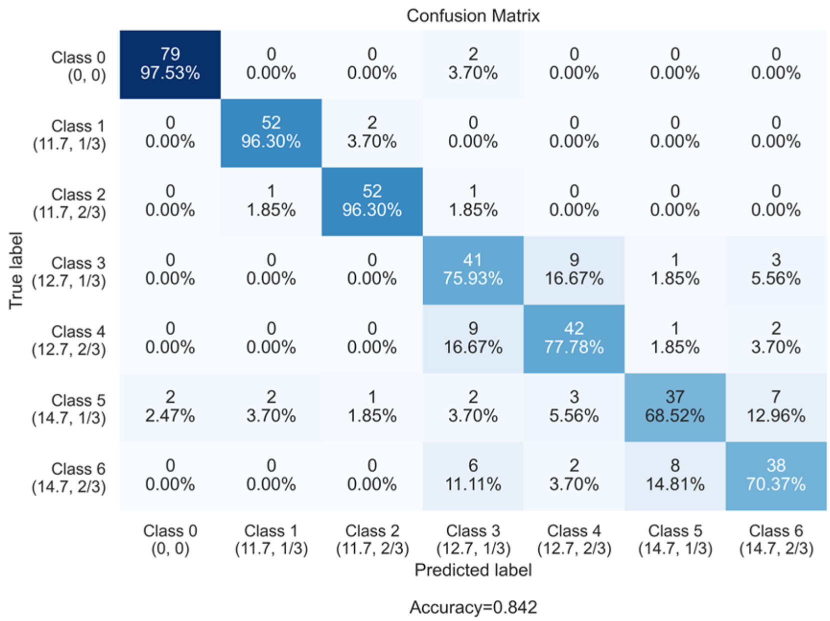


Figure 10 Classification performance

Table 2. RUL prediction for different locations on a class 3 sample (12.7kN, 1/3 fatigue life) with 90% confidence level

Repeat	5a	4a	3a	2a	1	2	3	4	5
1	[114290, 341856] 12.7kN (3)	[114290, 341856] 12.7kN (3)	[114290, 341856] 12.7kN (3)	[114290, 341856] 12.7kN (3)	[57145, 170928] 12.7kN (4)	[57145, 170928] 12.7kN (4)	[114290, 341856] 12.7kN (3)	[114290, 341856] 12.7kN (3)	[17340, 50523] 14.7kN (6)
2	[57145, 170928] 12.7kN (4)	[114290, 341856] 12.7kN (3)	[114290, 341856] 12.7kN (3)	[114290, 341856] 12.7kN (3)	[57145, 170928] 12.7kN (4)	[57145, 170928] 12.7kN (4)	[17340, 50523] 14.7kN (6)	[114290, 341856] 12.7kN (3)	[114290, 341856] 12.7kN (3)
3	[114290, 341856] 12.7kN (3)	[57145, 170928] 12.7kN (4)	[114290, 341856] 12.7kN (3)	[114290, 341856] 12.7kN (3)	[57145, 170928] 12.7kN (4)	[114290, 341856] 12.7kN (3)	[114290, 341856] 12.7kN (3)	[114290, 341856] 12.7kN (3)	[114290, 341856] 12.7kN (3)

We also developed regression models to predict residual stress and FWHM and used cross-validation to evaluate the prediction performance. The prediction errors for residual stress and FWHM are 4.73% and 0.8%, respectively. Further, Figures 11 and 12 show the scatter plots of predicted vs. actual values for residual stress and FWHM, respectively.

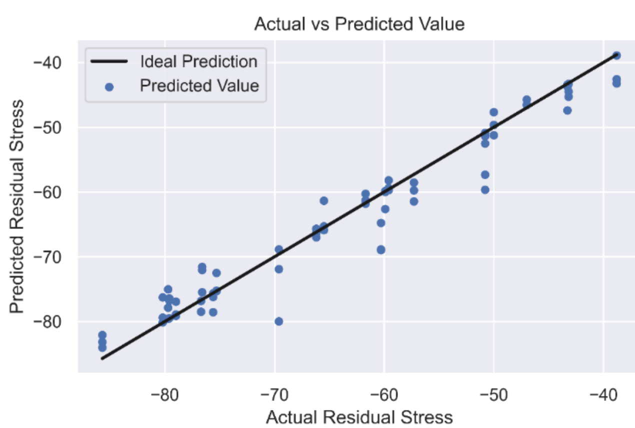


Figure 11 Scatter plot of actual vs predicted residual stress

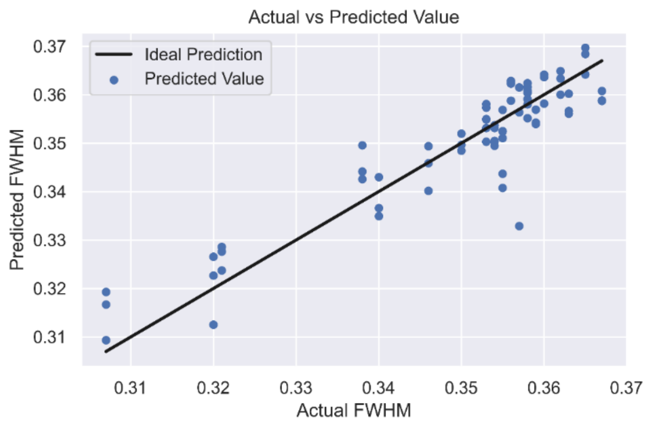


Figure 12 Scatter plot of actual vs predicted FWHM

Departure from the planned SOPO.

1. Predicting residual stress and FWHM was not included in the original project goals and objectives. This added capability is expected to be very helpful for determining important material properties in remanufacturing applications.
2. We were not able to find baseline methods for RUL prediction from literature, because state-of-the-art methods cannot predict RUL using intermittent measurements. We thoroughly tested he developed methodology using cross-validation and satisfactory performance was demonstrated.

Summary and Significance

In Task 3, we developed an RUL prediction framework and regression models for predicting residual stress and FWHM. As demonstrated using experimental data, our methodology was highly promising and achieved good accuracy. It also demonstrated that sensor fusion and machine learning were promising techniques for NDE of fatigue development. The development NDE methodology can be extended to other metal materials.

Task 4. Industry Outreach

Throughout the project, we actively reached out to industry and disseminate our results through webinars organized by REMADE.

Other Project Products

We created an interactive database as part of Task 1. The database website is http://remadende.web.illinois.edu.

Project Conclusions and Recommendations

A machine learning-based NDE methodology for assessing the accumulated fatigue damage level in used metallic components was successfully developed. The methodology can detect defects at various fatigue stages by combining the LU and NLU measurements and provide an *ex-situ* approach for the prognosis of useful life. Regression models were developed to estimate important material properties including FWHM and residual stress. The effectiveness of the methodology was demonstrated using experimental data. We envision that the developed NDE methodology will equip manufacturers with a responsive screening system for incoming used metallic components, and potentially lead to a significant increase in using used metallic components for remanufacturing.

Future work can be focused on testing the generalizability of the developed NDE technology and extending it to various industrial applications. It is also of great interest to develop integrated hardware and software (algorithms) for convenient usage in commercial practice.