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THESIS

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Abstract

To my parents, for their love and support.

Acknowledgments

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LIST OF ABBREVIATIONS

Chapter 1

Introduction

Remanufacturing has been considered an important role in reducing energy consumption and environmental pollution, and

Chapter 2

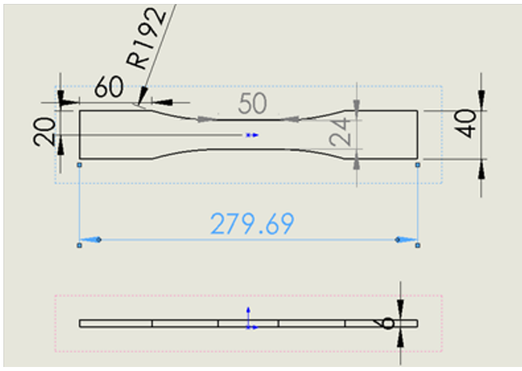
Experimental Dataset

This chapter describes the dataset and the experimental procedure used in this research for developing machine learning applications. First, the cyclic fatigue testing was conducted till the fracture of a specimen to acquire the fatigue characteristics of a material. Second, to mimic the scenarios in the remanufacturing industry, interrupted fatigue testing was utilized to produce specimens at different fatigue levels as a representation of end-of-life products. Then, linear and nonlinear ultrasound measurements are used to evaluate the fatigue damage of those specimens stopped at the predetermined number of cycles in the interrupted fatigue test. Besides, the residual stress and full width at half maximum data from X-ray diffraction are also presented.

2.1 Life cycle fatigue testing

The life cycle fatigue testing aims to collect fatigue life data to understand the fatigue behavior of our targeted material. The fatigue life of a material is defined as the total number of cycles that a material can sustain under a specified loading condition. In order to develop the S-N curve of a material, the material is tested at different loading stress amplitudes, and the fatigue test is repeated multiple times for each loading stress amplitude to account for the variance of fatigue life.

The fatigue testing in this research is led by Prof. Li's group at the Penn State University. The targeted material is 5052-H32 aluminum alloy which is widely used for car body construction in the automotive industry. Figure 2.1 shows the dimension of the specimen and the test machine. Three loading amplitudes, 11.7, 12.7, and 14.7 kN for the cyclic fatigue testing are selected to develop the S-N curve which is shown in Figure 2.2.



(a) Schematic of the 5052-H32 aluminum alloy specimen

(b) MTS 100KN Landmark fatigue testing system at Prof. Jingjing li's lab

Figure 2.1: Life cycle fatigue testing setup

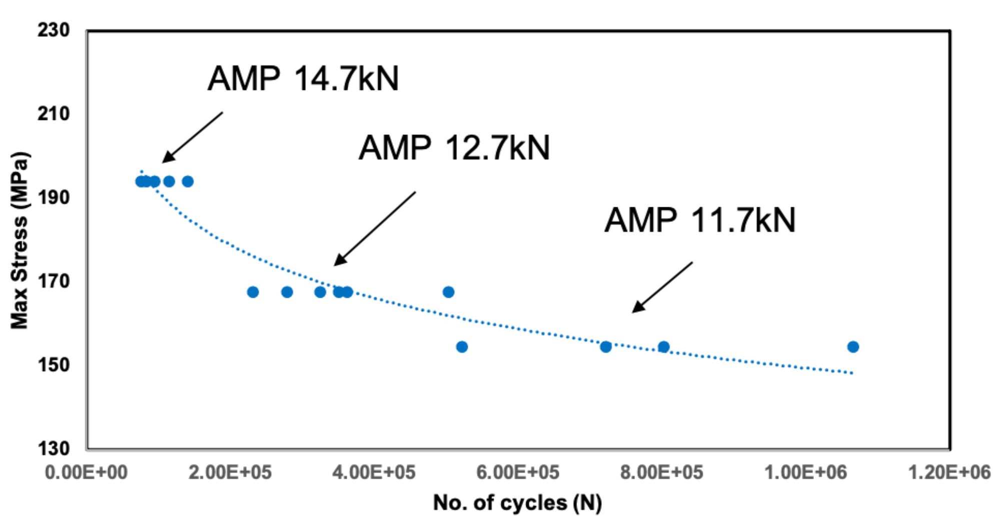


Figure 2.2: S-N curve for 5052-H32 aluminum alloy

2.2 Interrupted fatigue testing

The purpose of performing interrupted fatigue testing is to produce specimens at various fatigue levels by stopping the testing at several predetermined number of cycles. Considering the material cost and the time spent, the number of cycles applied to the specimens is set to be two levels, 33% and 67% fatigue life corresponding to the three loading amplitudes, 11.7, 12.7, and 14.7 kN. These specimens are used to represent the end-of-life products having different fatigue damage levels from the remanufacturing industry. Besides, three specimens without going through fatigue testing, i.e., 0% fatigue life, are included as specimens at the healthy state. The summary of

Table 2.1: Summary of the interrupted fatigue testing specimens

Specimen ID	Loading Amplitude (kN)	Percentage of Fatigue Life (%)	Max Stress Applied (MPa)
1	11.7	33	176
2	11.7	33	176
3	11.7	67	176
4	11.7	67	176
5	12.7	33	195
6	12.7	33	195
7	12.7	67	195
8	12.7	67	195
9	14.7	33	221
10	14.7	33	221
11	14.7	67	221
12	14.7	67	221
13	–	0	–
14	–	0	–
15	–	0	–

the interrupted fatigue testing specimens is presented in Table 2.1

2.3 Linear and nonlinear ultrasound measurements

In this research, linear ultrasonic (LU) and nonlinear ultrasonic (NLU) testing serve as the two main NDE methods for measuring the accumulated fatigue damage in the specimens. The ultrasonic testing is led by Prof. Matlack's group, and the testing system is shown in Figure 2.3. The LU and NLU measurements are both 1-D time domain signals, but the two approaches differ based on different theories and parameters, e.g., excitation wave shape, frequency, amplitude, etc. Examples of LU and NLU signals are presented in Figure 2.4.

LU and NLU measurements were collected at nine locations in a specimen as illustrated in Figure 2.5, and each location was measured three times to understand the measurement repeatability. As a result, for each specimen, there are $9 \times 3 = 27$ signal profiles produced.

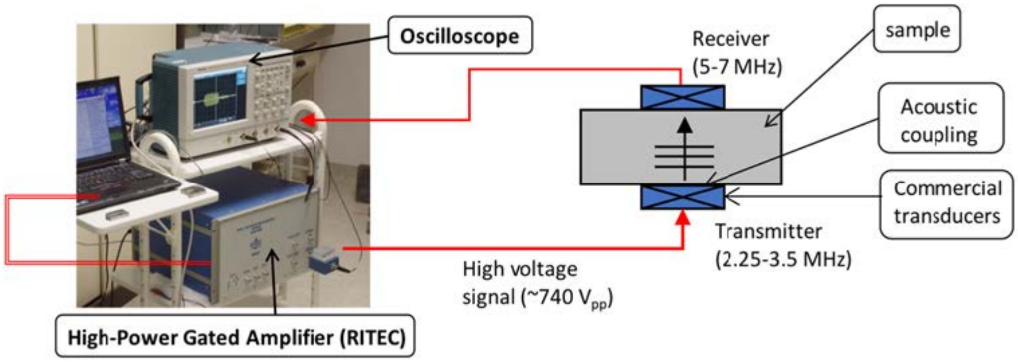
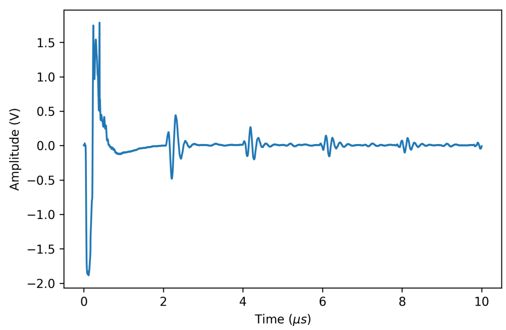
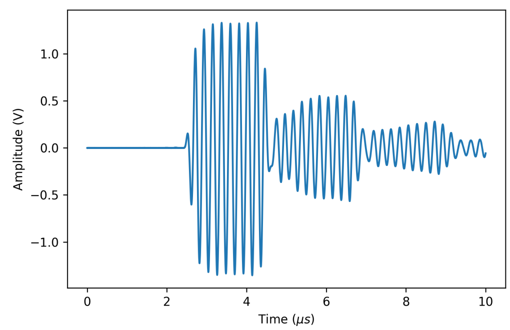


Figure 2.3: Experimental setup for LU and NLU at Prof. Matlack's Lab



(a) Linear ultrasonic signal



(b) Nonlinear ultrasonic signal

Figure 2.4: Examples of linear and nonlinear ultrasonic signals

2.4 X-ray diffraction measurement

Another quantity of interest, residual stress, is measured by X-ray diffraction (XRD) in this research. Residual stress is known to be associated with fatigue behaviors such as crack initiation and propagation. Besides, the full width at half maximum height (FWHM) of the diffraction peak in XRD is also extracted. Prof. Li's group performed the XRD measurements for a subset of specimens in the interrupted fatigue testing. The XRD data is used in the regression tasks in Chapter 5 as target variables.

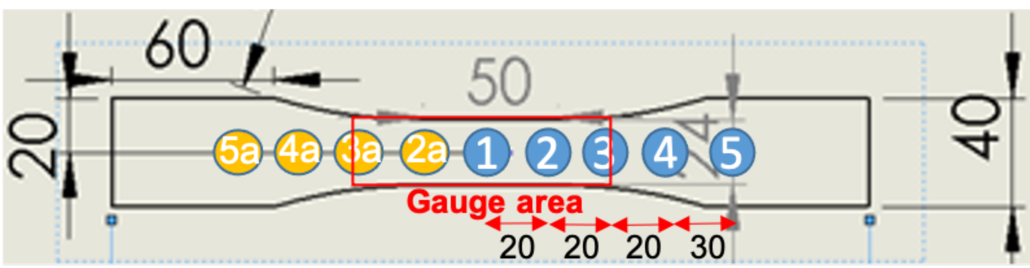


Figure 2.5: Schematic of the measurement locations for LU and NLU measurements. (The unit of length is in mm)

Chapter 3

Model Development

This chapter introduces a model development procedure used in both classification tasks in Chapter 4 and regression tasks in Chapter 5. The procedure involves: *a*) signal pre-processing, *b*) feature generation, *c*) feature selection, *d*) model training, *e*) model validation, and *f*) hyperparameter tuning, as shown in Figure .

3.1 Signal pre-processing

It is essential to reduce noises and extract regions of interest in signals by signal processing before we perform other analyses. Figure presents this process. First, DC bias was removed by subtracting the mean amplitude of a signal to prevent models from fitting on bias. Second, considering the computational cost from the high resolution data, we choose to downsample the ultrasonic signals. Third, we define the region or interest as the interval which contains the ultrasonic signal responses, and thus the other parts of a signal are discarded so that redundant information is not included.

3.2 Feature generation

Since ultrasonic sensor signals are unstructured, which is difficult to process, feature extraction methods are needed to create a representative set of values, i.e., features that aggregate the information from an entire signal. In this stage, physics-based and data-driven features are generated. The hybrid feature pool enables us to incorporate both physics knowledge and data-driven information into models.

3.2.1 Physics-based features

Given that physics modeling is built on theories or comprehensive experiment studies, physics-based features are robust, explainable, and suitable for applications having limited amounts of data such as the fatigue testing data in this research. Therefore, features from traditional LU and NLU testings become potential candidates for the model.

- Wave velocity

  In LU testing, ultrasonic wave velocity is a stiffness based measure which is associated with macroscopic damage such as crack/void coalescence and propagation. The wave speed is the distance divided by the time-of-flight (TOF) that a ultrasonic wave transverses in the material, as shown by Equation (3.1)

  $$v = \frac{2D}{\Delta t} \tag{3.1}$$

  where wave velocity is denoted by v, and D is the thickness of the specimen. Δt is the time difference between the actuation pulse and the response signal. Notice that, in our LU testing setup, one transducer severs as both the transmitter and receiver. Thus, the excitation signal travels $2D$ and the phase is changed 180° when received.

- Nonlinear acoustic parameter β

  While wave velocity from LU testing is able to detect fatigue damage at macro-scale, it is limited because it cannot detect defects much smaller than the probing wavelength, e.g., 1mm. In contrast, NLU techniques are based on a different physical principle: nonlinear elasticity from nano- and micro-scale defects induce harmonic generation. The nonlinear acoustic parameter is related to the amplitude of generated harmonics. This nonlinear parameter changes due to defects such as dislocations, local plastic strain, precipitates, and micro-cracks, all of which are orders of magnitude smaller than the probing wavelength. Here, we apply fast Fourier transform (FFT) to a NLU measurement and simply calculate the nonlinear parameter by using the ratio between the amplitudes of the fundamental and the harmonic waves given by Equation (3.2)

$$\beta = \frac{A_2}{A_1} \tag{3.2}$$

where A_1, A_2 is the amplitude of the fundamental wave and the second-order harmonic wave, respectively.

3.2.2 Data-driven features

The physics-based features alone, however, are not enough to capture all of the information from the LU and NLU signals. As a result, a large number of features engineered from the time domain, frequency domain, and time-frequency domain of ultrasonic measurements are added to the feature pool.

- Time domain features

  Time domain features are peak amplitudes, ratios between peak amplitudes, and components from Principal Component Analysis (PCA) and Independent Component Analysis (ICA). Statistics in time domain such as median, quantiles, variance, skewness, and kurtosis are also included. Besides, from the envelope analysis of a NLU signal, wave duration, wave energy, and the ratios between these quantities are calculated.

- Frequency domain features

  Frequency domain analysis offers some of the information that is not presented in the time domain. This information is especially valuable for periodic signals such as ultrasonic measurements. Thus, after applying fast Fourier transform (FFT), peak amplitudes, ratios between peak amplitudes, peak frequencies, frequency centroid and variance in FFT spectrum are extracted as the frequency domain features.

- Time-frequency domain features

  Ultrasonic signals are usually not stationary, i.e., frequency changes in time, because the interaction between ultrasonic waves and discontinuities within the material. Therefore, time-frequency analysis is needed to describe the phenomena. Discrete wavelet transform (DWT) is adopted to decompose ultrasonic measurements into several frequency bands. Then, statistics such as mean, median, kurtosis, and skewness are recorded for each frequency band.

The feature pool contains XXX features in total, and a list of candidate features for LU and NLU measurements is displayed in Table

3.3 Feature selection

Feature selection aims to remove features that are redundant. Irrelevant features are common to see when we construct features without fully understanding a physical process. For example, the relationship between fatigue mechanism and ultrasonic responses. By including only the best subset of features for a prediction task, feature selection helps develop robust models against overfitting and improve model generalizability. There exists various feature selection techniques which can be mainly classified into three categories: filter methods, wrapper methods, and embedded methods. Each of these methods has its advantages, disadvantages, and suitable application scenarios.

In the model development pipeline, we adopted a wrapper method called Recursive Feature Elimination with Cross-validation (RFECV) to obtain the optimal feature subset that achieves the best predictive performance in multiple training/test data splits for a single model. Figure X shows the RFECV algorithm. First, recursive feature elimination (RFE) starts from a set with all available features and eliminate k features step by step based on the feature ranking with regressors/classifiers until the predetermined number of features n is reached. Nevertheless, the best number of features to select n^* is not determined. To find out n^* while alleviating the problem of overfitting, cross-validation (CV), a statistical model validation technique, is used along with RFE. CV partitions a dataset into training set and validation set in each fold. A model is evaluated multiple times with different partitions, and n^* is determined by the overall validation results. Then, RFE selects the optimal n^* features from the feature pool. We choose 5-fold classification in this feature selection procedure to avoid adding too much computation cost due to the fact that RFE is already computationally expensive.

3.4 Model training and validation

Model training and validation involve another CV loop. Notice that, however, the CV here is not for finding the best feature subset but for providing a generalized estimate of a model's performance. Specifically, leave-one-group-out CV (LOGOCV) is applied, where each group contains three repeated measurements at one measurement location in one specimen. Here, we make an assumption that each group, i.e., each measurement location in a specimen, is an independent sample because of the differences in microstructure. In LOGOCV, each group is tested once and received validation scores by a predictor trained on the other groups, which efficiently utilizes the dataset and assesses the generalization capacity of a model.

3.5 Hyperparameter tuning

Searching an optimal set of hyperparameters is another crucial stage that significantly influences model performance in ML model development. We use grid search accompanied with the validation scores from the LOGOCV to tune hyperparameter in a simple and faster manner. Grid search exhaustively considers all candidates from predefined hyperparameter combinations. The number of hyperparameters and the range of each hyperparameter vary in different learning algorithms. The detailed settings will be discussed in Chapter 4 and 5.

Chapter 4

Remaining Useful Life Prediction

In this chapter, we propose a framework for predicting RUL of EoL products based on the ultrasonic testing. The framework has two parts: *a*) a ML classification task and *b*) a RUL inference procedure based on S-N curve. First, a ultrasonic signal is fed into ML classifiers to predict the loading condition and the number of fatigue cycles that a sample has gone through. Second, we estimate RUL from S-N curve with the predicted loading condition and fatigue cycles.

Chapter 5

Residual Stress & FWHM Prediction

Chapter 6

Conclusion

References