Electromagnetic Methods for the Determination of Early Stage Fatigue

EPRI Meeting – Sep 24, 2020

Nondestructive Evaluation (NDE) Laboratory
Michigan State University

Accomplishments

- Non-Linear Eddy Current (NLE) & Magnetic Barkhausen Noise (MBN) data collection
- Data-Processing/Feature-extraction of NLE & MBN data for all 36 EPRI samples
- Categorizing samples into clusters, with respect to loading cycles and fatigue levels

Magnetic Barkhausen Noise (MBN)

Principle:

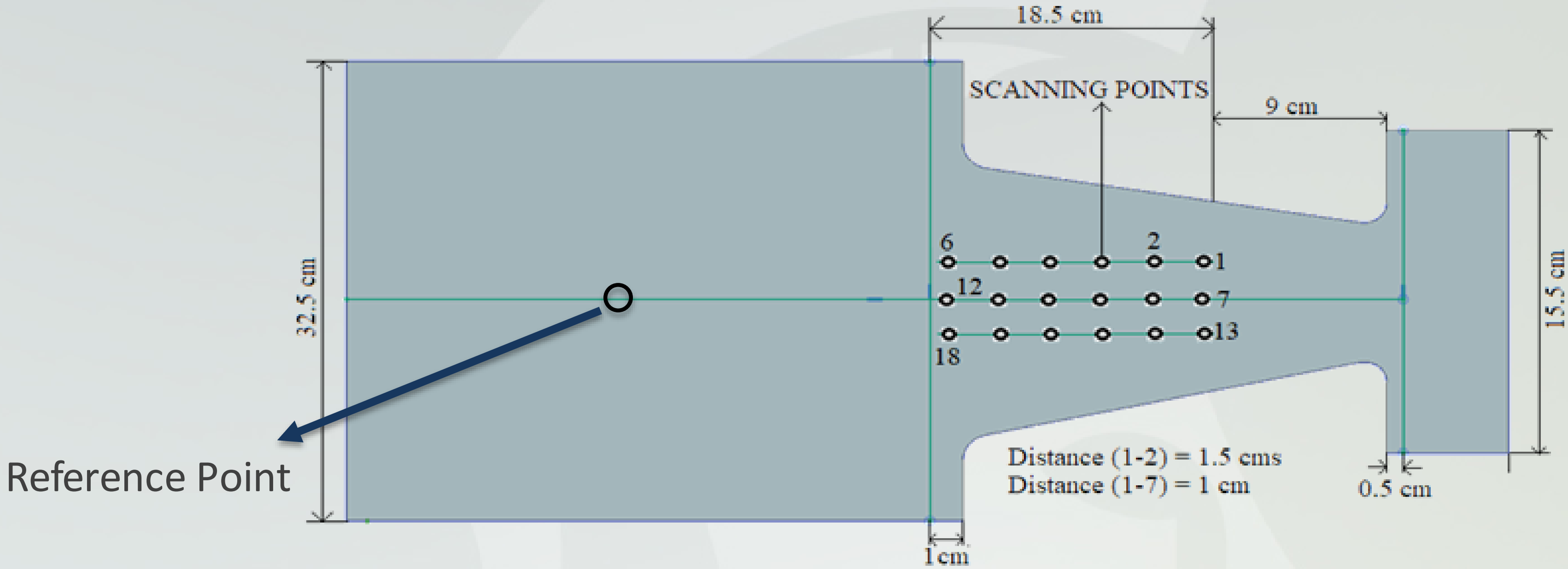
- Magnetic domains show random orientation without external magnetic field.
- Those domains with moments aligned most closely with the applied field will increase in volume.
- The discontinuous domain wall for encountering pinning sites will lead to uneven change in magnetization.

MBN is a very sensitive method for characterization of the microstructure and, consequently, it is suitable to determine the mechanical technological properties and residual stress states.

EPRI Sample Database

Sample ID	Cycles	Sample Category
41C 43C 44C 45C	0 (Untested)	No-Fatigue
7C 13C 8C 35C	150,000	Mid-Fatigue
24C 34C 9C 10C	300,000	
19C 30C 32C 46C	450,000	
23C 25C 21C 47C	600,000	
26C 27C 28C 48C	750,000	
37C 39C 42C 49C	900,000	High-Fatigue
20C 14C 38C 16C	2000,000	
6C 31C 29C 36C	Cracked	Cracked

Data Collection Process



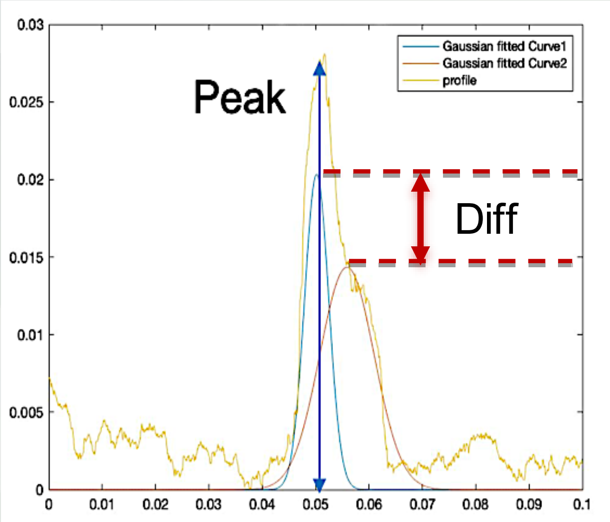
Normalized feature value for each sample

$$N_{kl} = \frac{\sum_{i=1}^{18} S_{ikl}}{18 * R_{kl}}$$
$$i \in [1,18], k \in [1,36], l \in [1,5]$$

i: each scanning point at fatigue area
k: the sample number
l: the corresponding feature
S_{ikl}: each sample point's feature representation
R_{kl}: the corresponding reference point's feature

Time Domain Features

The shape of the MBN profile is modeled by a mixture of two Gaussian distributions, which shows systematic and distinct variation in the magnetization process with respect to different microstructures.



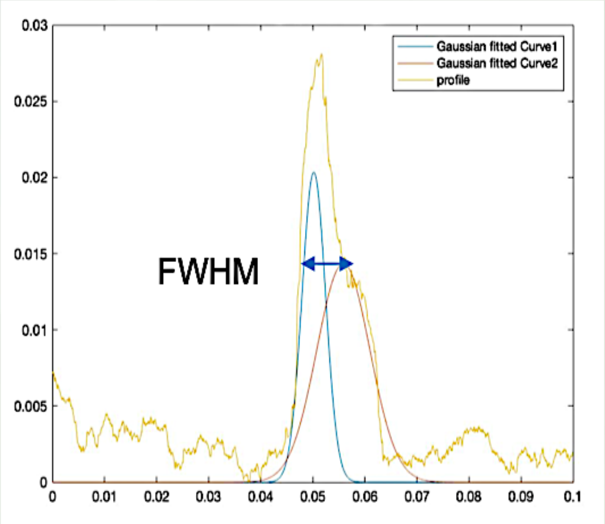
1. MBN Signal Peak

Peak represents movement of reverse domain walls from the pinning effect of dislocations, grain boundaries. and/or inclusions.

2. Full Width at Half Maximum

FWHM of MBN signals denotes distribution of domain wall pinning strength of phase boundaries.

$$FWHM = 2\sqrt{2ln2}\sigma$$



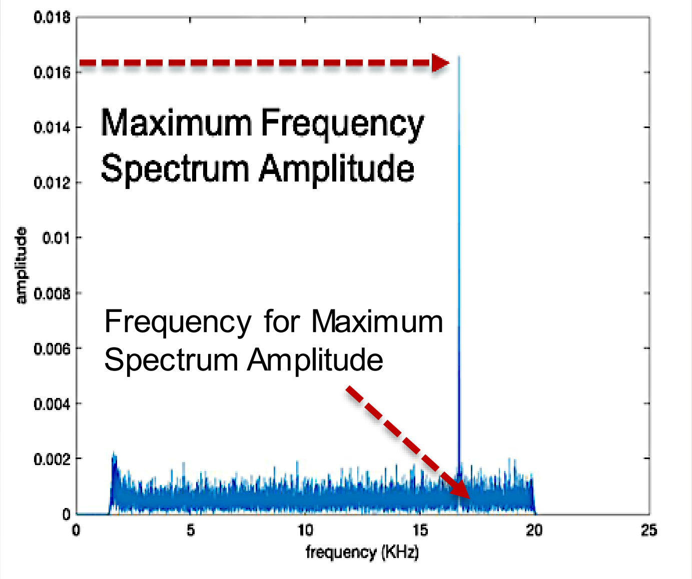
3. Differences Between Two Curves' Peak (Diff)

Frequency Domain Features

- Fast Fourier Transform (FFT) is applied to time domain MBN signals to obtain the frequency spectrum of the MBN signal.
- A bandpass filter from 1.5kHz to 20kHz is applied to obtain the relevant frequency components.

1. Maximum Spectrum Amplitude (AMP)

2. Frequency for Maximum Spectrum Amplitude (POS)

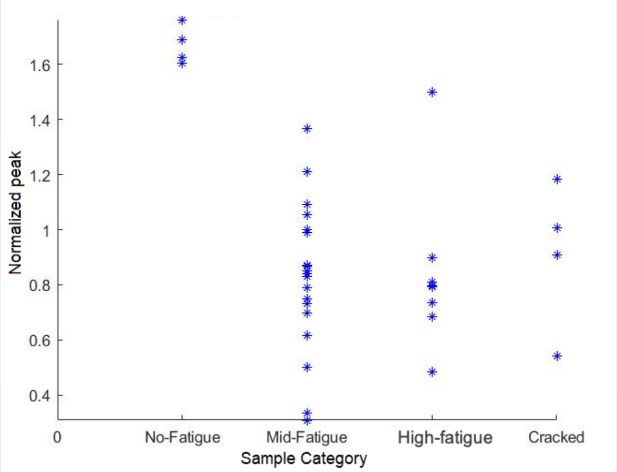


3. Energy

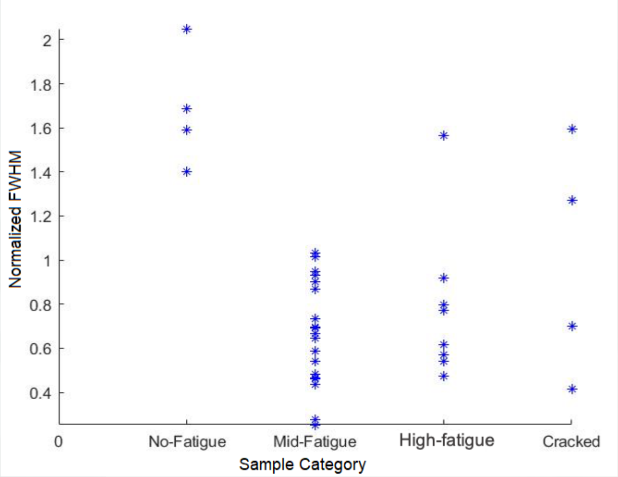
MBN energy is related to grain boundary misorientation angle that influences the arrangement of magnetic domains along the boundary.

Comparison Results

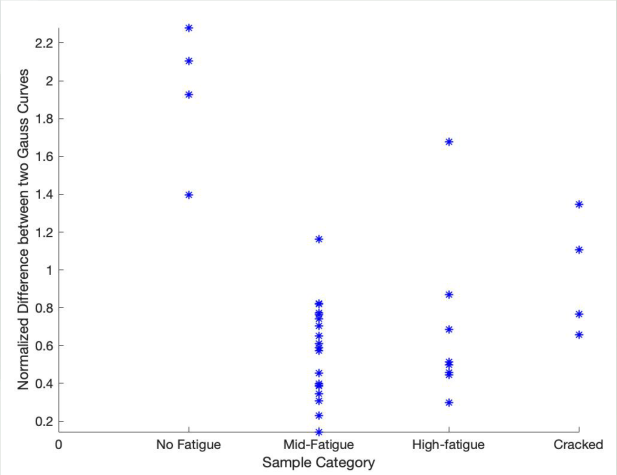
Feature1 : MBN signal peak



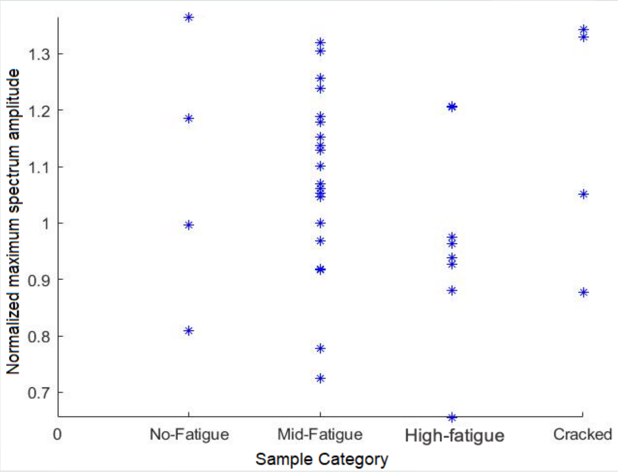
Feature2: MBN signal's FWHM



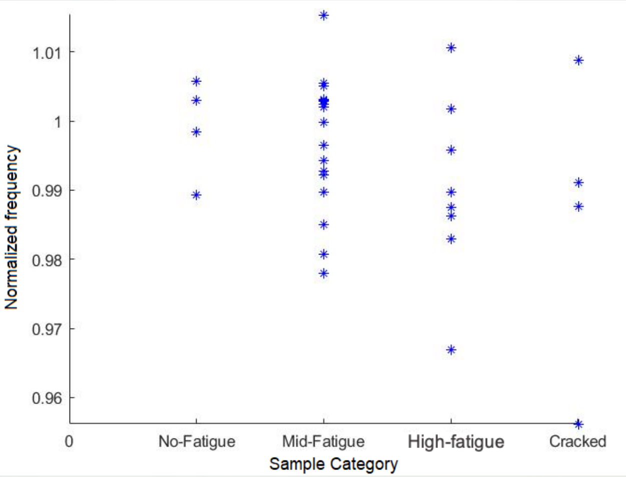
Feature3: Diff



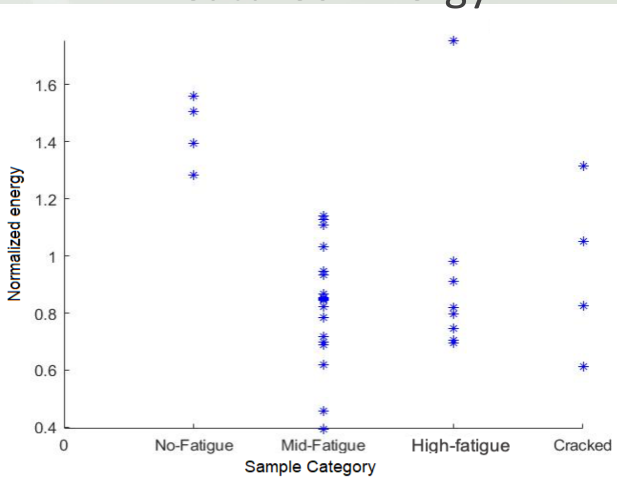
Feature4: AMP



Feature5: POS



Feature6: Energy



Principal Component Analysis(PCA)

Why is PCA?

- Extracting higher order MBN features to have better indications to fatigue life.
- Reducing the dimensionality of datasets, increasing interpretability and minimizing information loss.

In our case, original feature space (**Original feature**) are reduced to higher dimension feature space (**New feature**), which is referred as extracted Principal components (PC)

Case 1: Time domain features and energy
2 components (PC1 and PC2) account for 98% of the multivariate variability
New_feature = {PC1, PC2}

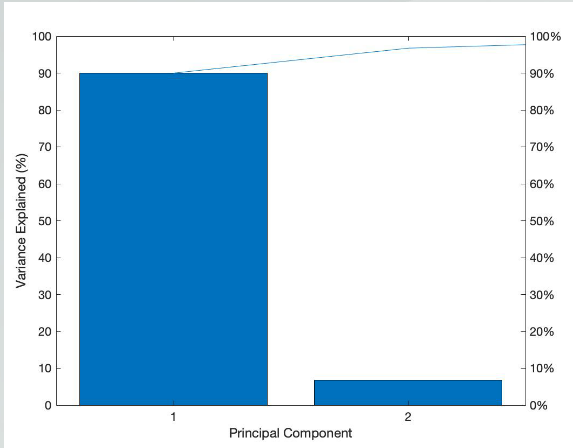
Case2: All 6 features
3 components (PC1, PC2 and PC3) account for 98% of the multivariate variability
New_feature = {PC1, PC2, PC3}

PCA Results Comparison

Case 1

New_feature

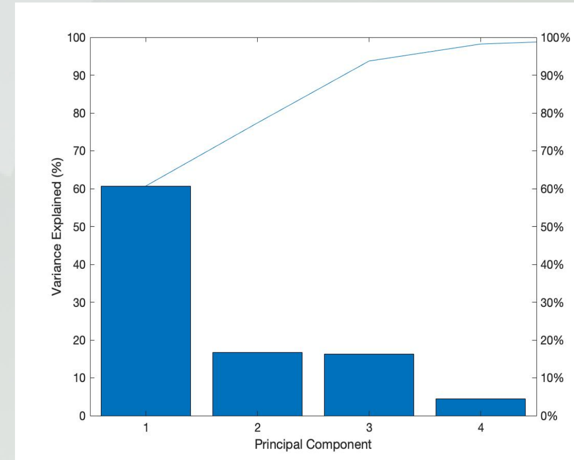
{PC1, PC2}

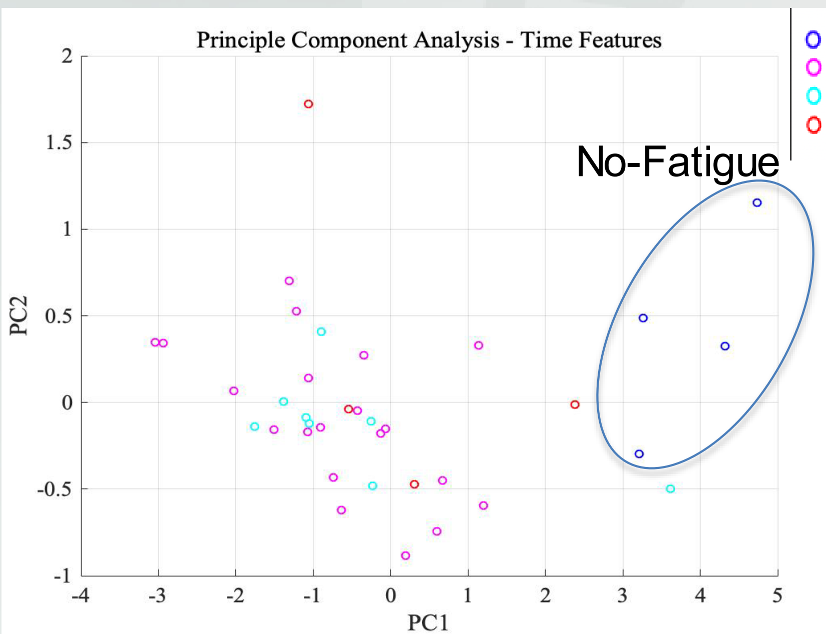


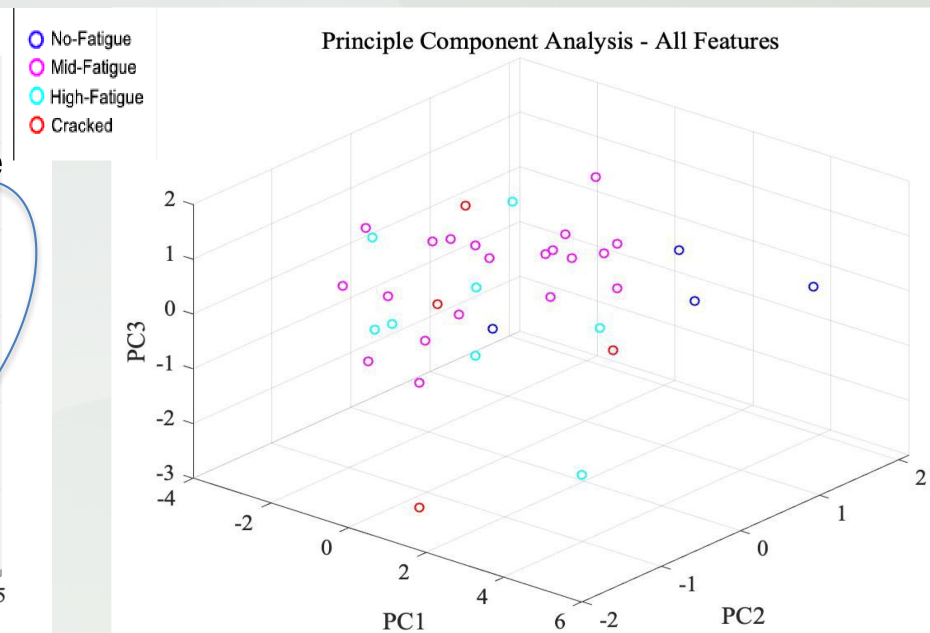
Case 2

New_feature

{PC1, PC2, PC3}







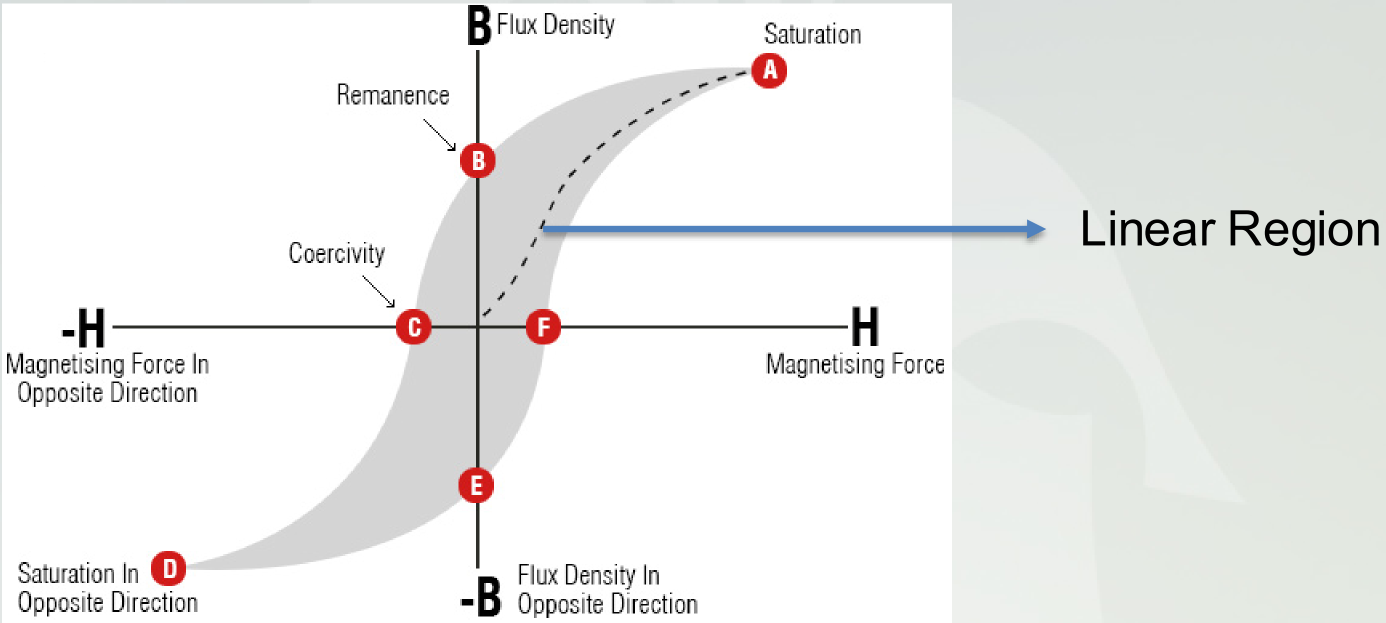
Discussion for MBN

- Through PCA, higher order features are selected to present the results and features in time domain contains more useful fatigue information than in frequency domain.
- Some separations are shown in PCA results, but not directly correlated with loading cycles.
- MBN is a promising method to detect early onset of fatigue.

- The absence of sample information is hard for us to have more accurate fatigue life prediction and further detailed uncertainty evaluation.
- Unpredictable noises in the measurements bring uncertainties.

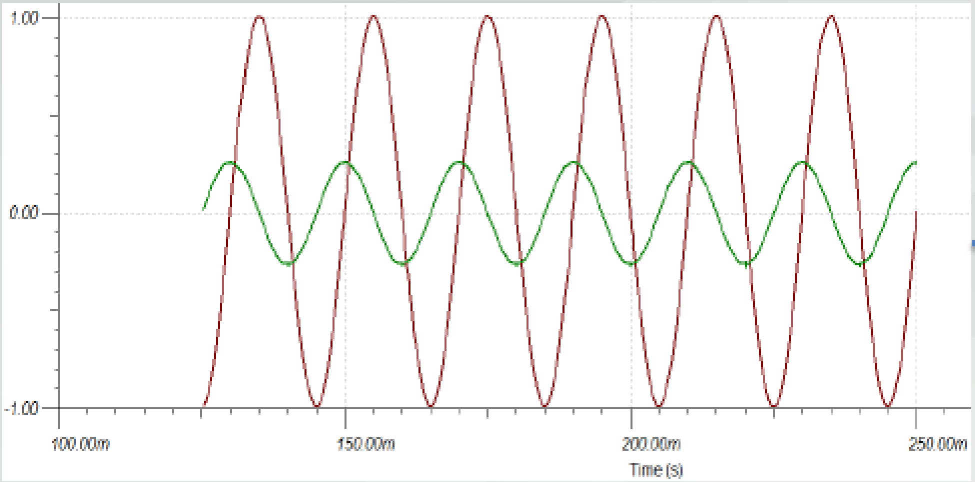
Non-Linear Eddy Current Principle

- The idea is to apply a strong periodic excitation field forcing the material to operate in the non-linear region of its magnetization characteristic

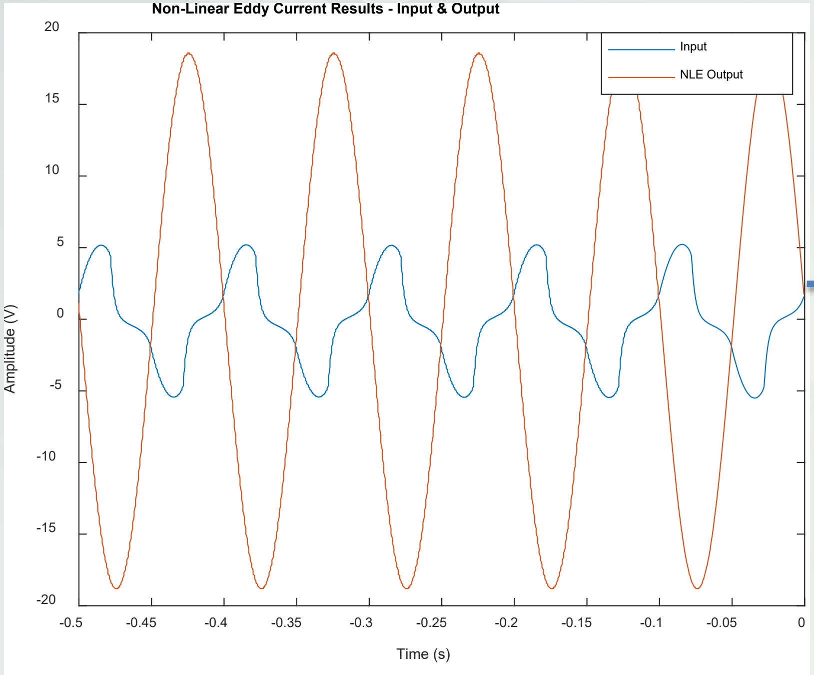


- The nonlinear eddy current technique has been applied to evaluate the case hardening profile of automotive bearing assemblies, in NDEL at MSU

Linear vs Non-Linear Eddy Current

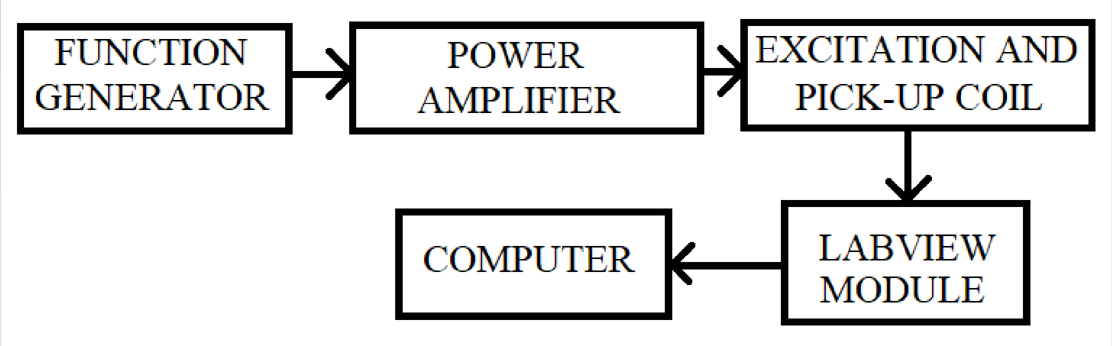


Conventional (Linear)



Non-Linear Eddy Current Method

System Details - 1



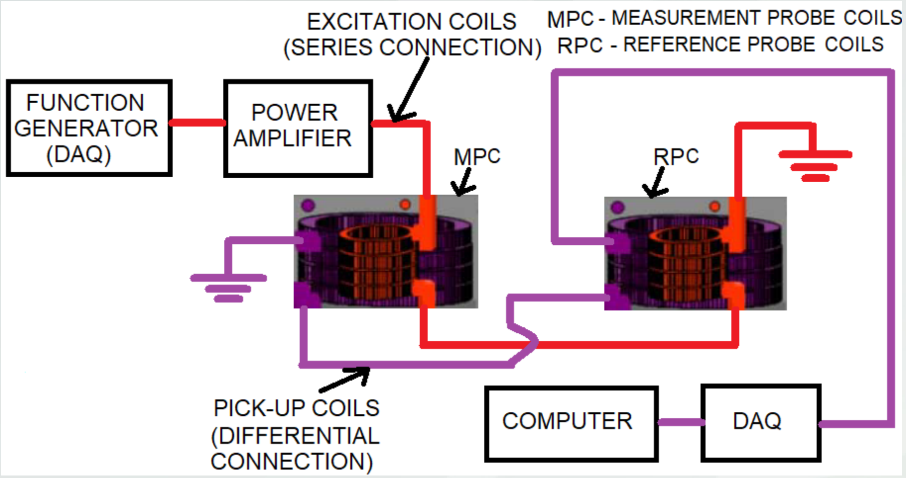
Block Diagram

Experimental Parameters:

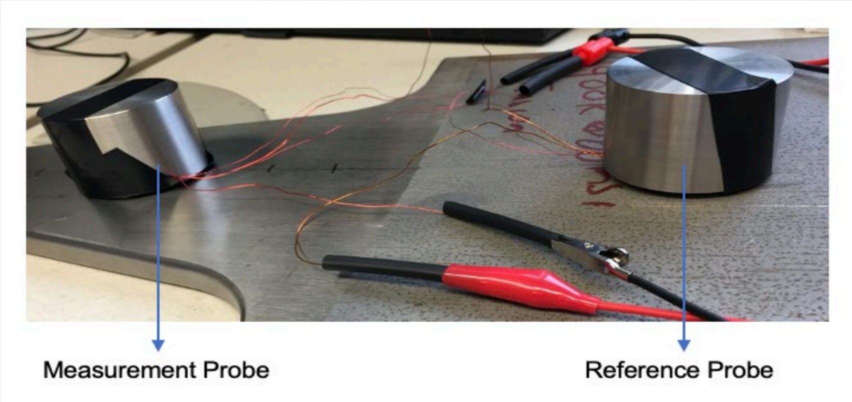
- Function generator output: Sinusoidal signal of 14 V (peak to peak) and frequency of 17 Hz
- Power amplifier gain: 10 V/V
- Pick Up coil: 600 turns (32 AWG)
- Excitation coil: 1200 turns (26 AWG)
- Sampling rate: 10,000 Sa/s

System Details - 2

- **Differential Non-Linear Eddy Current (DNLE) probe**, consists of measurement and reference probes
- Each probe comprises of an excitation and pick-up coil

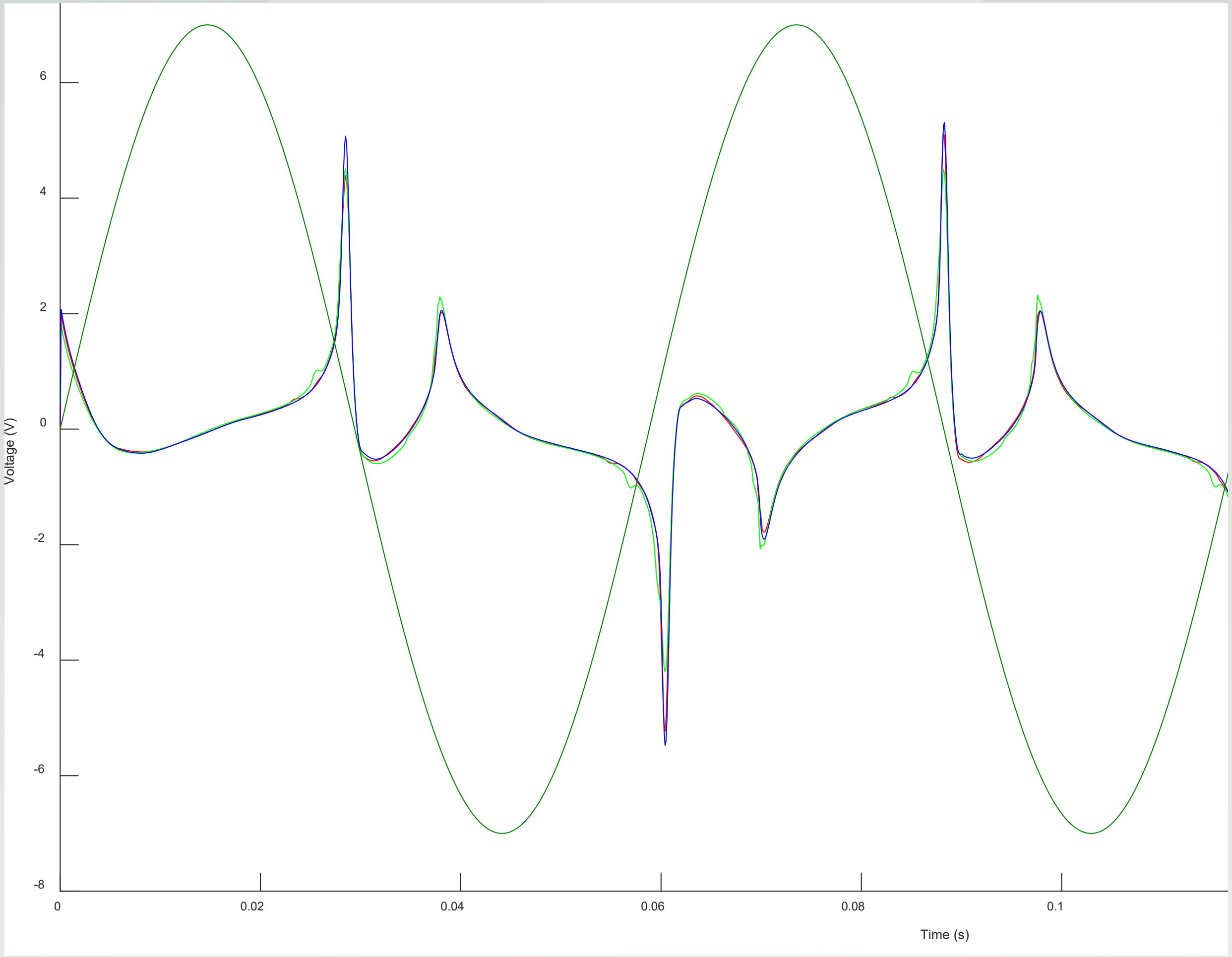


Schematic of connections of NLE probe coils

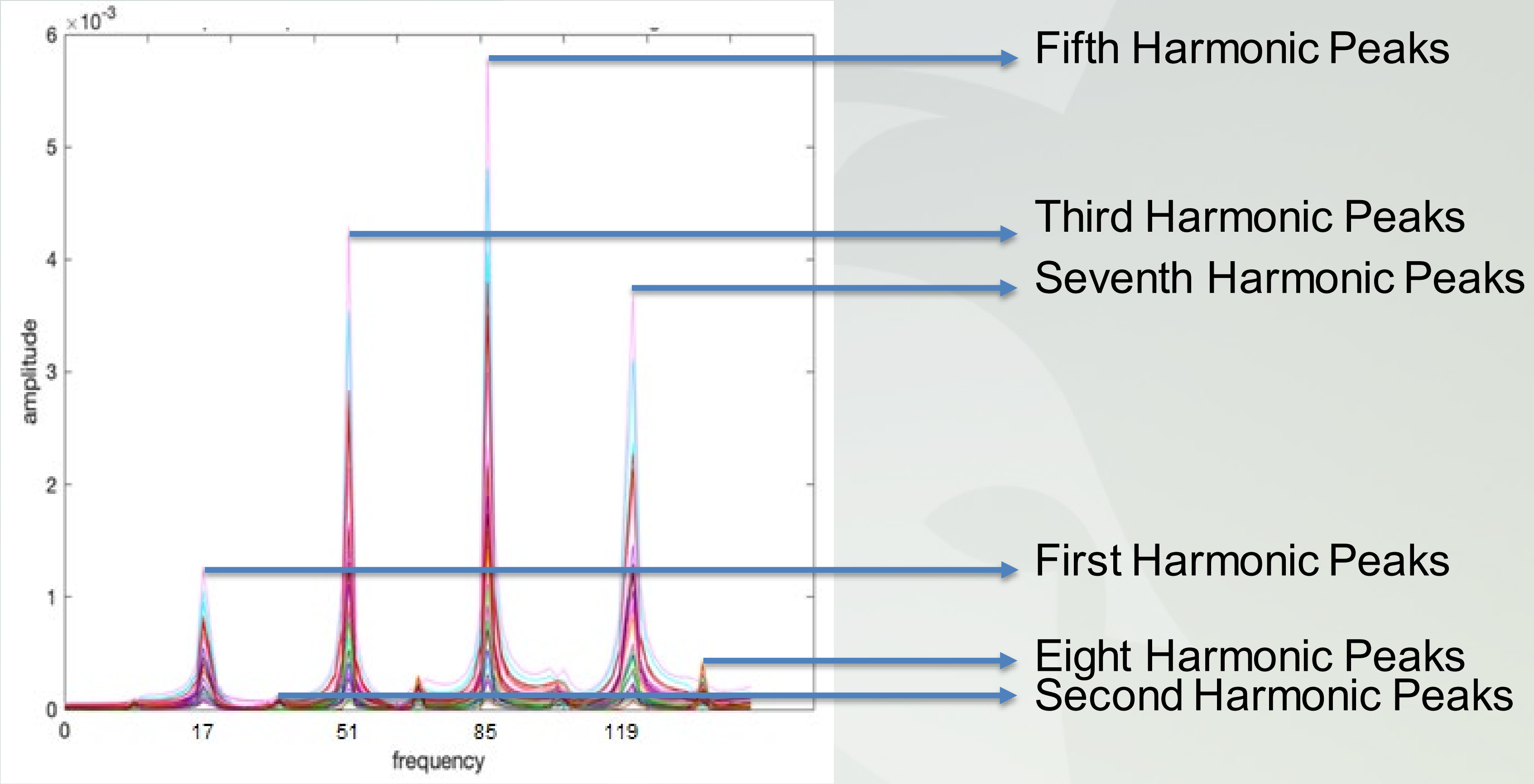


DNLE Probe

Typical NLE signal - Time Domain

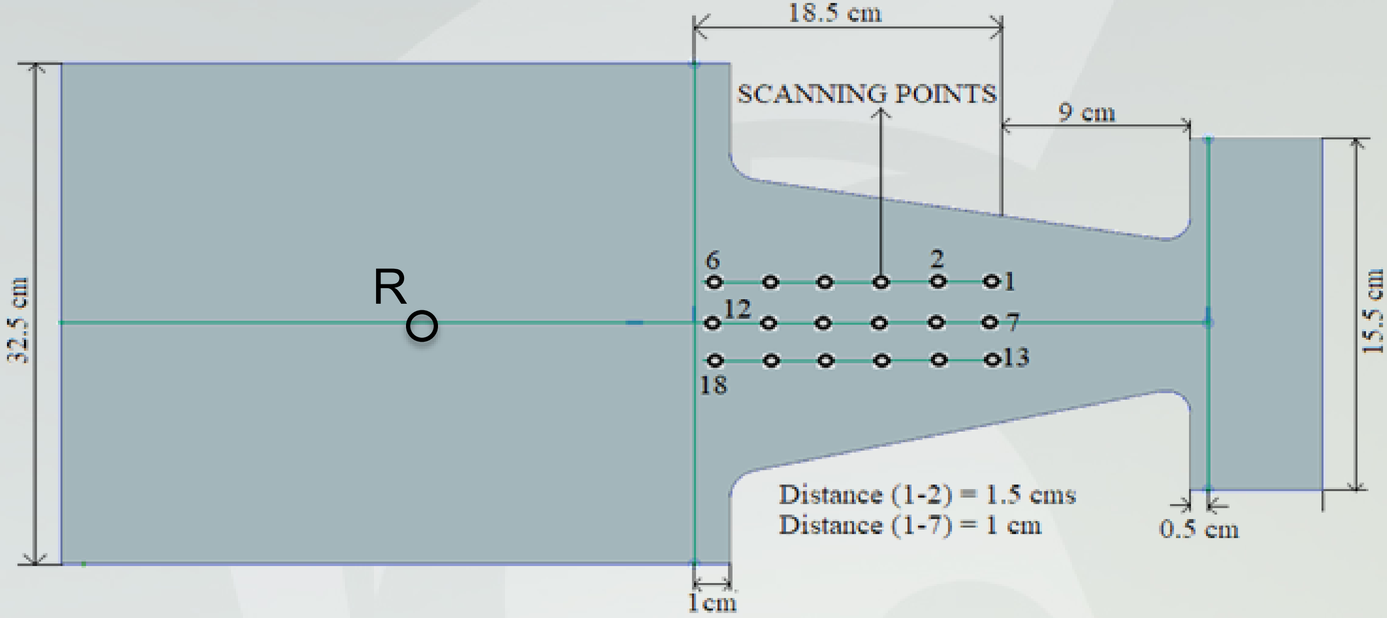


Frequency Domain



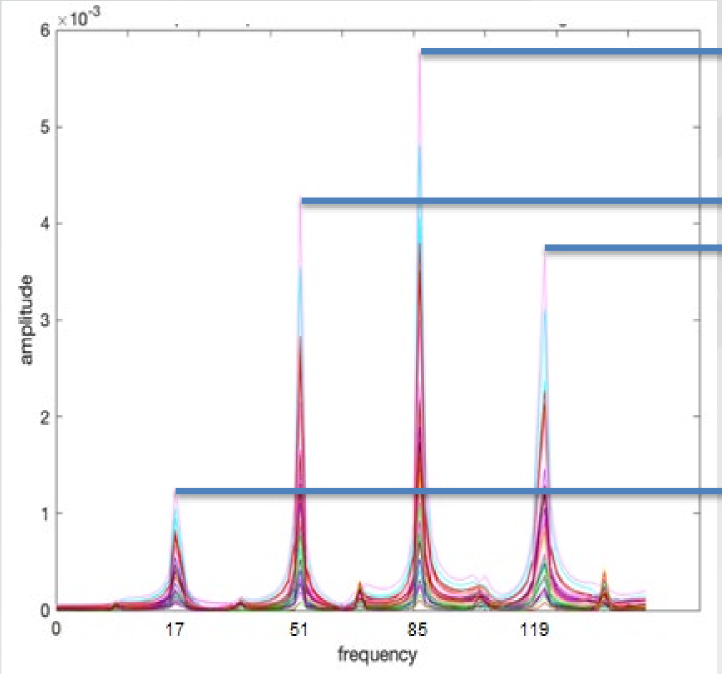
Observation: Odd harmonic peaks show higher amplitudes and variations, when compared to even harmonics. So, they are considered as NLE signal features

Data Collection Process



- **R** is the reference probe position
- Measurement probe is moved from S10 – S12 to collect differential NLE data
- Average of the collected differential measurements at S10-S12 points are considered for data-processing

Feature Extraction



Fifth Harmonic Peaks

Third Harmonic Peaks

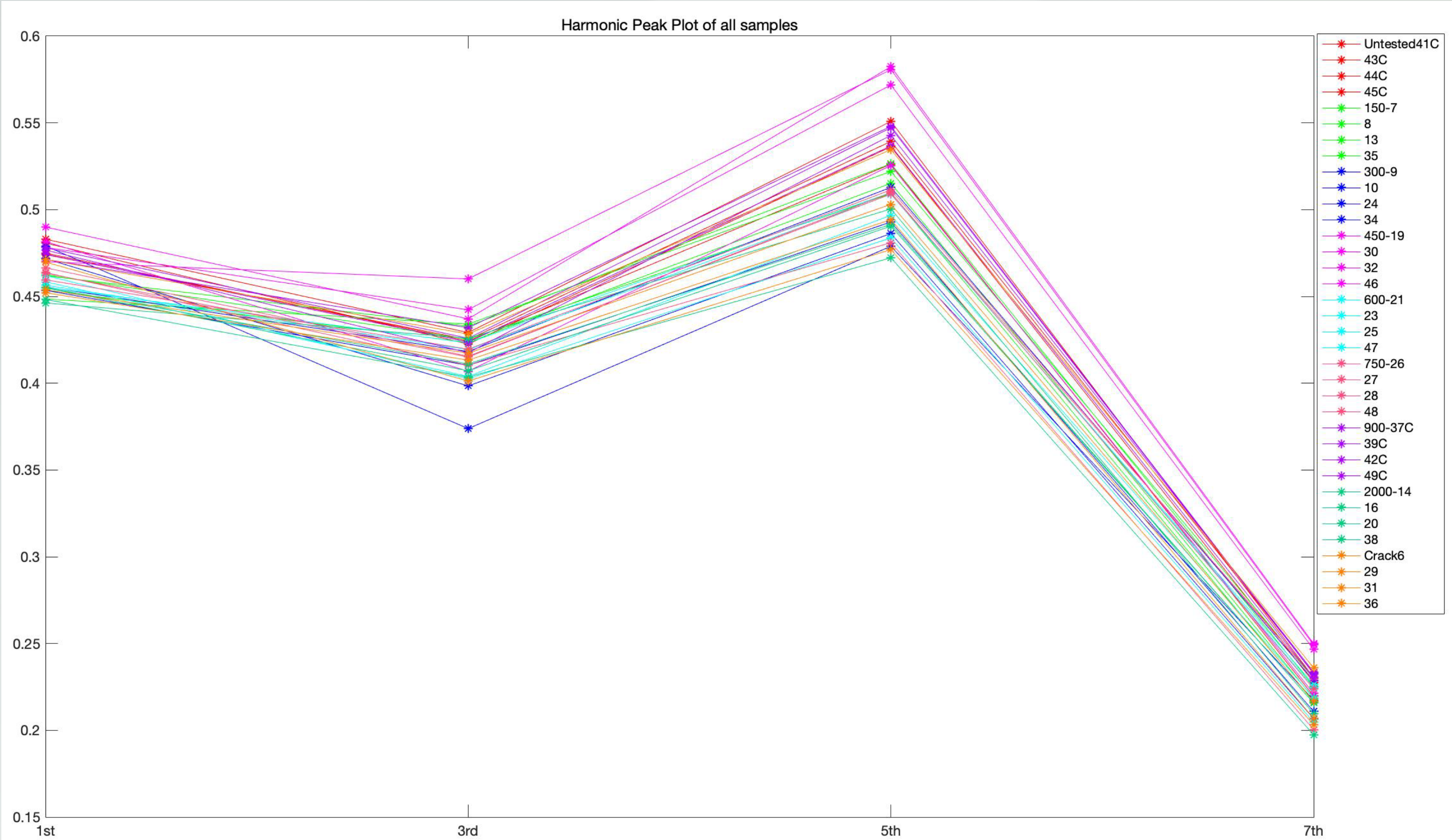
Seventh Harmonic Peaks

First Harmonic Peaks

Features:

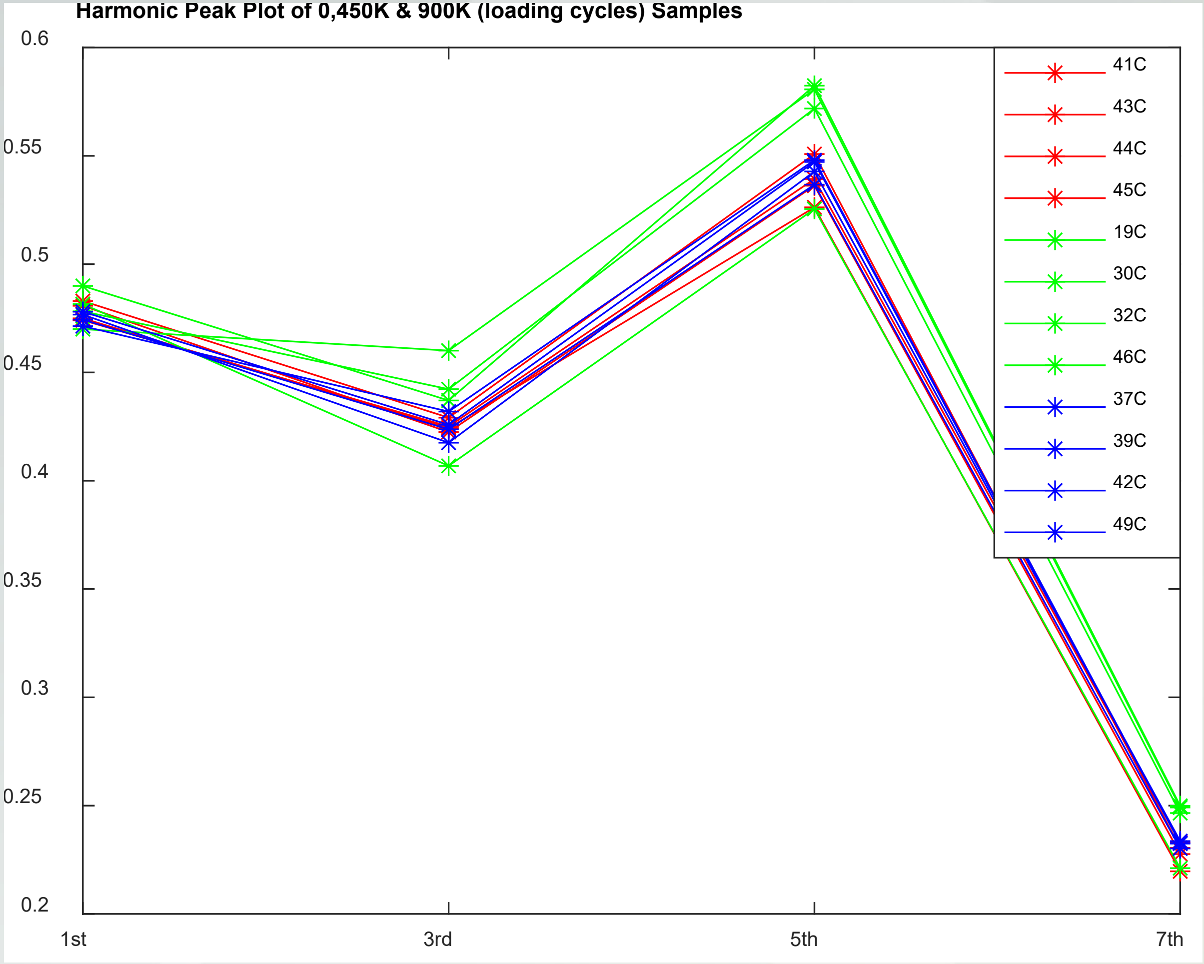
- Odd harmonic peaks **(Feature 1)**
- Odd harmonic peak ratios **(Feature 2)**

Feature 1 (Odd Harmonic Peaks) – All Samples



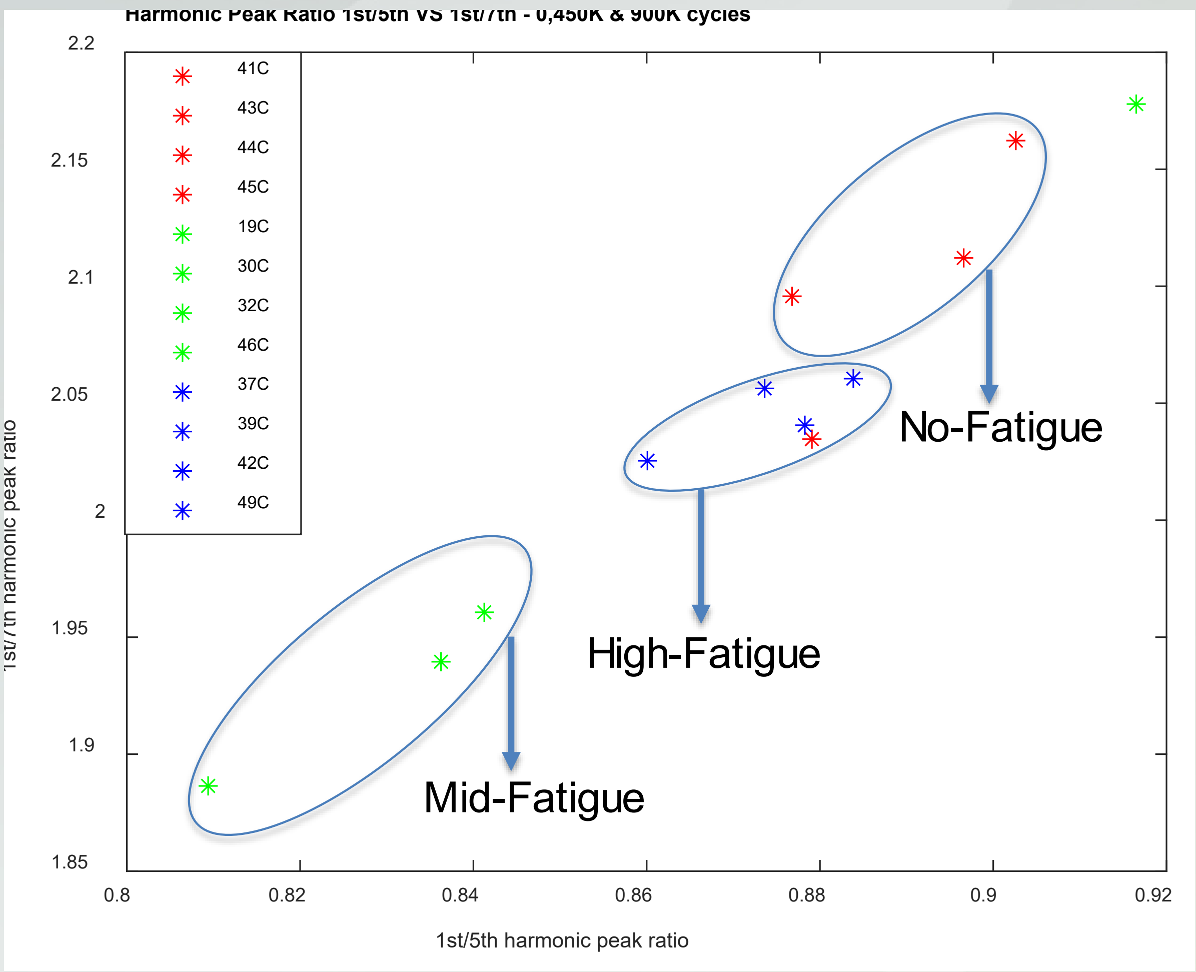
<u>Observation:</u> Odd harmonic peaks show some separation w.r.t. sample categories, but it is not clearly visible in the above plot. Hence, we consider a smaller sample set and make observations, as will be seen in the next result plot.

Feature 1 – Three categories (12 samples)



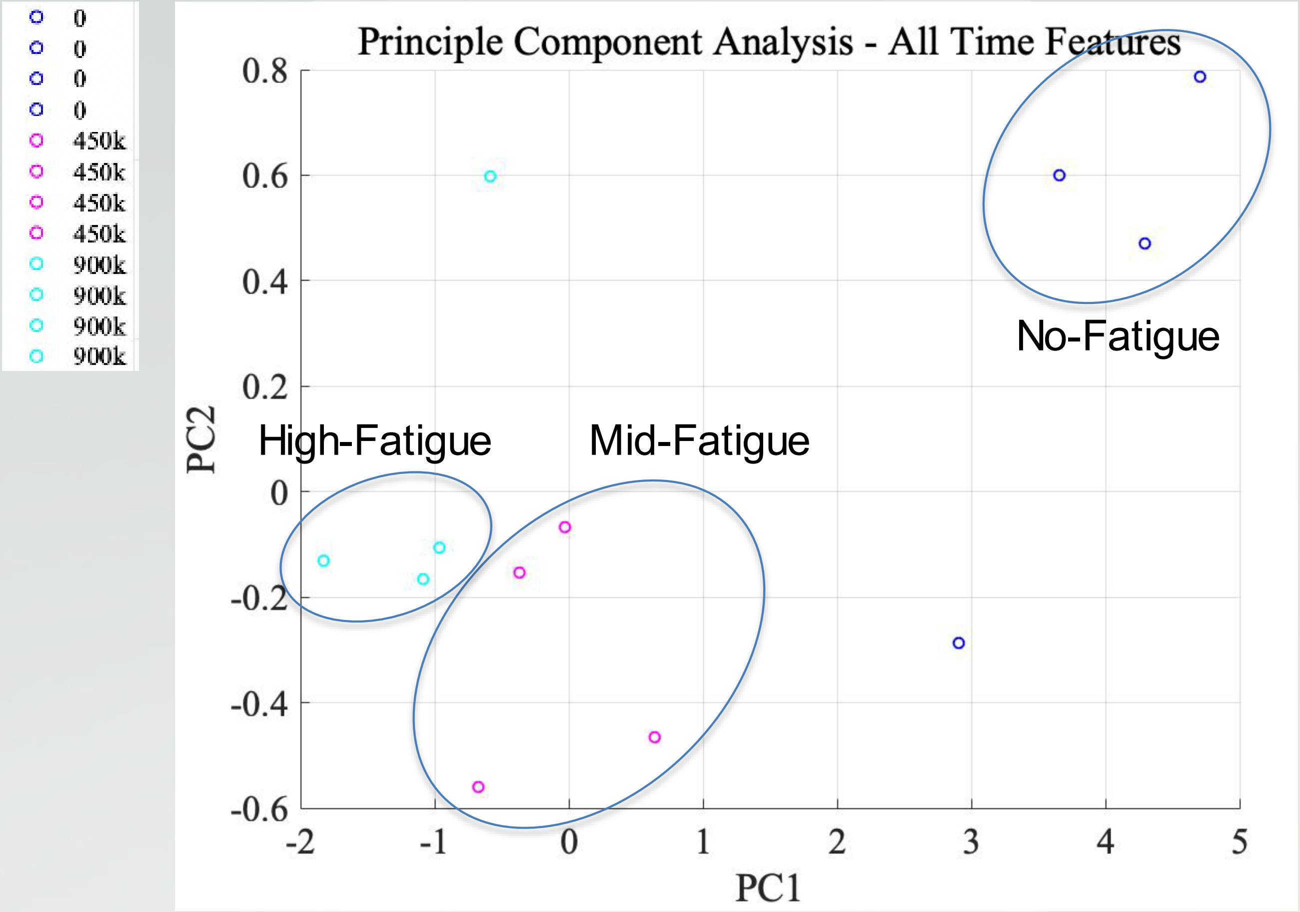
Observation: 3rd & 5th harmonic show the best separation between No-Fatigue, Mid-Fatigue and High-Fatigue sample categories. Based on this, we go to the feature space (i.e. Feature 2: Odd harmonic peak ratios)

Feature Space (NLE-2D) – $1^{st}/5^{th}$ vs $1^{st}/7^{th}$



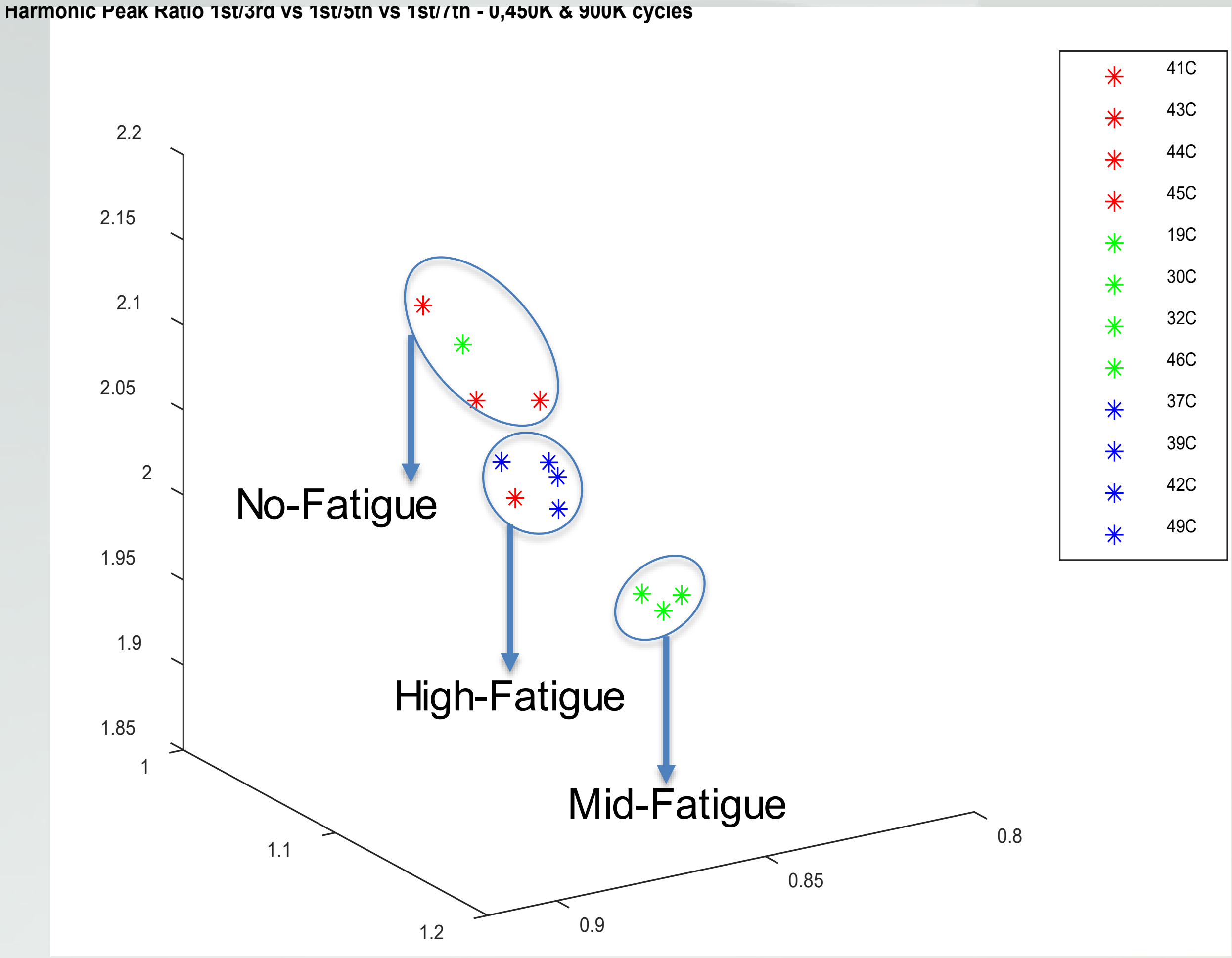
Separation between No-Fatigue, Mid-Fatigue (450K loading cycles) and High-Fatigue (900K loading cycles) sample categories is observed

Comparison of MBN vs NLE (PC1 and PC2 Features)



Consistent with results obtained using the NLE technique

Feature Space (NLE-3D) – 1st/3rd vs 1st/5th vs 1st/7th



Summary

- Design and development of differential NLE (DNLE) probe
- Identifying features from NLE output signal’s
- Categorizing samples into clusters, with respect to loading cycles and fatigue levels
- Initial results indicate that, the different sample categories can be differentiated using harmonic peak ratios, as features
- The features chosen do not show a monotonic correlation with the number of loading cycles
- More extensive study needs to be done to validate the approach

Thank you!