

22 Mar 2023

Probability of Detection in Structural Health Monitoring

Genda Chen

Missouri University of Science and Technology, gchen@mst.edu

Follow this and additional works at: https://scholarsmine.mst.edu/inspire_webinars



Part of the [Structural Engineering Commons](#)

Recommended Citation

Chen, Genda, "Probability of Detection in Structural Health Monitoring" (2023). *INSPIRE Archived Webinars*. 23.

https://scholarsmine.mst.edu/inspire_webinars/23

This Video - Presentation is brought to you for free and open access by Scholars' Mine. It has been accepted for inclusion in INSPIRE Archived Webinars by an authorized administrator of Scholars' Mine. This work is protected by U. S. Copyright Law. Unauthorized use including reproduction for redistribution requires the permission of the copyright holder. For more information, please contact scholarsmine@mst.edu.

The logo for INSPIRE features the word "INSPIRE" in large, bold, green capital letters. Above the letter "I" is a green Wi-Fi symbol. Below the word, a yellow drone is shown flying through a stylized bridge structure. The background of the logo is a light gray grid pattern.

INSPIRE

INSPECTING AND PRESERVING
INFRASTRUCTURE THROUGH
ROBOTIC EXPLORATION

Probability of Detection (POD) in Structural Health Monitoring

Dr. Genda Chen, Professor and Abbett Chair in Civil Engineering
Director of the INSPIRE University Transportation Center
Director of the Center for Intelligent Infrastructure
March 22, 2023, gchen@mst.edu



Notes about This Presentation

- **This set of slides (posted) are slightly updated from the original presentation on March 22.**
- **The full citation to the original developers (Meeker, Roach, and Kessler) of the two basic approaches for POD calculations are added to provide full details of the approaches.**
- **Meeker, Roach, Kessler and my group agree on the use of two new names (SODAD and RPM) to describe the two approaches.**



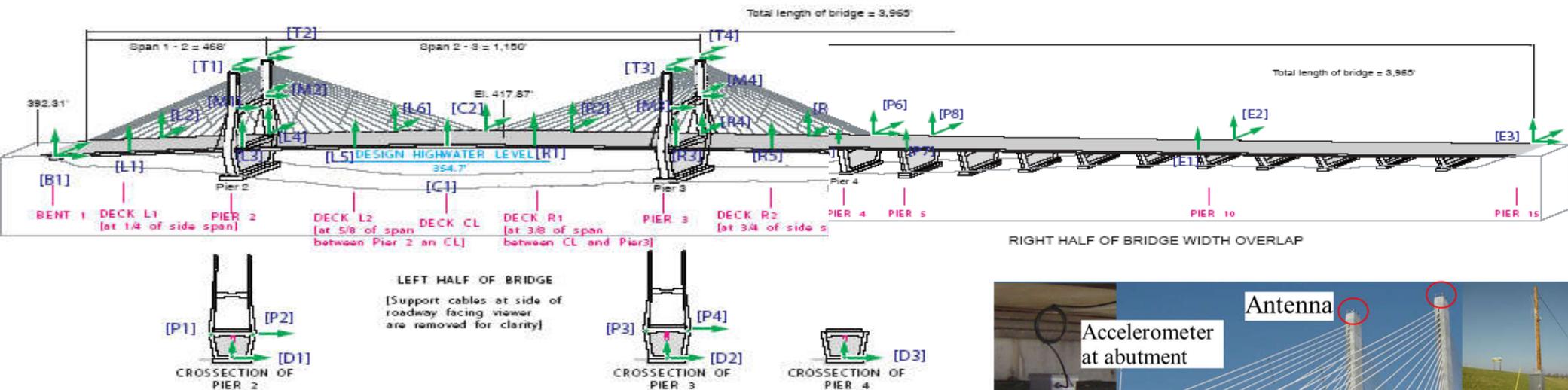
Outline of This Presentation

- **Motivation**
 - **Successful Structural Health Monitoring (SHM) Case Study**
 - **Sensor Data Variation**
- **Introduction to Corrosion Monitoring as an SHM Example**
 - **Problem Statement**
 - **Objectives**
- **Probability of Detection (POD)**
 - **Basic concepts**
 - **Two mathematically-rigorous methods**
- **Long Period Fiber Gratings (LPFG) Sensors**
 - **Principle, Fabrication, and Application**
- **Corrosion Experiment**
 - **Sensor preparation**
 - **Test setup**
- **Results and Discussion**
 - **Summary results**
 - **Corrosion characteristic curve**
 - **POD analysis**
- **Concluding Remarks**

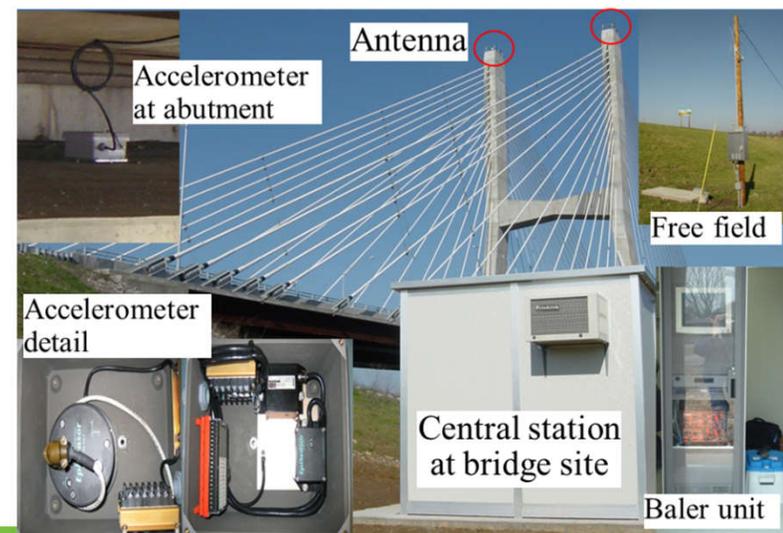
Motivation

Successful SHM Case Study

- **Seismic Instrumentation System to Understand Earthquake Loads and Bridge Behavior**
 - 84 accelerometers with wireless transmission
 - One data recorder inside each tower
 - A central computer connected to internet for real-time monitoring

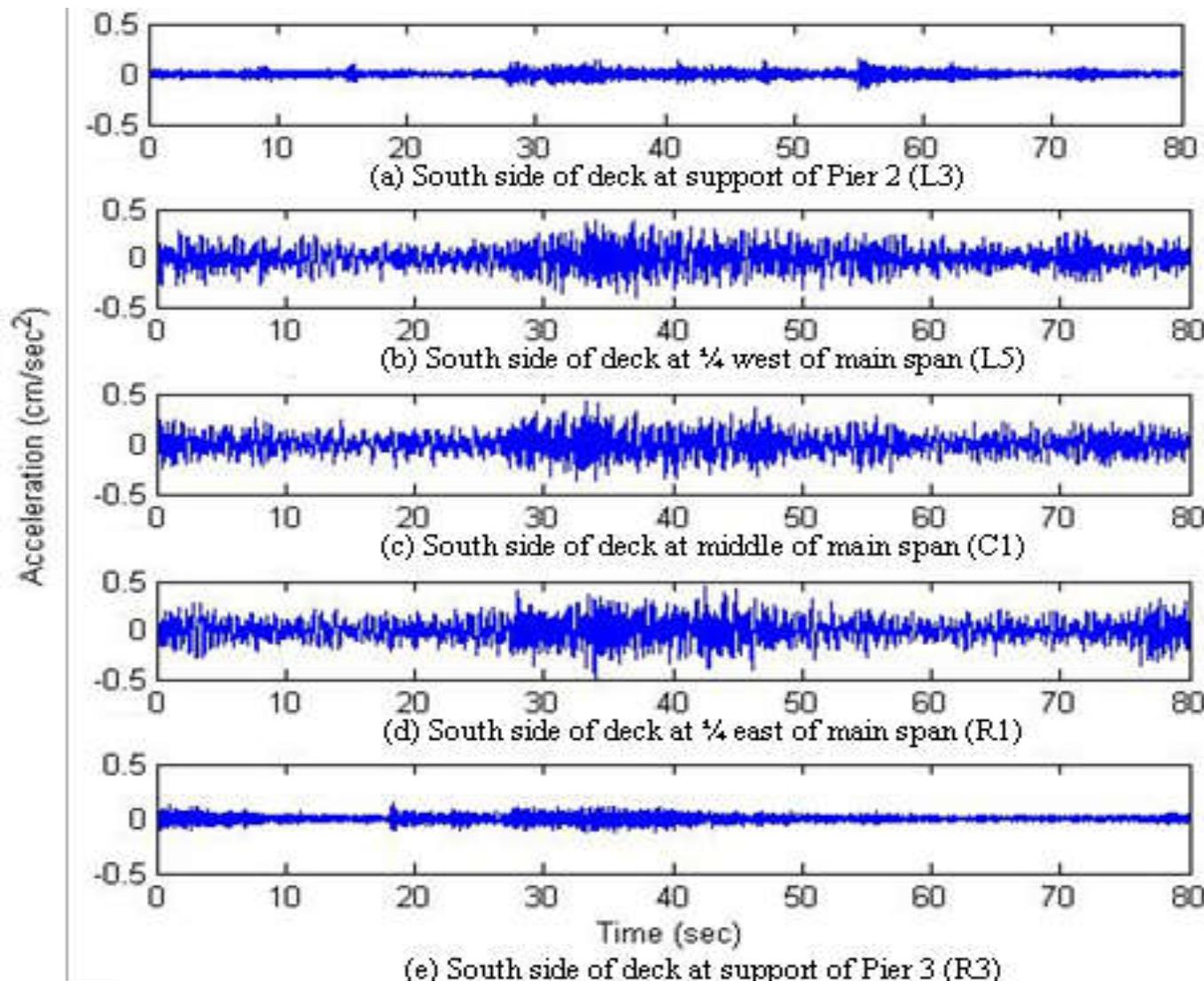


- **Cooperative effort among FHWA, USGS, MoDOT and MCEER**



Successful SHM Case Study

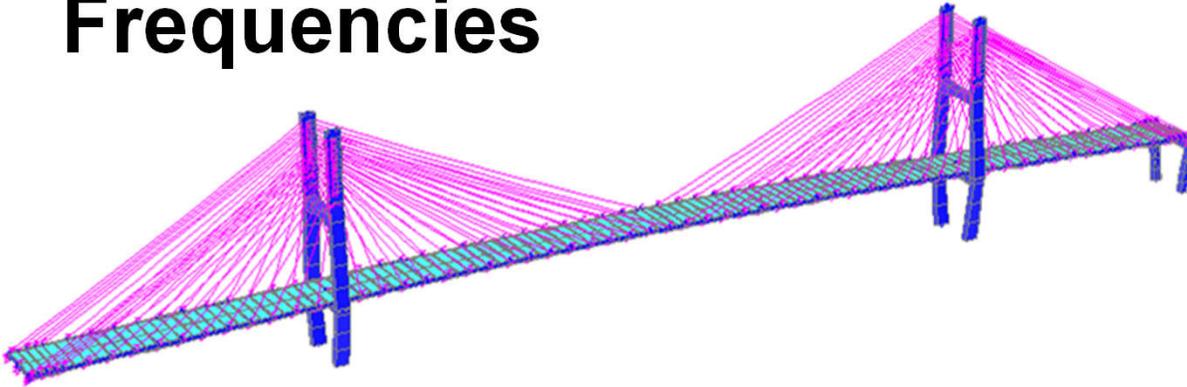
- Vertical Accelerations in Bridge Deck during May 1, 2005, M4.1 EQ



More details about this earthquake recording are referred to: Celebi, M. (2006). Real-time seismic monitoring of the new Cape Girardeau Bridge and preliminary analysis of recorded data: an overview. *Earthquake Spectra*, 22(3), pp. 609-630.

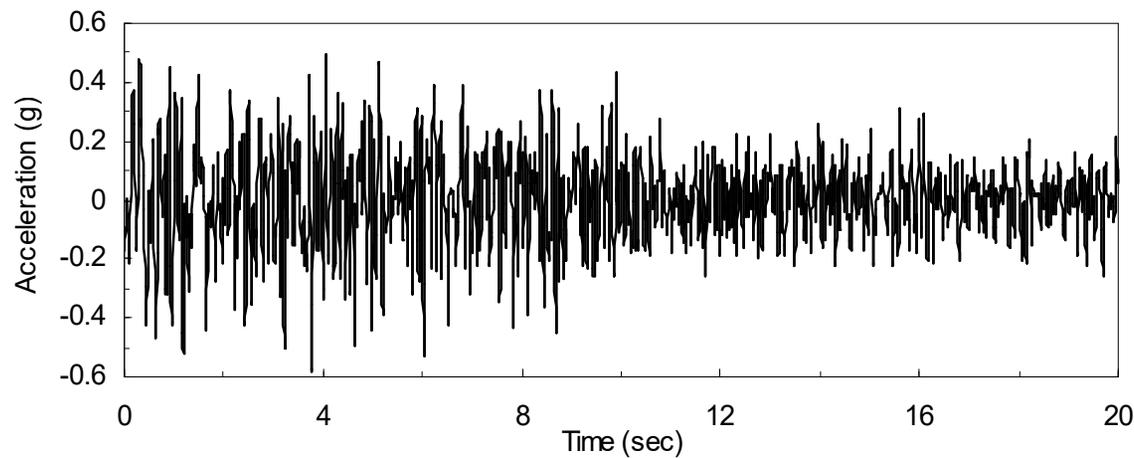
Successful SHM Case Study

- **Bridge Model Validated by Measured Frequencies**



2012 (2943) joints
128 (128) cable elements
2120 (3596) frame elements
244 (853) shell elements
274 (394) rigid link elements
Total: 10326 (14754) DOFs

- **Scaled-up Rock Motion from May 1, 2005, EQ**

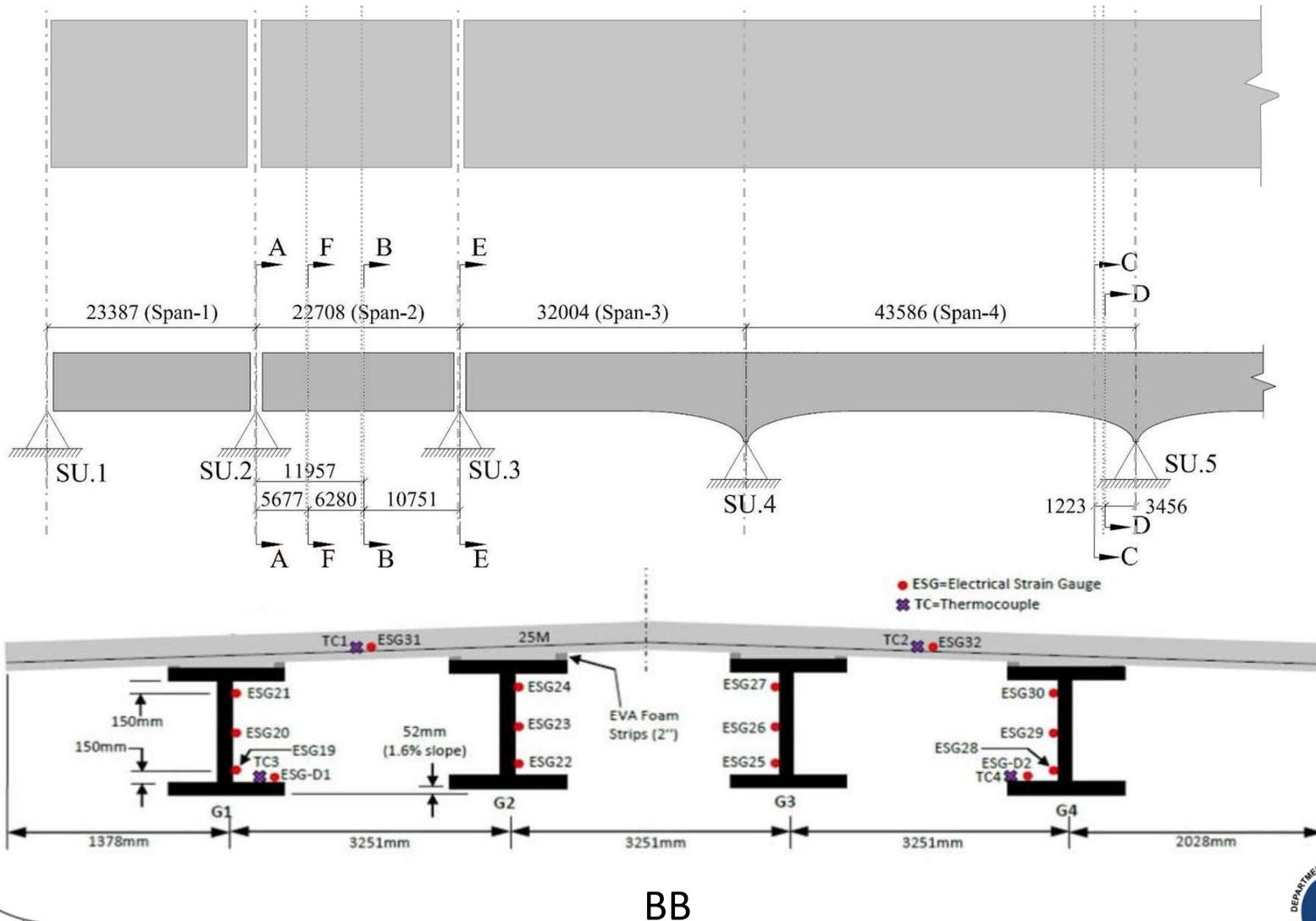


Transverse Acceleration at Station D1

1. Accelerations at Station D1 were scaled up and used as ground motions in analysis.
2. Three components of acceleration were input.
3. Peak values in global X, Y and Z are 0.57g, 0.57g and 0.42 g, respectively.

Sensor Data Variation

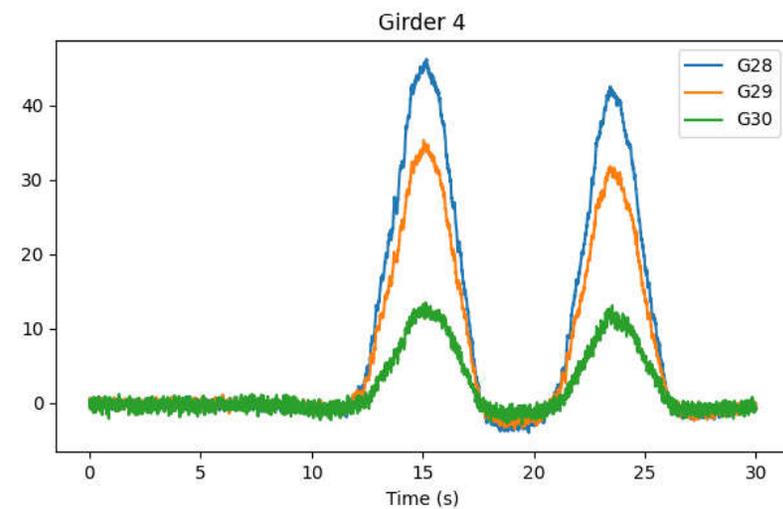
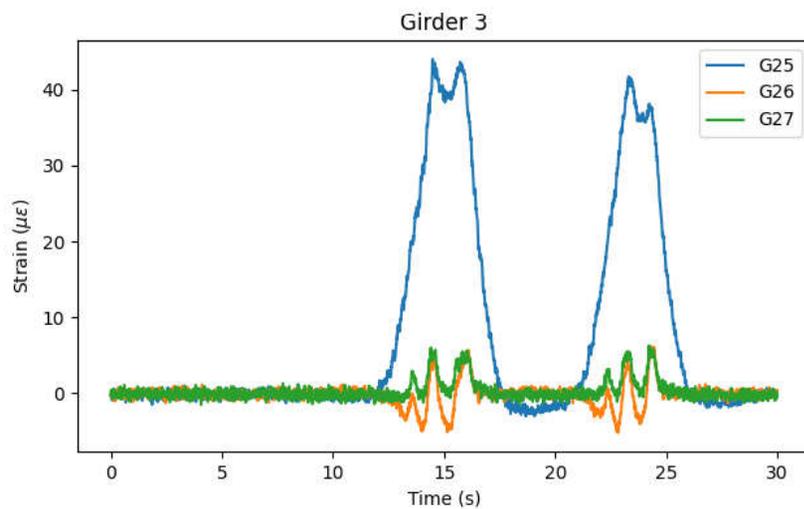
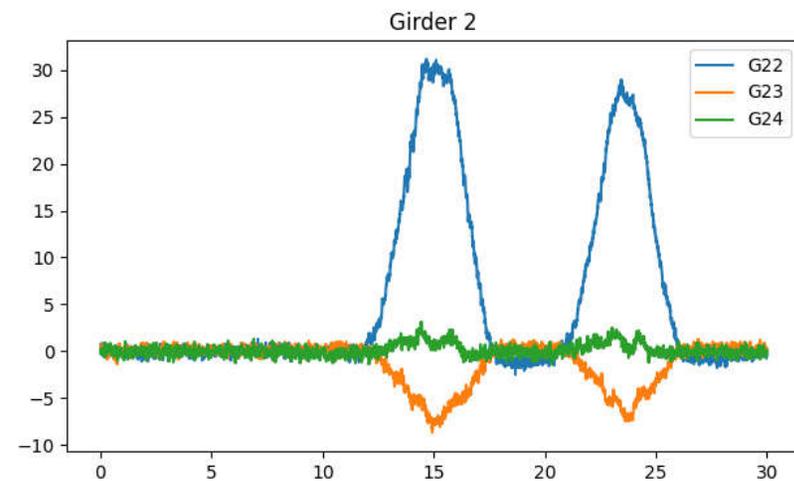
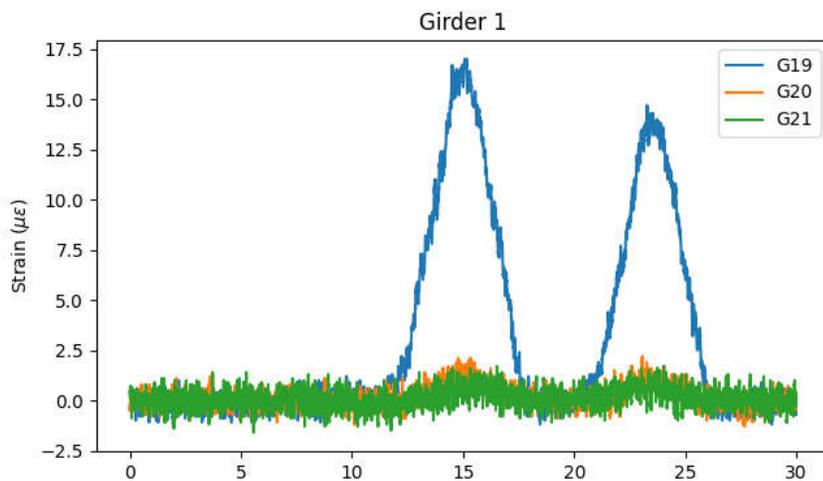
- ISHMII Benchmark – Strain Gauge Placement
 - Courtesy of Dr. Douglas Thomson from U. of Manitoba



BB

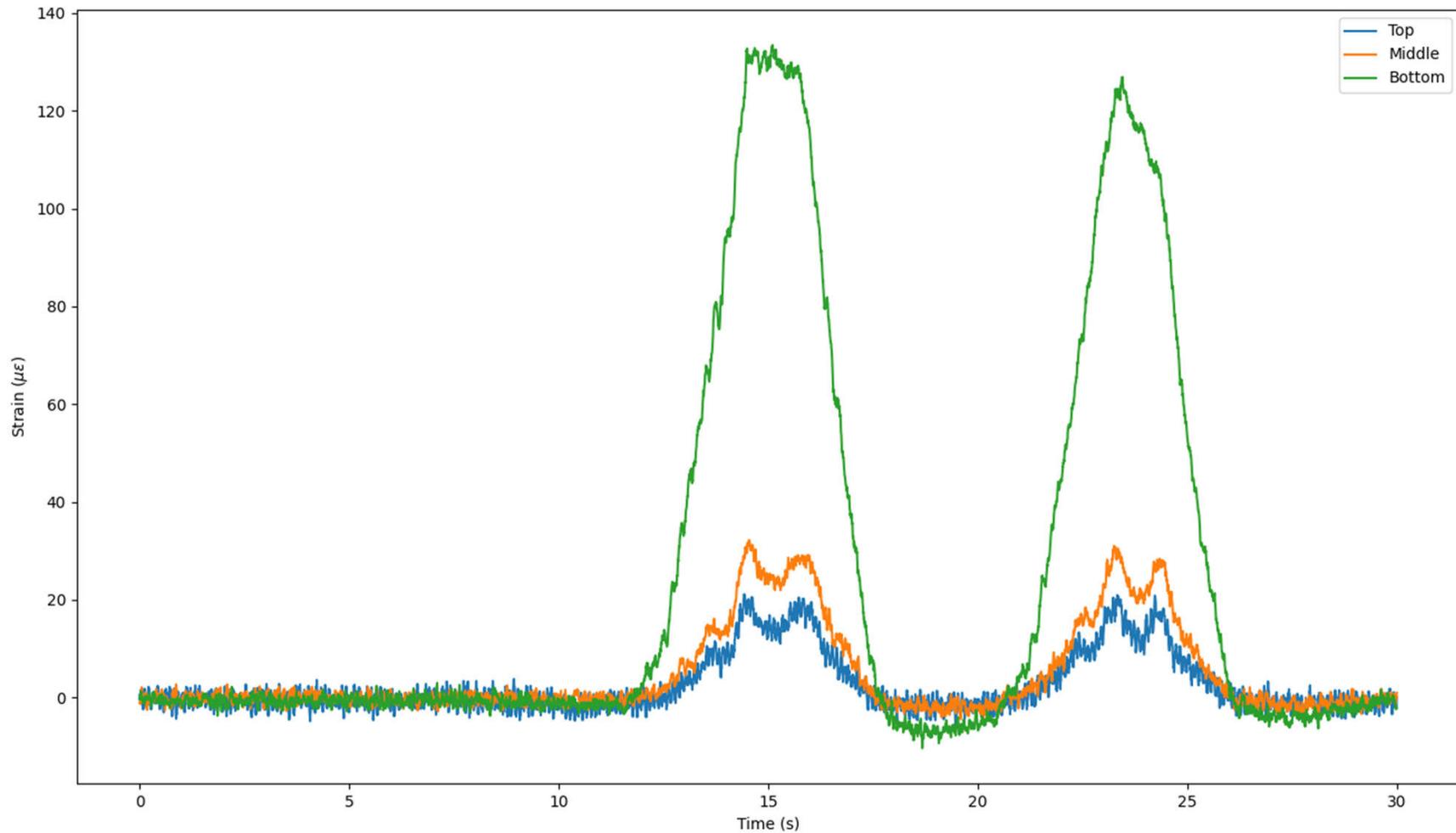
Sensor Data Variation

- Strain Time Histories at Midspan



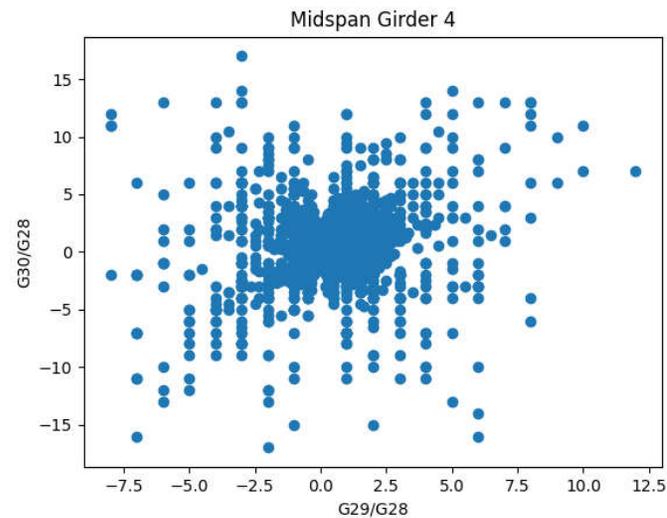
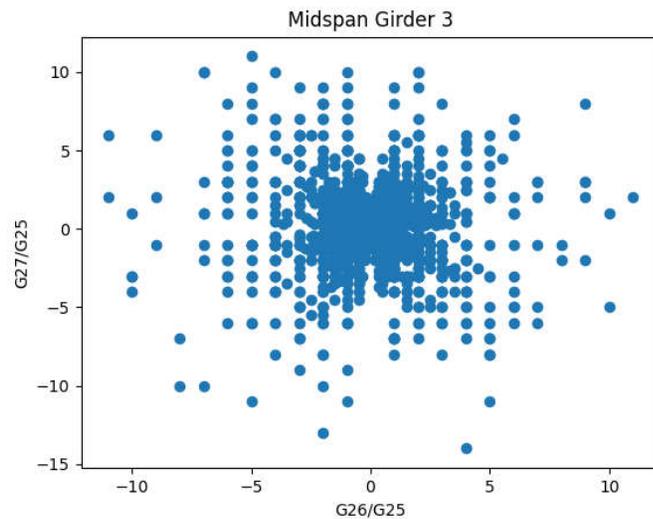
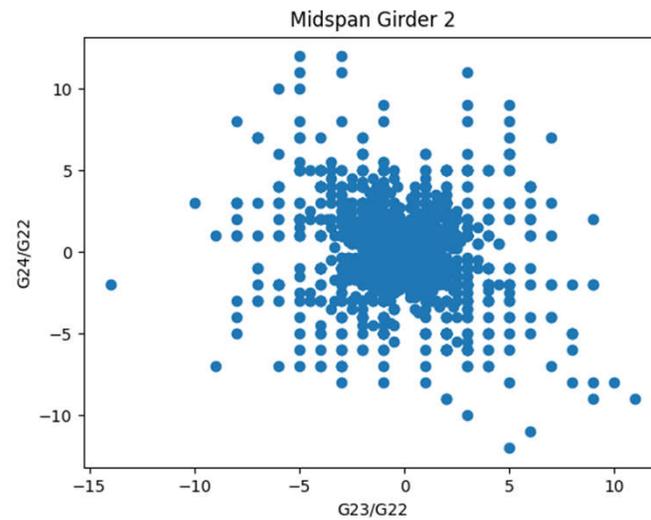
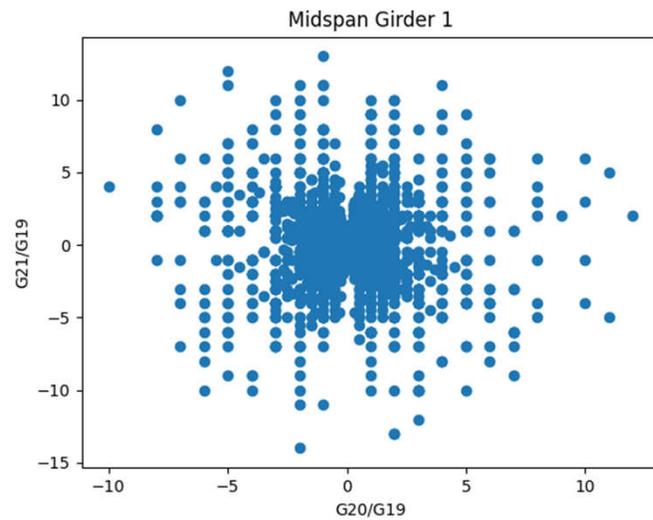
Sensor Data Variation

- Sum of Strain Time Histories at Midspan



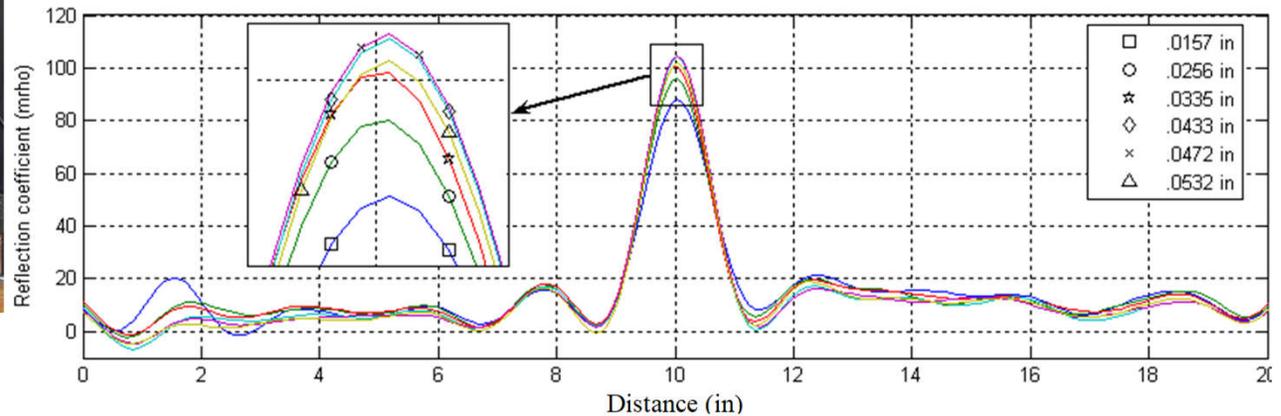
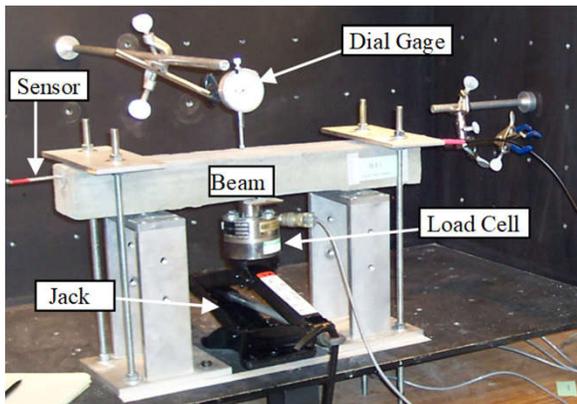
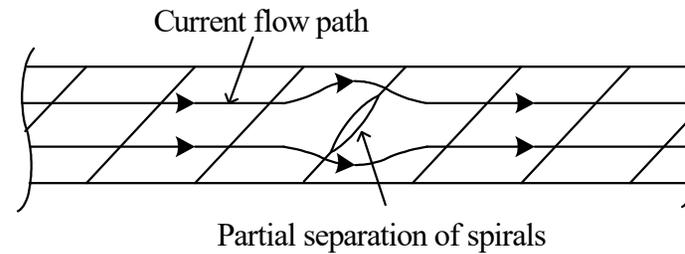
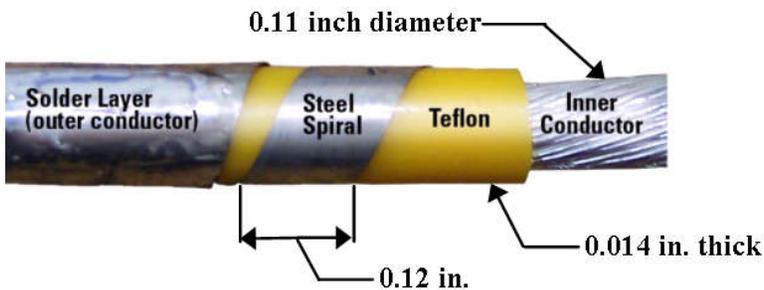
Sensor Data Variation

- Strain Ratios at Midspan



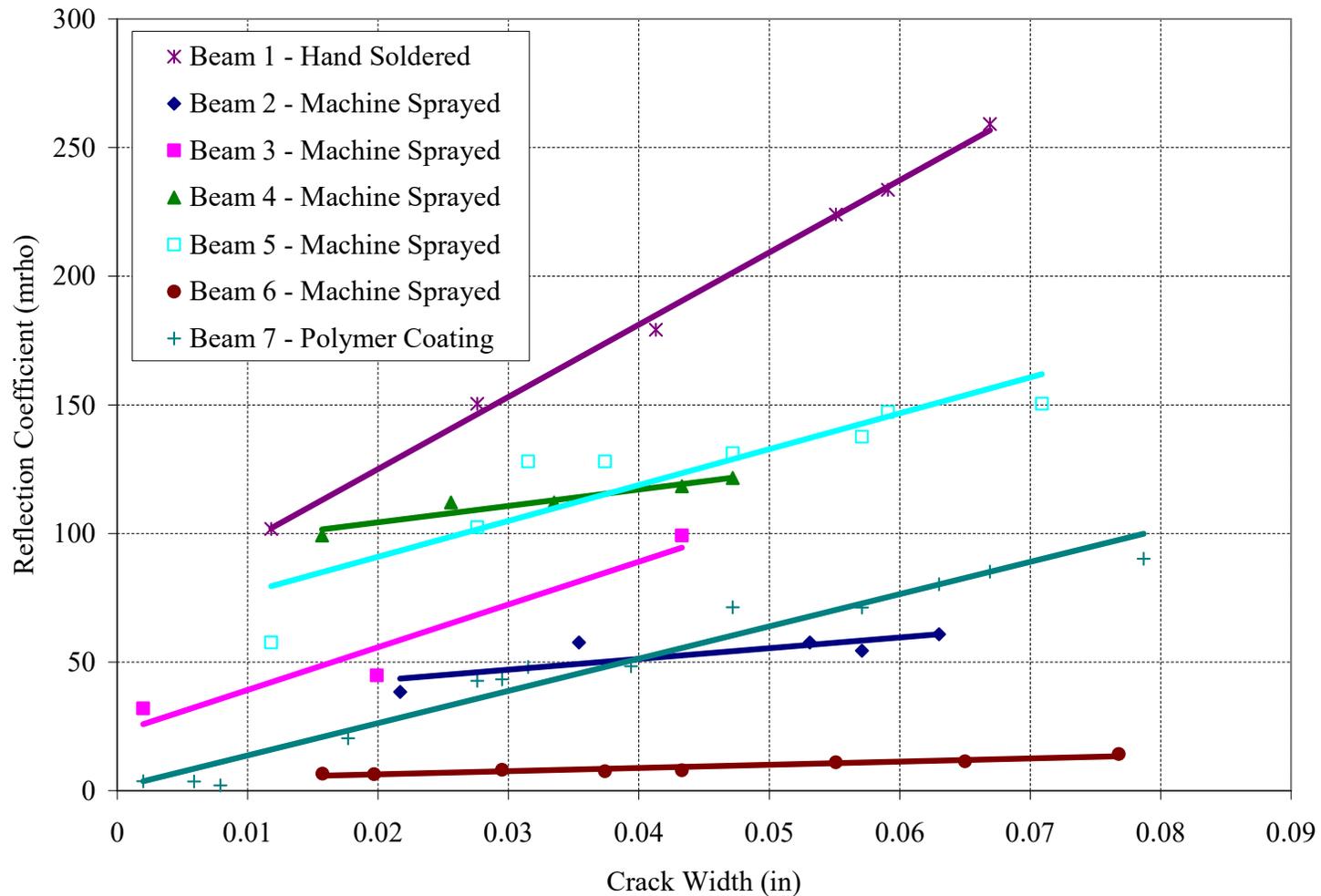
Sensor Data Variation

- Distributed Strain/Crack Sensors



Sensor Data Variation

- **Distributed Strain/Crack Sensors**



Sensor Data Variation

- Thus, it would be highly desirable to develop methods that can be used to assess POD in SHM applications.
- POD can be analyzed using the traditional statistical methods as described in the 2009 MIL-HDBK 1823A for NDE and sample test data. These data are obtained through independent, repeated tests.
- However, while NDE experiments involve a set of specimens with fatigue cracks (as an example), SHM sensors are fixed and acquire data over time as cracks grow, which could be partially correlated.

Introduction

Problem Statement

- **Bridges are often exposed to deicing salts and/or marine environments, subjected to daily and seasonal changes in operation temperature, and strained under traffic or extreme loads over years.**
- **Corrosion induced deterioration of steel structures and steel bars in reinforced concrete structures is the No.1 reason for bridge maintenance, repair or replacement in the U.S. It accounts for approximately \$10B per year direct costs.**
- **Corrosion of steel elements is affected by a few factors such as service life, surrounding moisture, chloride content, and permittivity of cover materials. Unless these factors are well understood, it is difficult to provide engineers with a definitive mass loss of steel elements in practice.**



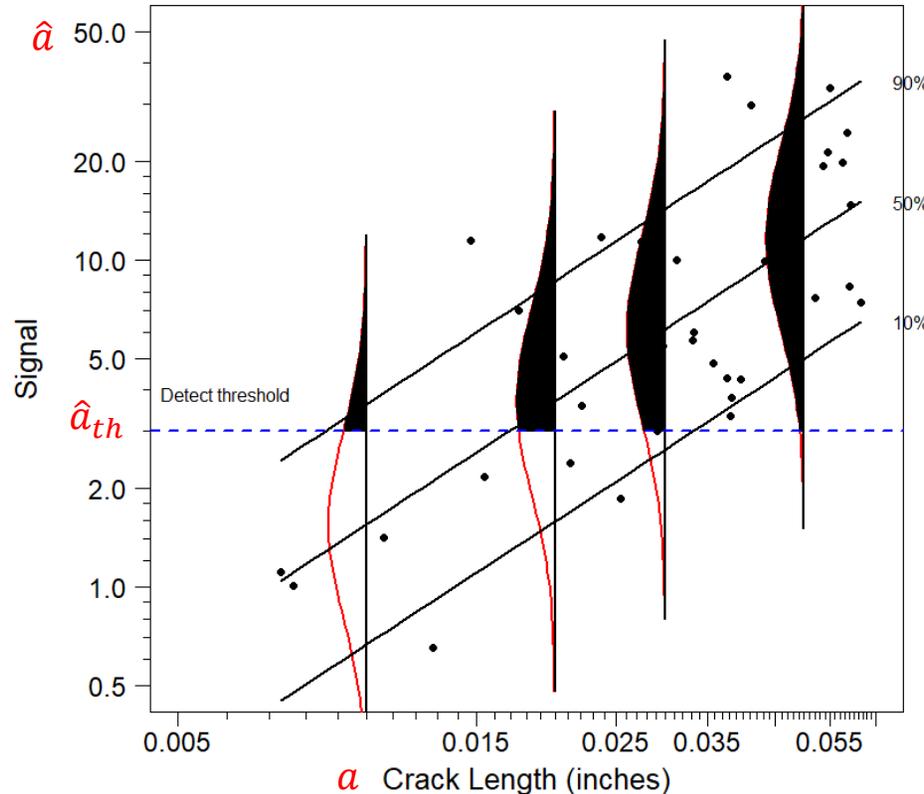
Objectives

- **To develop two statistical methods for determining the POD in corrosion monitoring using Fe-C coated LPFG sensors**
- **To validate the methods from independent laboratory tests**
- **To determine the steel mass loss at 90% POD and the largest steel mass loss that may miss from a corrosion inspection at 95% lower confidence bounds**

Probability of Detection (POD)

Basic Concepts of POD

- **POD** is a method used to determine the capability of an inspection as a function of defect type and size (ultrasonic test data for crack length taken from Meeker, Roach, and Kessler 2019).



$$\hat{a} = \beta_0 + \beta_1 a + \varepsilon \quad (1)$$

$$\varepsilon \sim \text{Normal}(0, \sigma_\varepsilon)$$

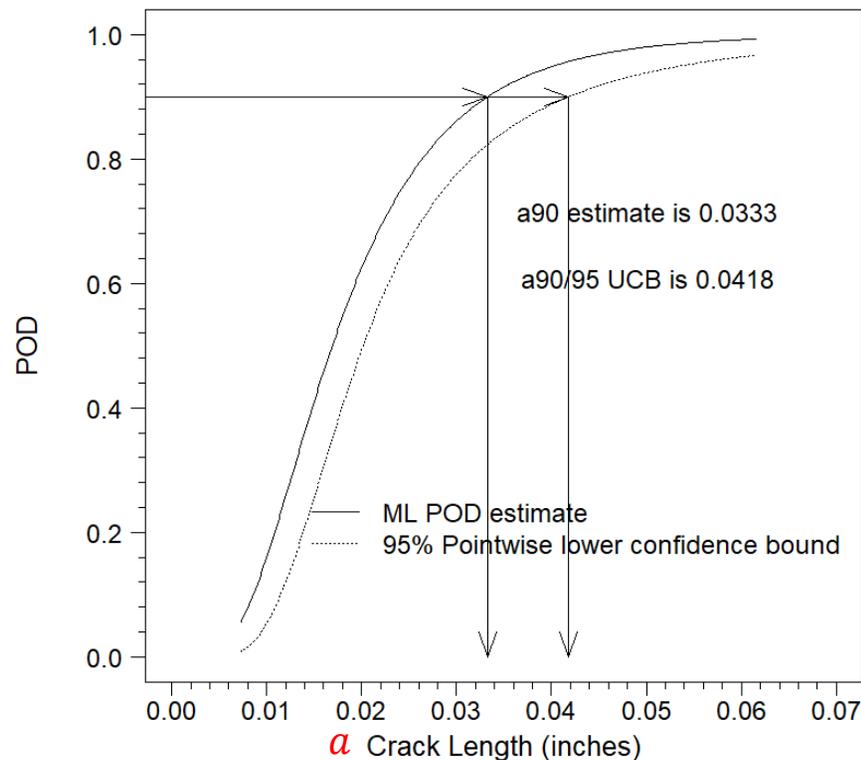
$$POD(a) = P(\hat{a} > \hat{a}_{th}) = 1 - \Phi(z) \quad (2)$$

$$z = \frac{\hat{a}_{th} - (\beta_0 + \beta_1 a)}{\sigma_\varepsilon} \quad (3)$$

Meeker WQ, Roach D, Kessler SS. Statistical Methods for Probability of Detection in Structural Health Monitoring. In: Structural Health Monitoring 2019. DEStech Publications, Inc. Epub ahead of print 15 November 2019.

Basic Concepts of POD

- **POD** is a method used to determine the capability of an inspection as a function of defect type and size (illustrated using a series of ultrasonic tests on samples taken from Meeker, Roach, and Kessler 2019)



a_{90} - target size at 90% POD

$a_{90/95}$ - a 95% confidence value for a_{90}
the largest crack that might be missed

Two Methods of POD

- The **Size of Deterioration at Detection (SODAD)** method for corrosion monitoring is generalized from the Length-at-detection (LaD) introduced for fatigue crack data analysis developed by Meeker, Roach, and Kessler (2019).
- The SODAD method only uses the size of deterioration when first detected corresponding to a threshold of the response signal.

$$POD(a) = P(A < a) = \Phi\left(\frac{a - \bar{a}}{\sigma_a}\right) \quad (5)$$

- \bar{a} and σ_a are the mean and standard deviation of random variable A for the size of deterioration.

Two Methods of POD

- The **Random Parameter Model (RPM)** is a direct extension of the traditional method as described in the MIL-HDBK-1823A.
- Renamed from the original term “Random Effects Generalization” developed by Meeker, Roach, and Kessler (2019), the RPM assumes that each signal/sensor specimen in the population has its own intercept and slopes. The POD of the RPM is then evaluated by Eq. (2) and

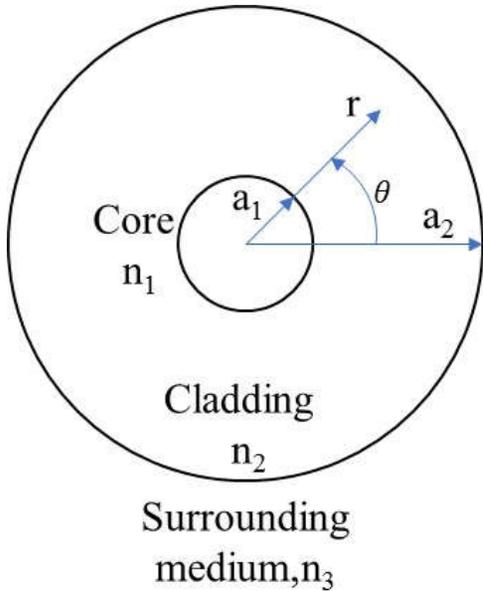
$$POD(a) = P(\hat{a} > \hat{a}_{th}) = 1 - \Phi(z) \quad (2)$$

$$z = \frac{\hat{a}_{th} - (\mu_{\beta_0} + \mu_{\beta_1} a)}{\sqrt{\sigma_{\beta_0}^2 + a^2 \sigma_{\beta_1}^2 + 2\rho a \sigma_{\beta_0} \sigma_{\beta_1} + \sigma_{\varepsilon}^2}} \quad (6)$$

Long Period Fiber Gratings (LPFG) Sensors

Principle of LPFG

- **Long period fiber gratings (LPFG)** is a light loss element with the refractive index of a fiber core periodically modulated. Its grating period is about $10^2 \sim 10^3 \mu\text{m}$.



Propagating constant

$$\beta = \frac{2\pi}{\lambda} n_{eff} \leftarrow \text{effective refractive index}$$

Coupling condition

$$\beta_{co} - \beta_{cl}^{0j} = \frac{2\pi}{\Lambda}$$

fundamental core mode β_{co} β_{cl}^{0j} \leftarrow grating period Λ
 j th order cladding mode

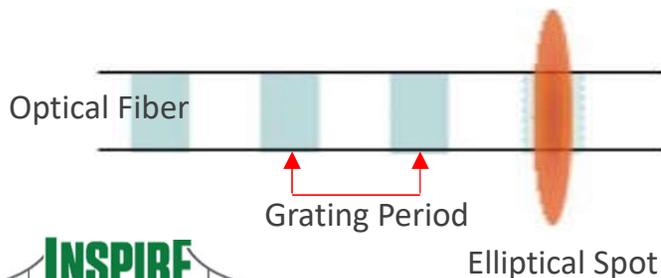
Resonant wavelength

$$\lambda_{eff} = (n_{eff}^{co} - n_{eff}^{cl,0j}) \Lambda$$

For our experiment

$$\Lambda = 350 \mu\text{m}$$

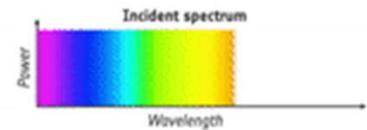
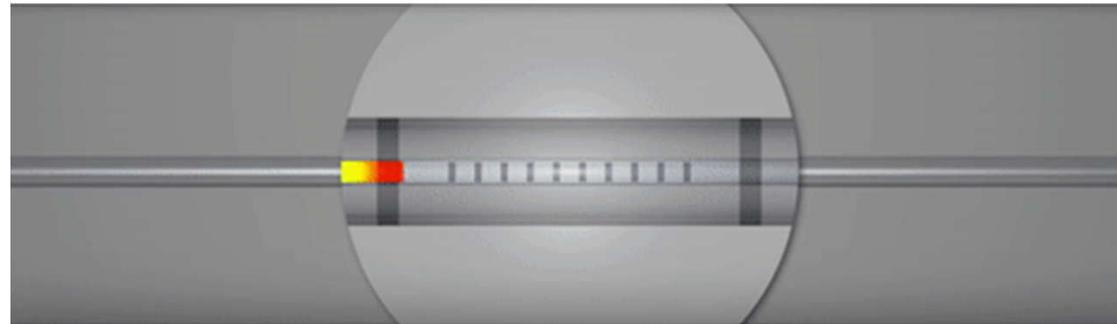
$$\lambda_{eff} = 1550 \text{ nm}$$



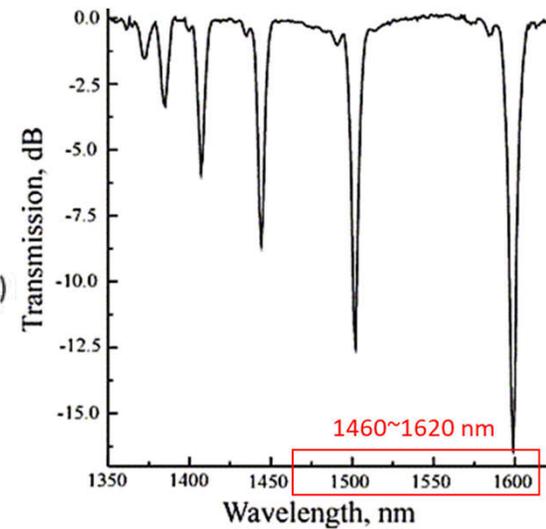
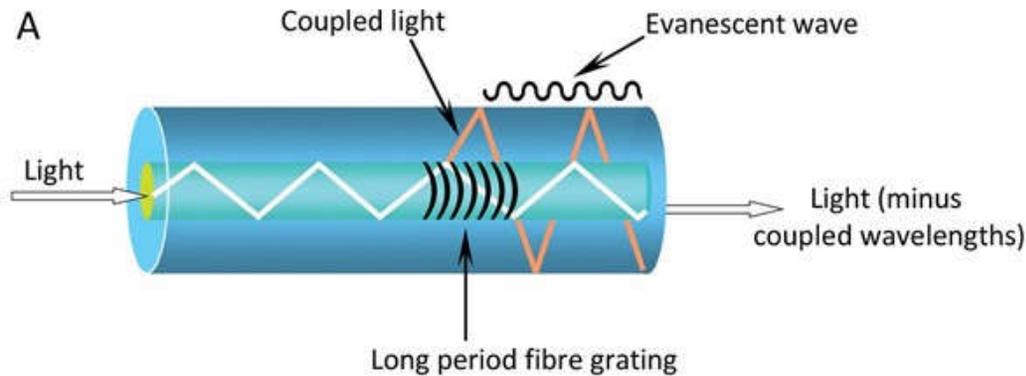
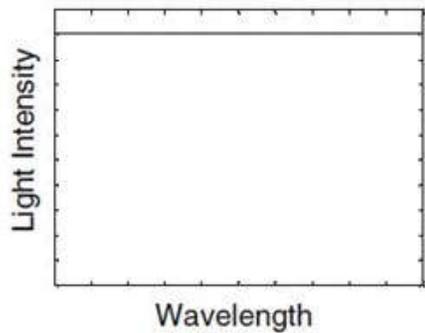
Principle of LPFG

- Operation Principle

- Fiber Bragg Gratings (FBG)

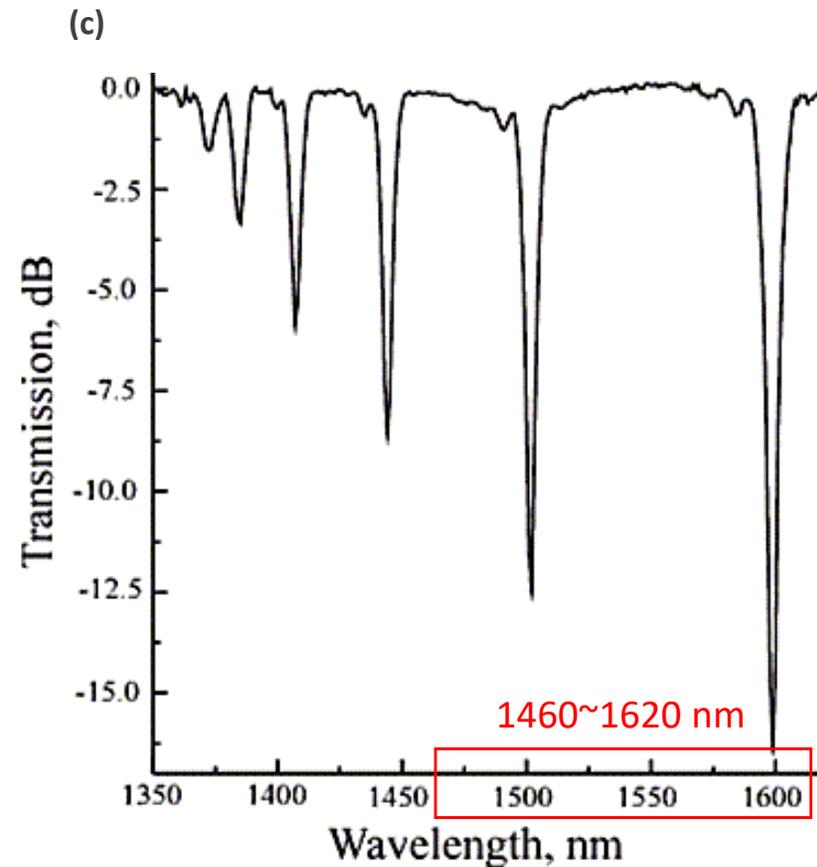
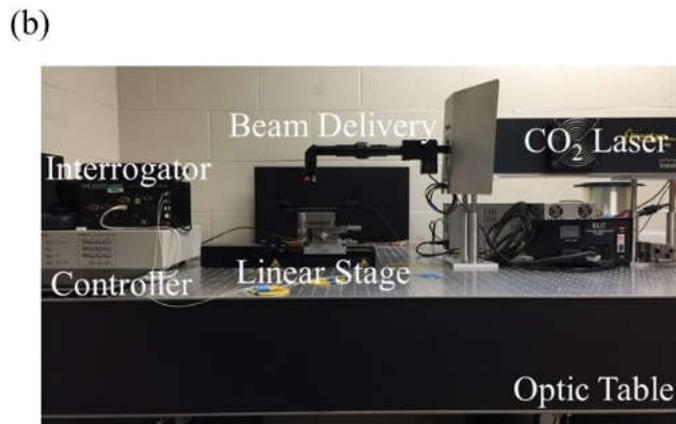
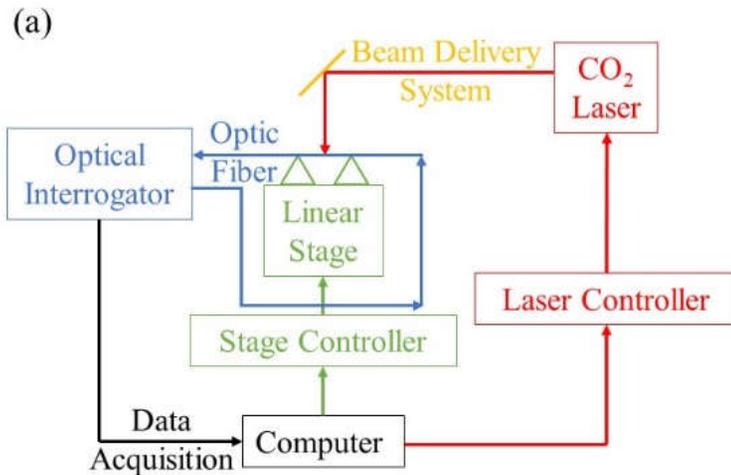


- LPFG



Fabrication of LPFG

- CO₂ Laser Grating System



Application of LPFG

$$\lambda_{eff} = (n_{eff}^{co} - n_{eff}^{cl,0j}) \Lambda$$

Change with strain and temperature

Change with surrounding medium index

• Temperature

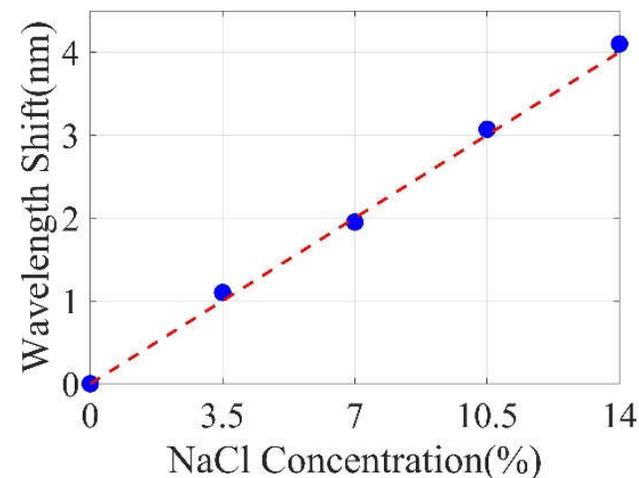
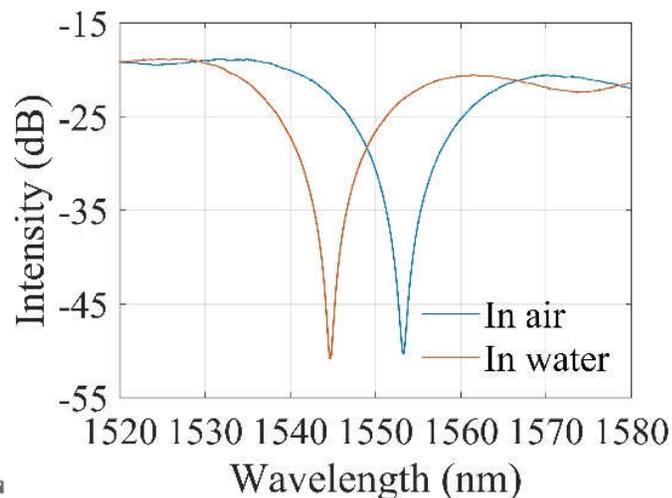
Thermal-optical Thermal expansion

$$\frac{d\lambda_{res}^m}{dT} = \left(\frac{dn_{eff}^{co}}{dT} - \frac{dn_{eff}^{cl,j}}{dT} \right) \Lambda + (n_{eff}^{co} - n_{eff}^{cl,j}) \frac{d\Lambda}{dT}$$

• Strain

$$\frac{d\lambda_{res}^m}{d\varepsilon} = \left(\frac{dn_{eff}^{co}}{d\varepsilon} - \frac{dn_{eff}^{cl,j}}{d\varepsilon} \right) \Lambda + (n_{eff}^{co} - n_{eff}^{cl,j}) \frac{d\Lambda}{d\varepsilon}$$

• Refractive Index

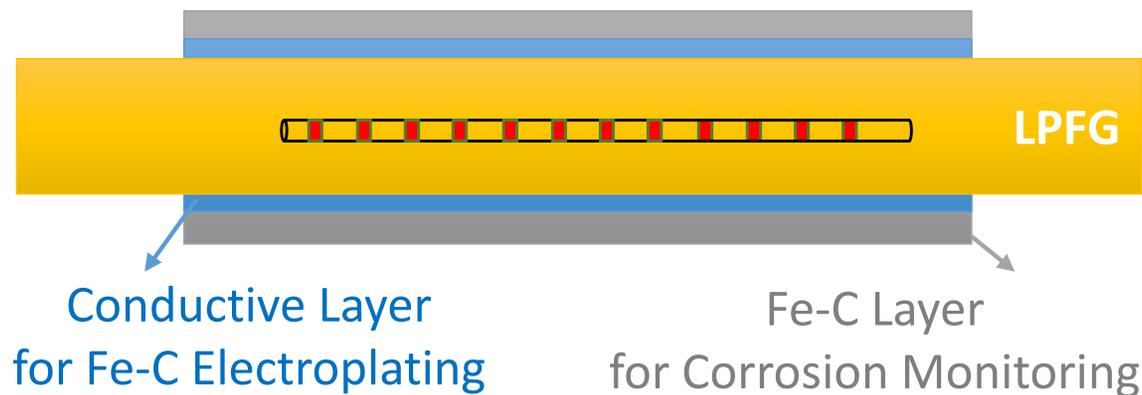


Corrosion Experiment

Sensor Preparation

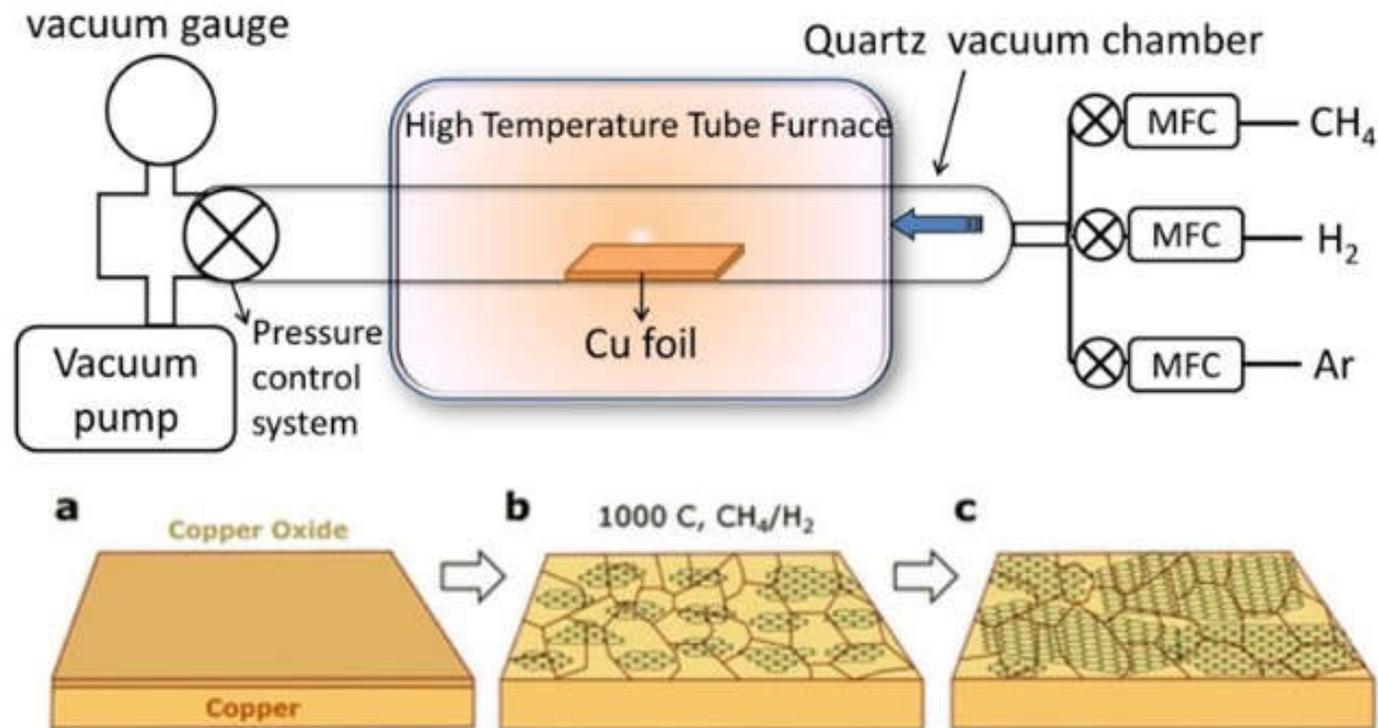
- **Fe-C Coated LPFG Sensors**

- The Fe-C mix represents the chemical composition of steel rebar and thus experiences the same corrosion process when deployed in the same corrosion environment.
- A conductive yet transparent layer is needed to electroplate a Fe-C layer on the surface of LPFG while maintaining the sensitivity of sensors



Sensor Preparation

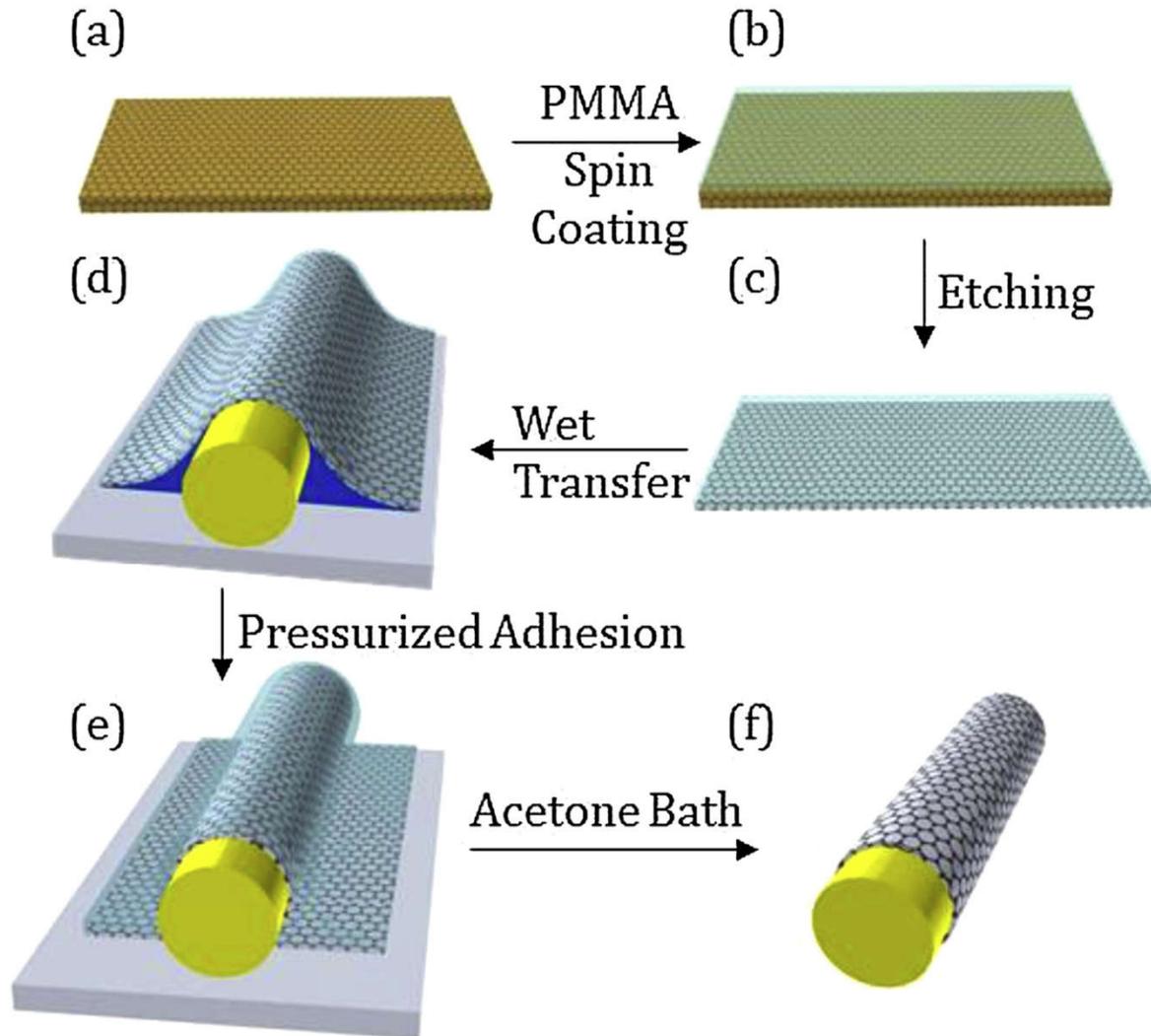
- Graphene (Gr) Growing



Low Pressure Chemical Vapor Deposition (LPCVD) System

Sensor Preparation

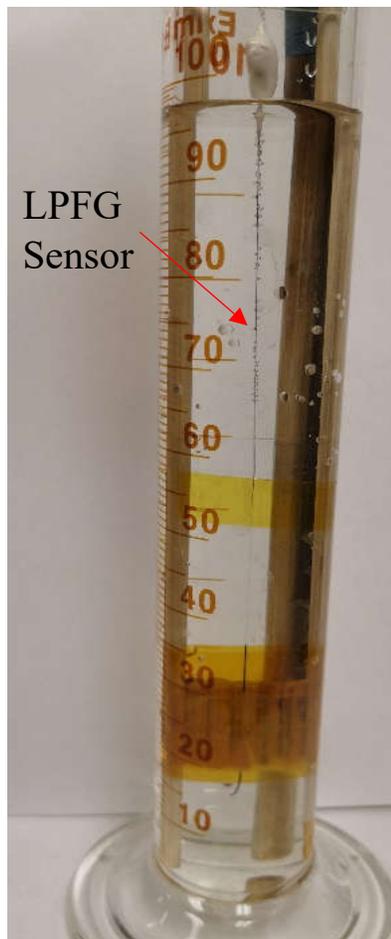
- Gr Coating on the Surface of LPFG Sensor



■ copper ■ graphene ■ PMMA ■ water ■ LPFG

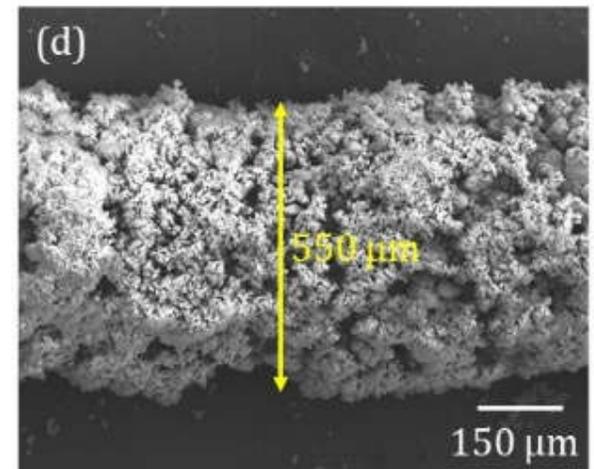
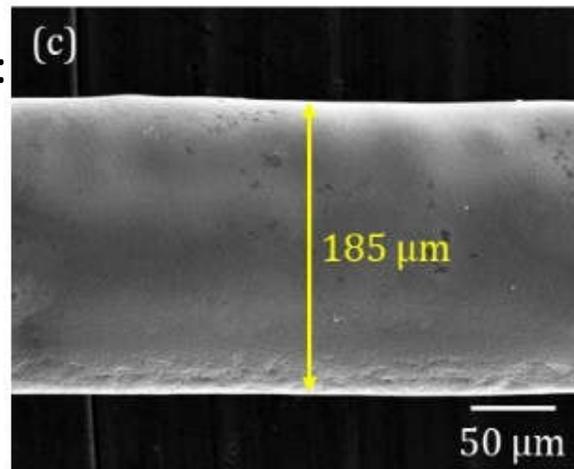
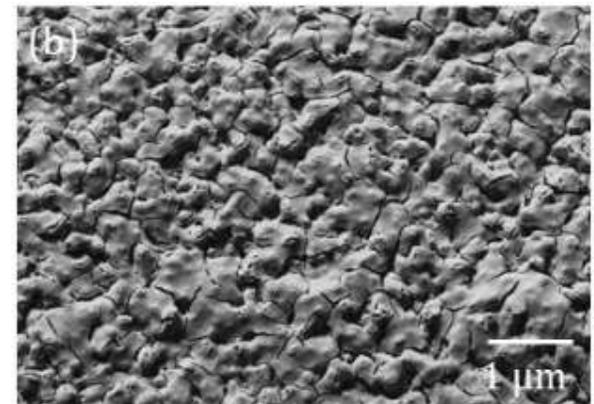
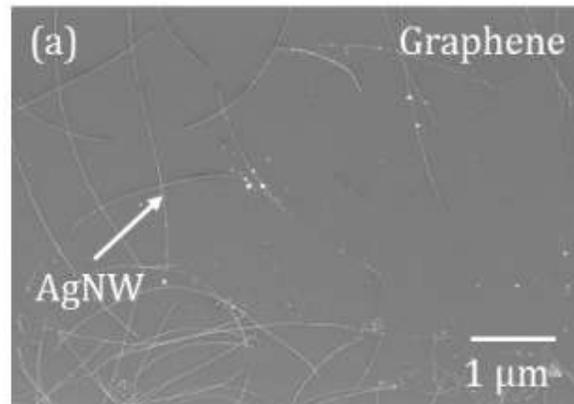
Sensor Preparation

- Fe-C Coating through Electroplating



5 mA
1.5 h

Thickness:
30 μm



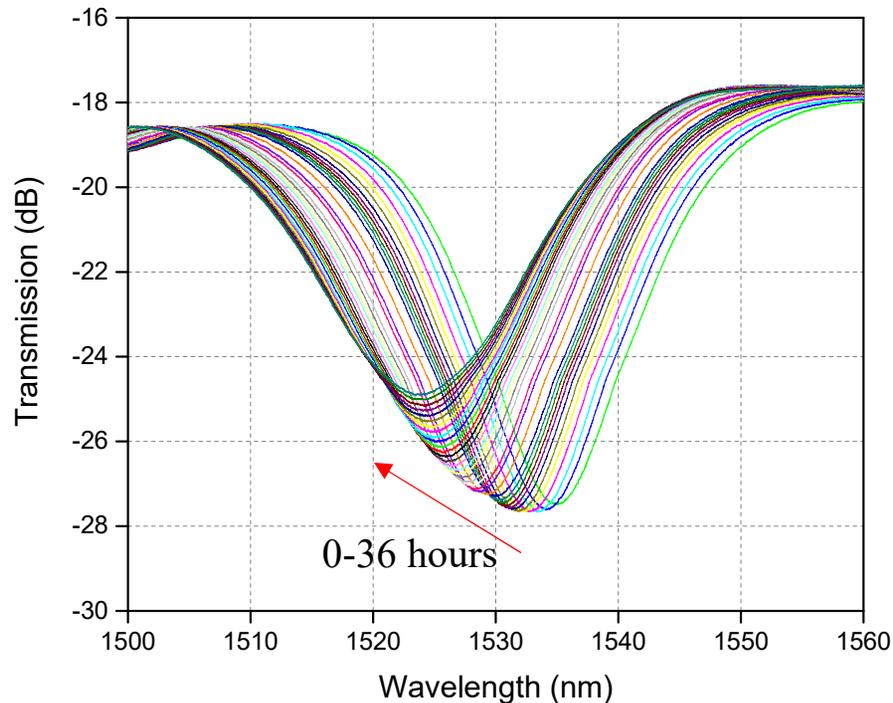
Test Setup

- **Sensors were immersed in 3.5 wt.% NaCl solution.**
- **An optical interrogator (Micron Optics si255) records optical spectra every hour.**
- **A Gamry instrument (Potentiostat/EIS 300) with a standard three-electrode configuration records the electrochemical impedance spectroscopy (EIS) every hour.**

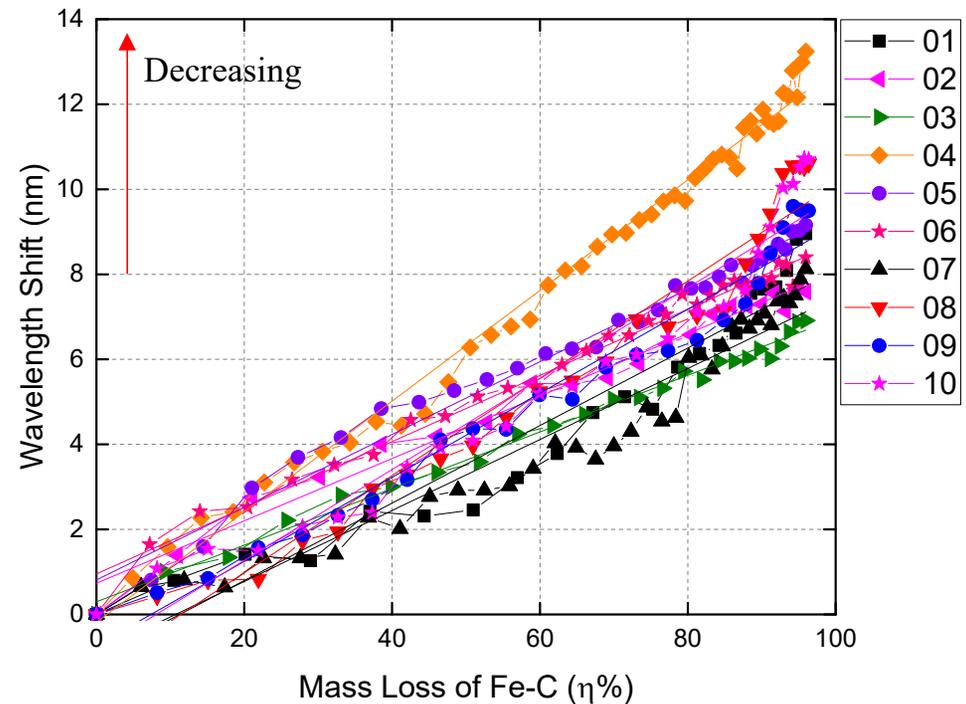
Results and Discussion

Summary Results

- **Transmission spectra and wavelength shift**



Transmission spectra of a Fe-C coated LPFG sensor in 3.5 wt. % NaCl solution for 36 h



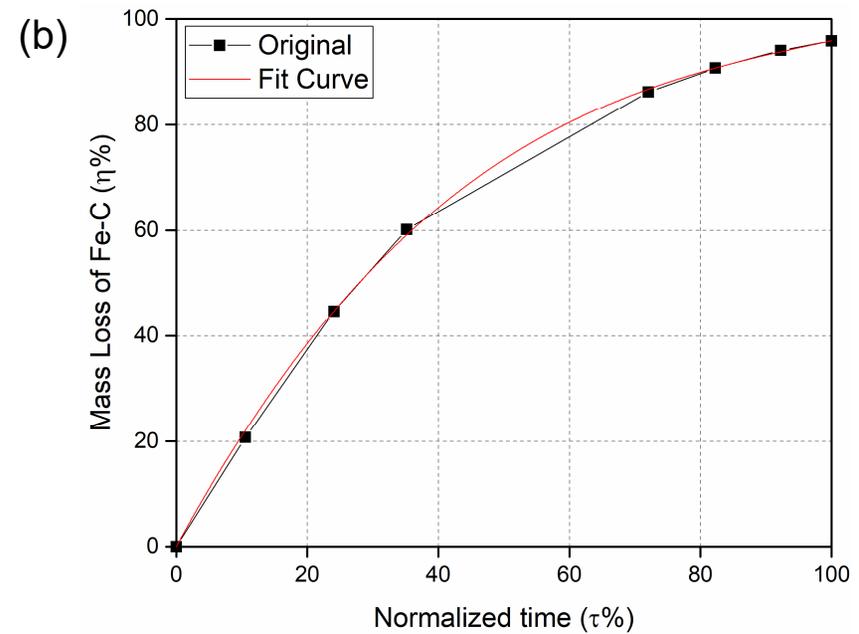
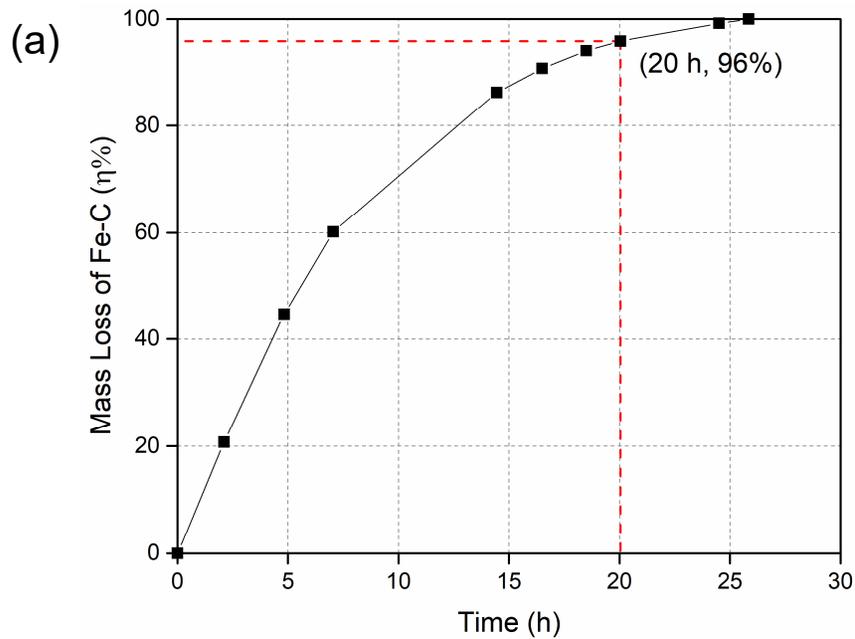
Wavelength shift of Fe-C coated LPFG sensors in 3.5 wt.% NaCl solution for 36 h

Corrosion Characteristic Curve

- Assume that the corrosion processes of all sensors are similar.

$$\eta = 6.38 \times 10^{-5} \tau^3 - 1.98 \times 10^{-2} \tau^2 + 2.30 \tau$$

Coefficient of determination R^2 is 0.9996

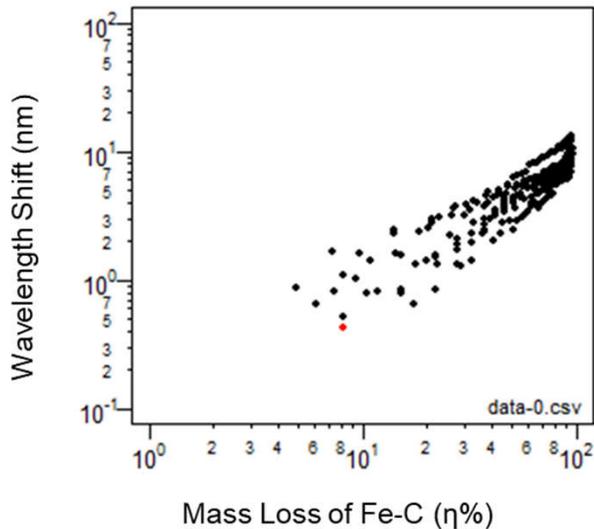
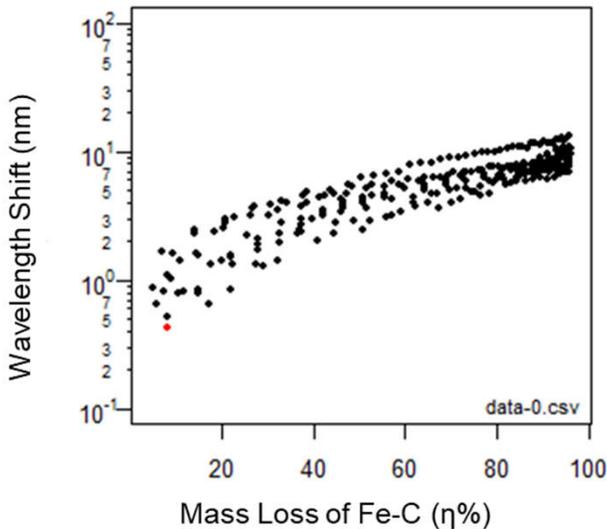
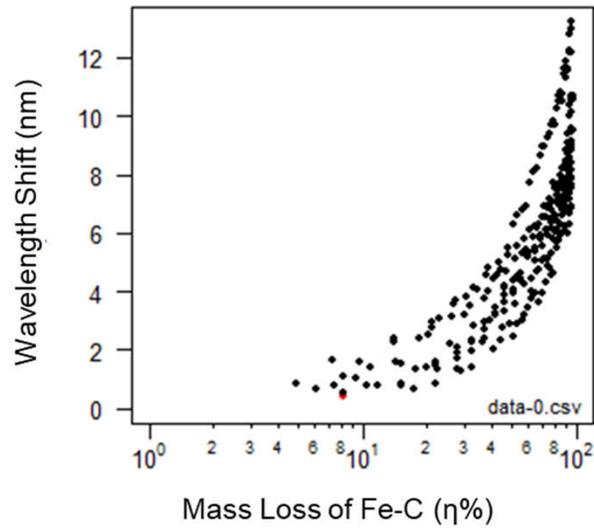
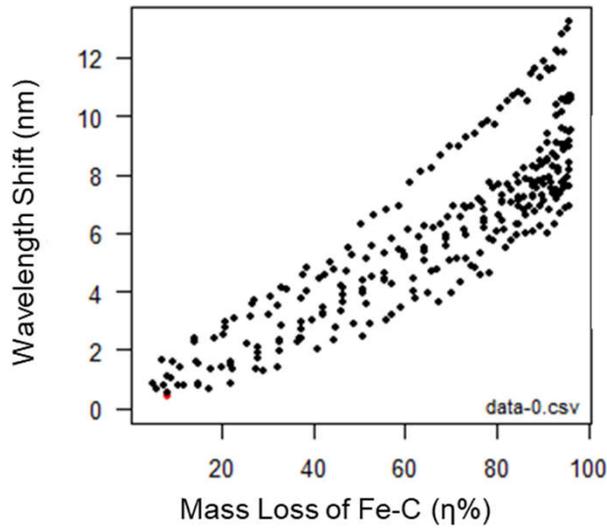


The Fe-C coated LPFG sensors in 3.5 wt.% NaCl solution

(a) mass loss of Fe-C coating over time, and (b) mass loss of Fe-C coating over normalized time

POD Analysis

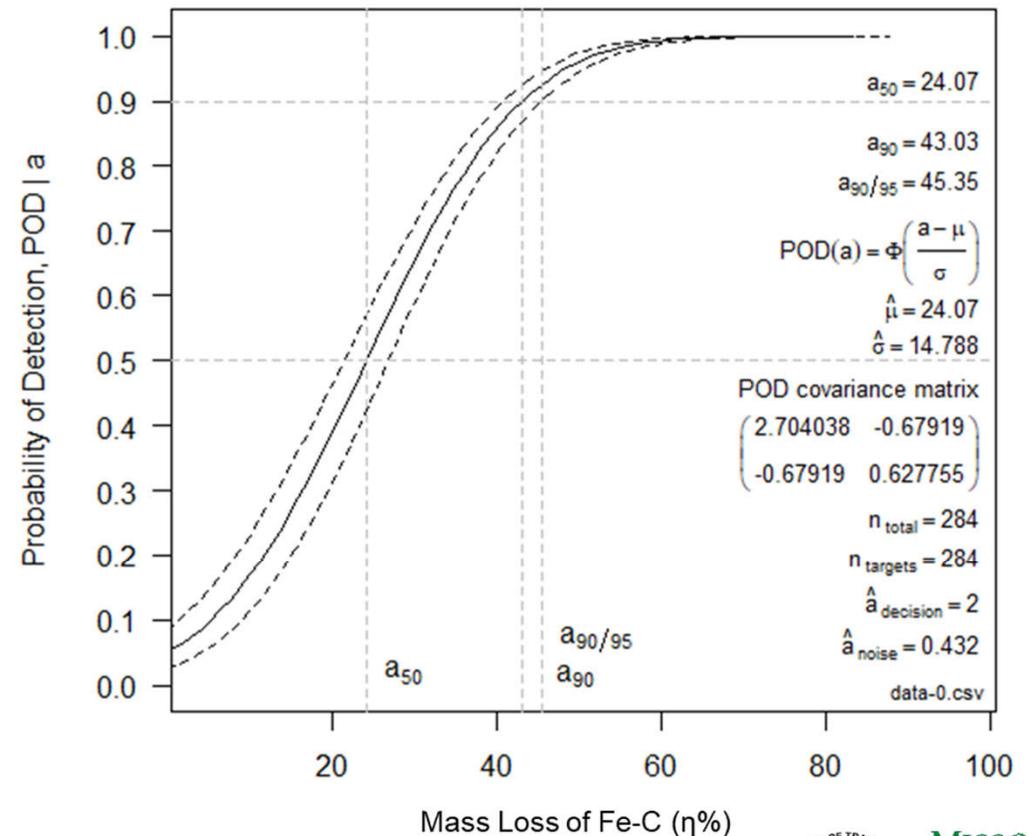
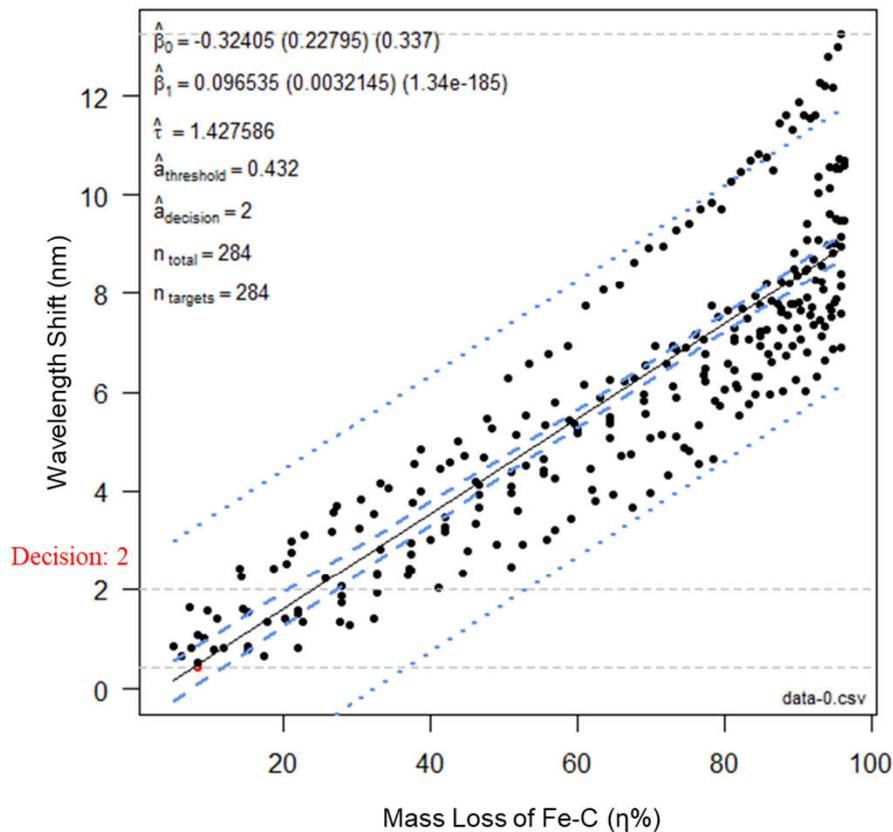
- Traditional Method: Diagnostic Plots



POD Analysis

- Traditional Method

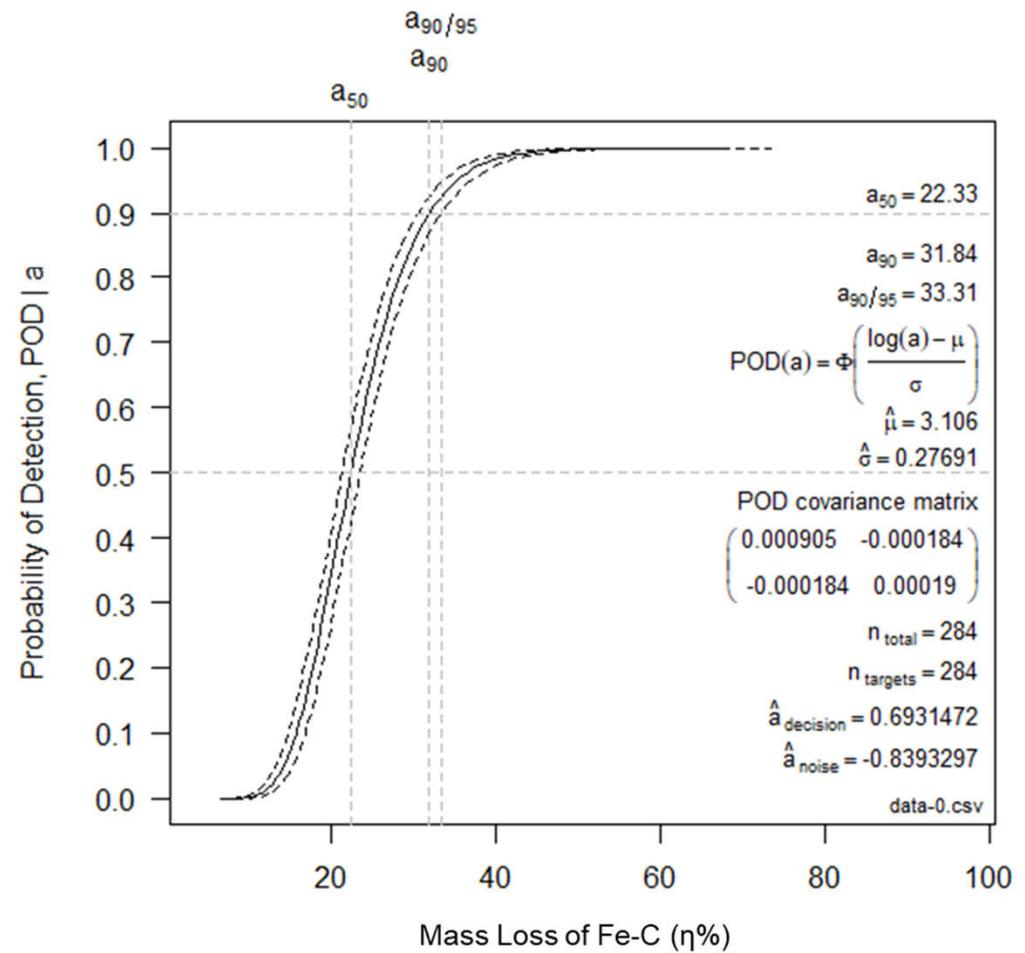
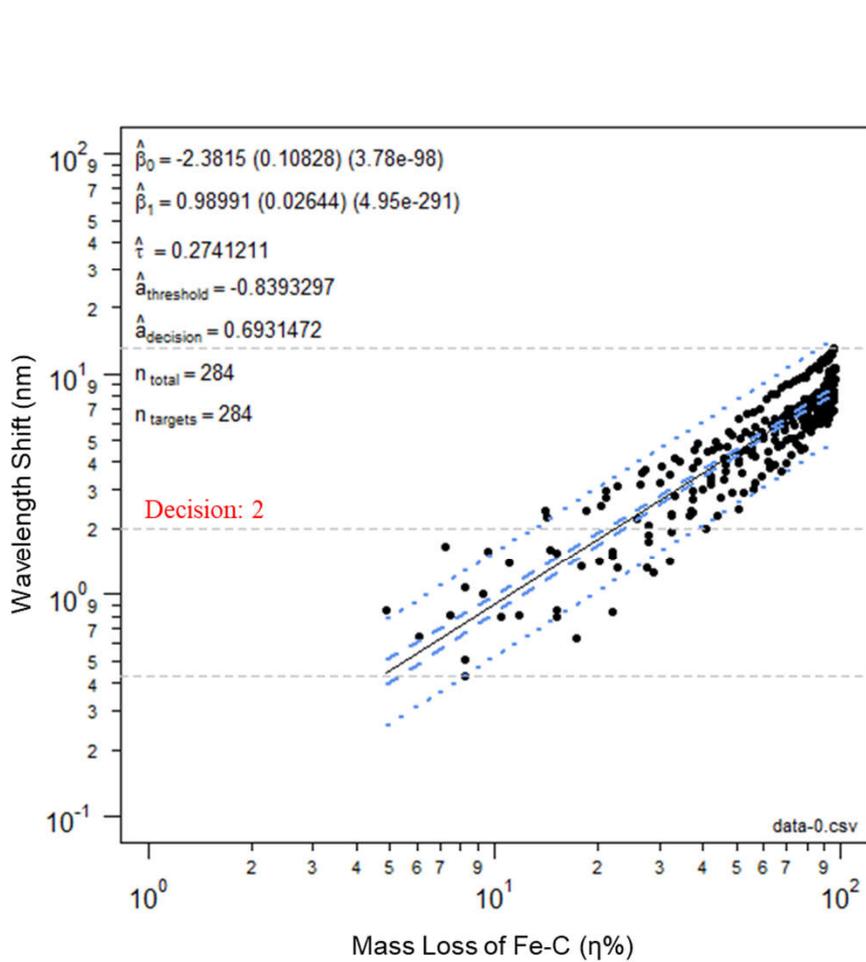
- Linear-x vs Linear-y – Normal Distribution
- a_{90} & $a_{90/95}$ Calculated Using the Software that was Developed by Meeker, Roach, and Kessler (2019)



POD Analysis

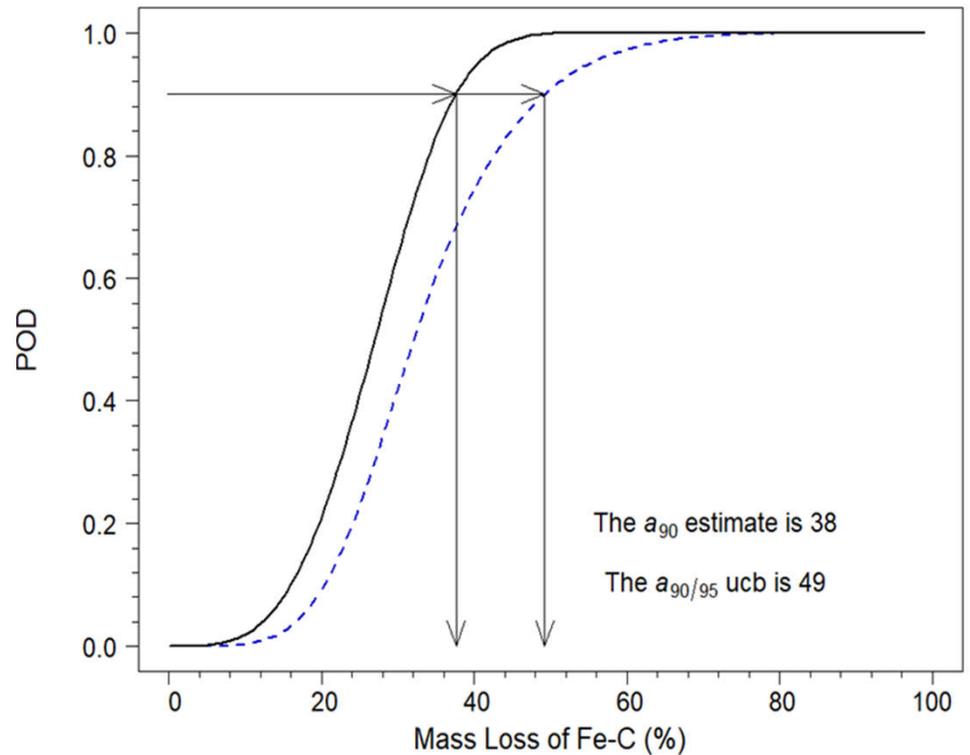
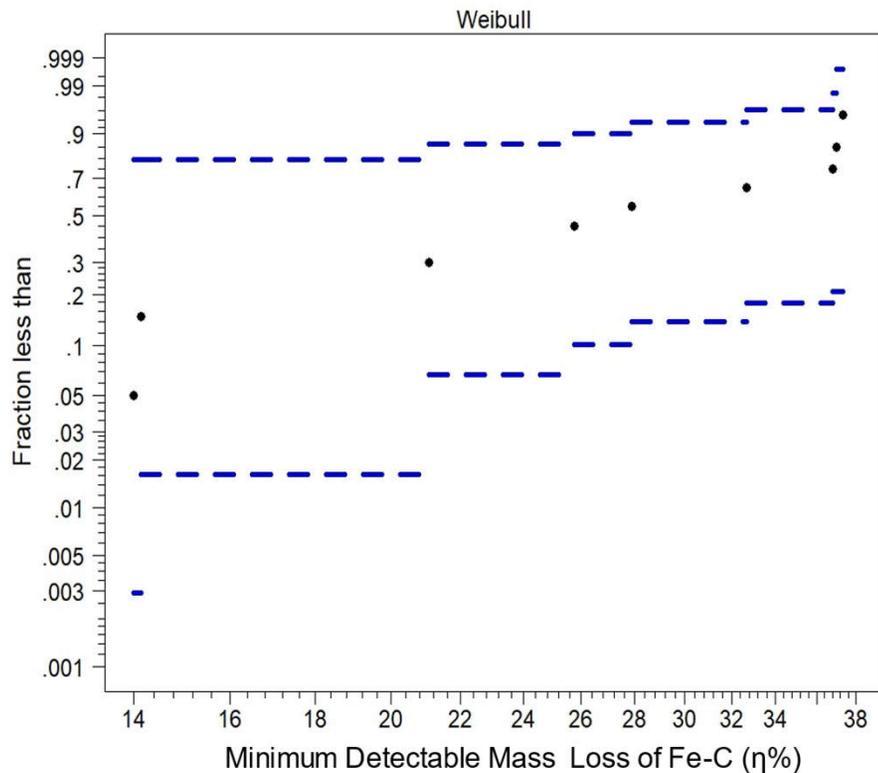
- Traditional Method

- Log-x vs Log-y – Lognormal Distribution



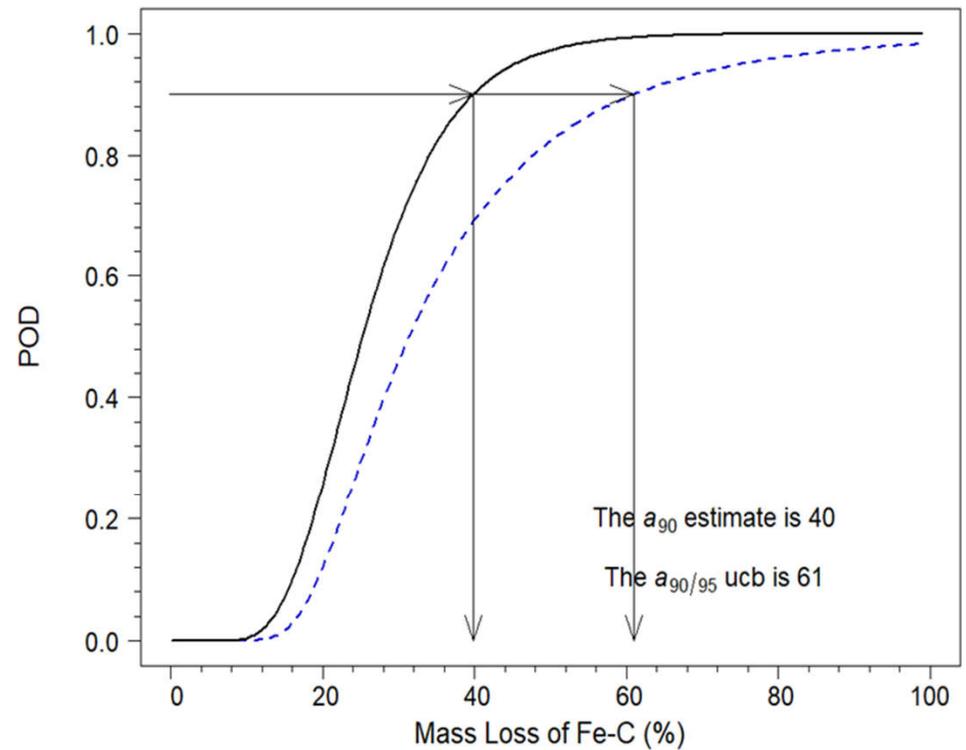
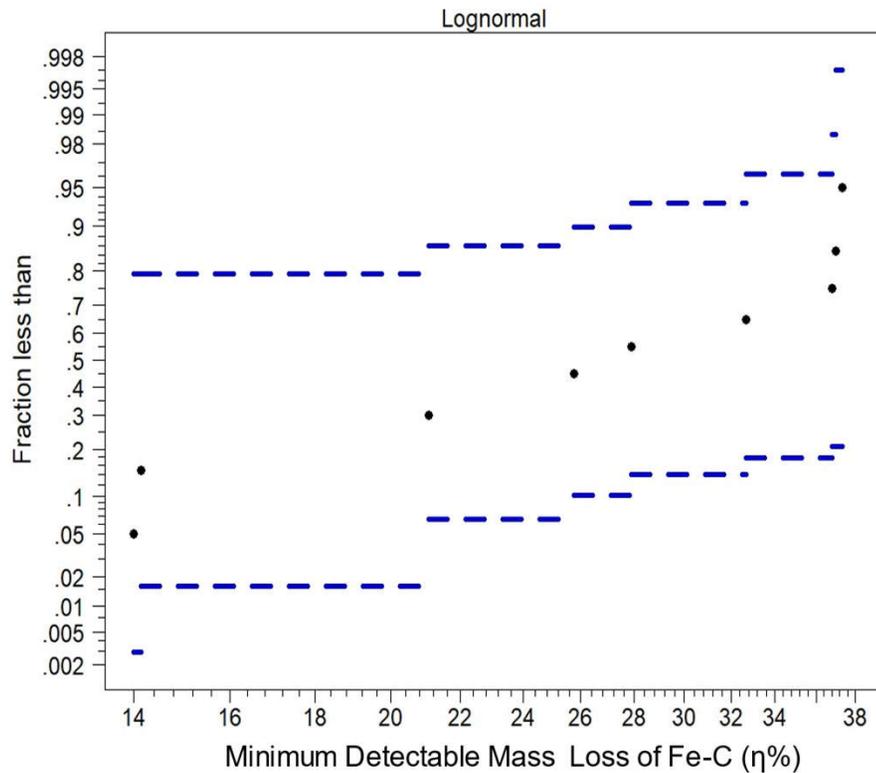
POD Analysis

- SODAD Method
 - Weibull Distribution



POD Analysis

- SODAD Method
 - Lognormal Distribution

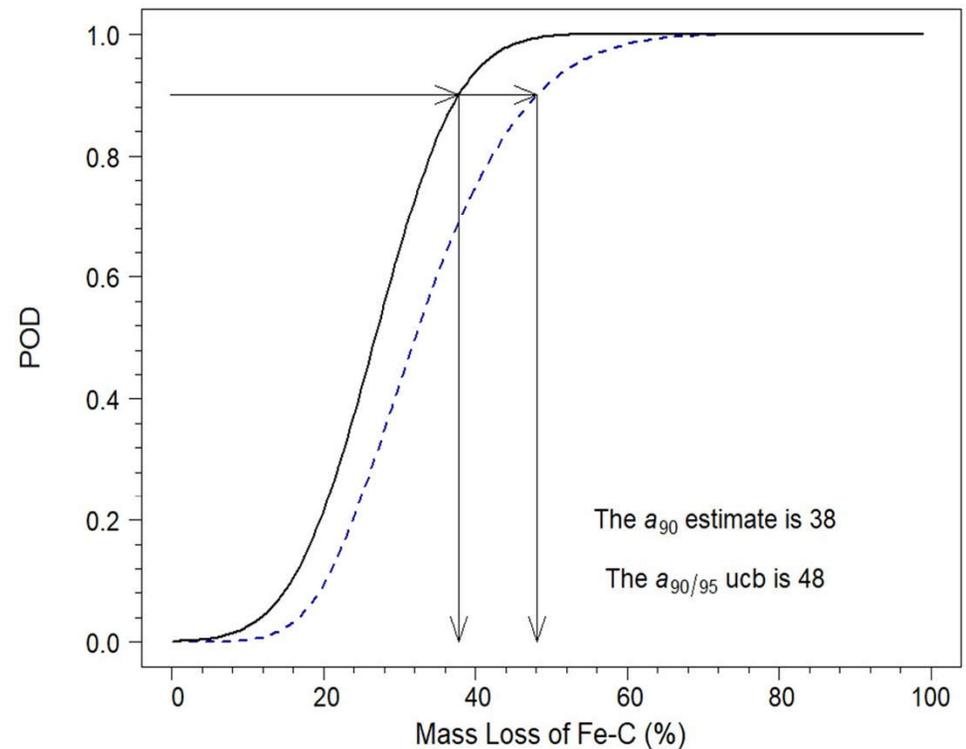
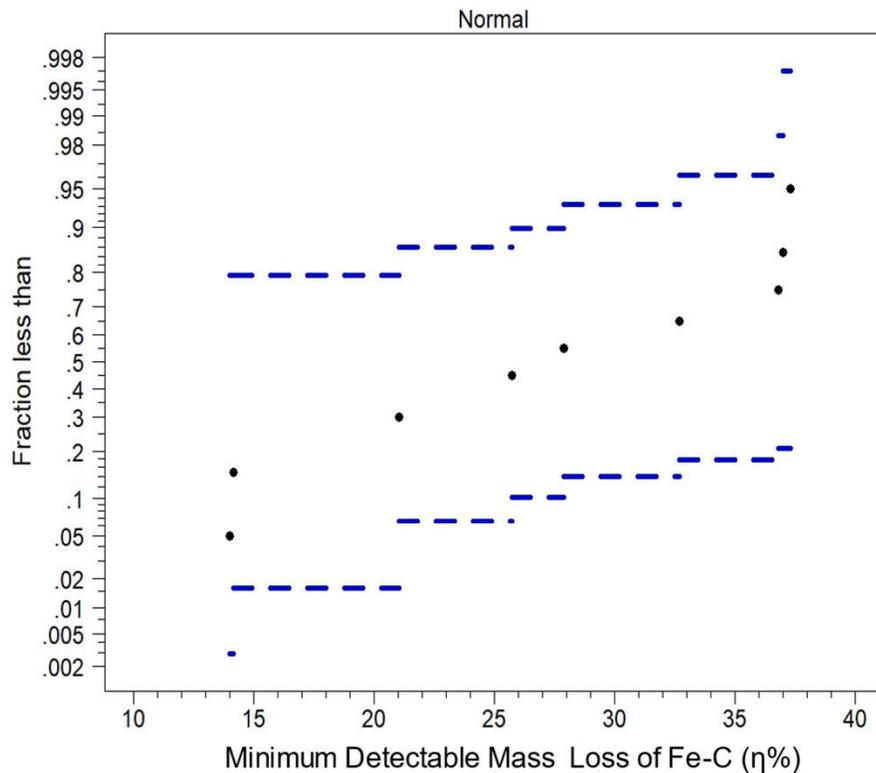


POD Analysis

- **SODAD Method**

- **Normal Distribution**

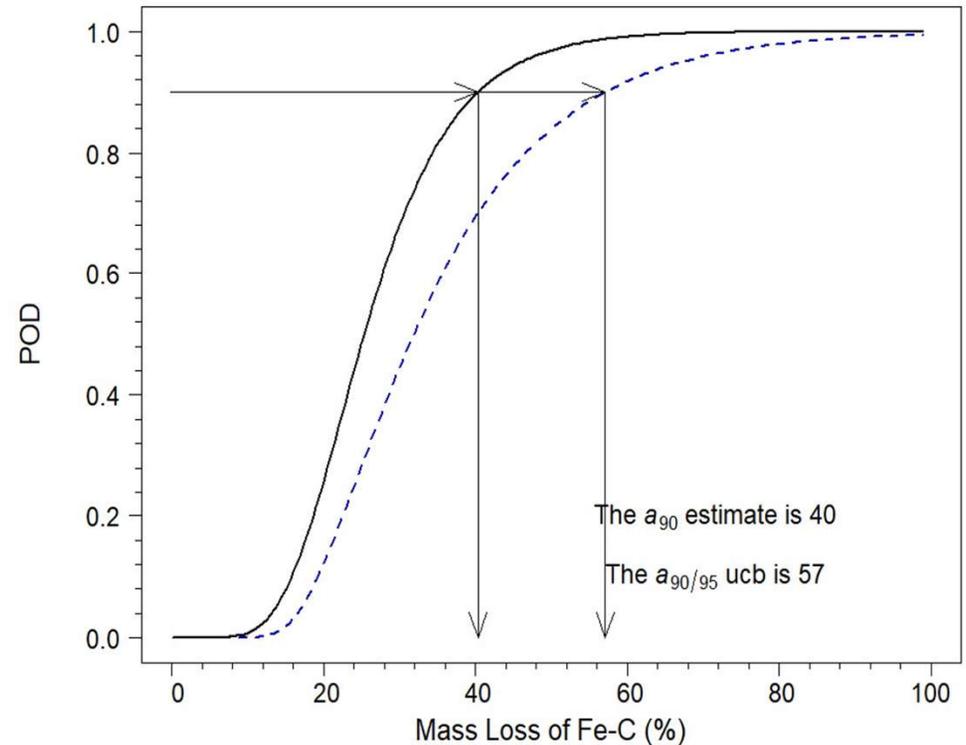
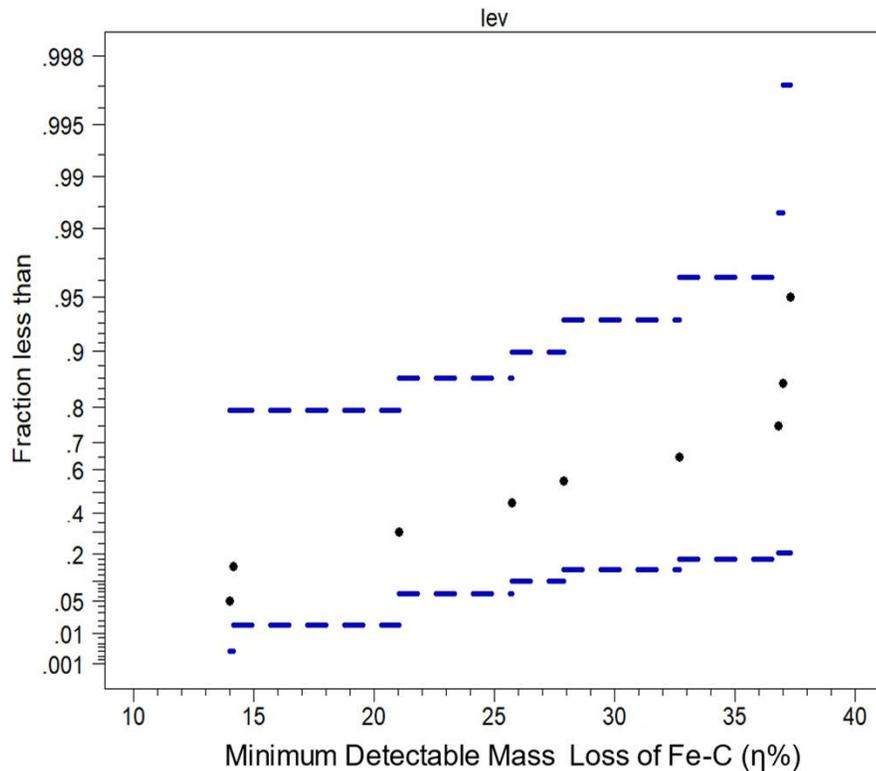
- **Selected for Later POD Comparison**



POD Analysis

- **SODAD Method**

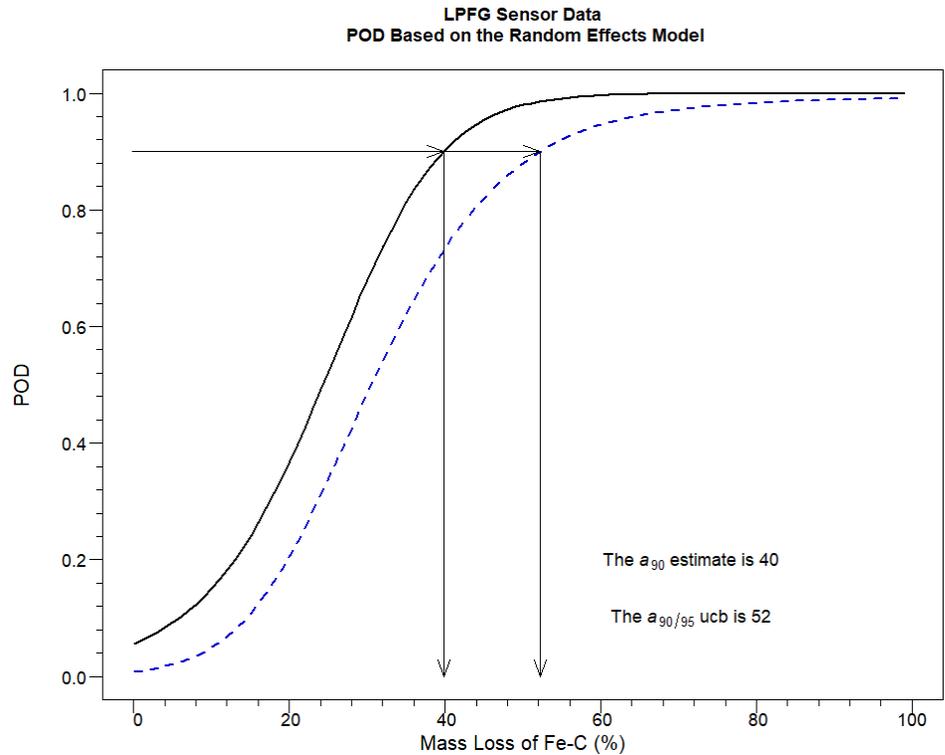
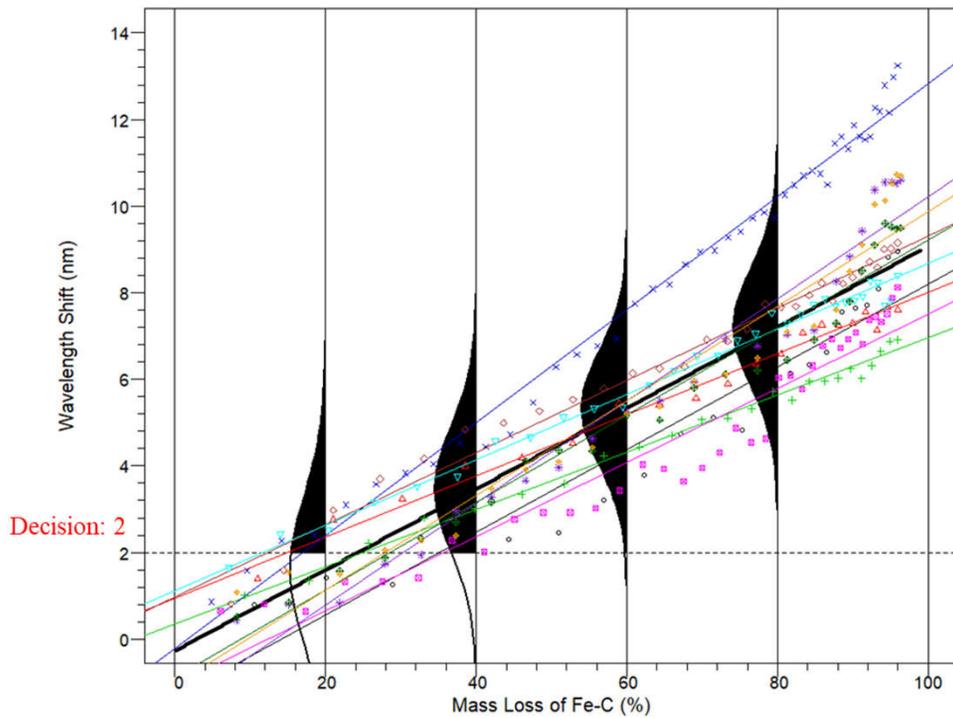
- **The Largest Extreme Value (lev) Distribution**



POD Analysis

- RPM

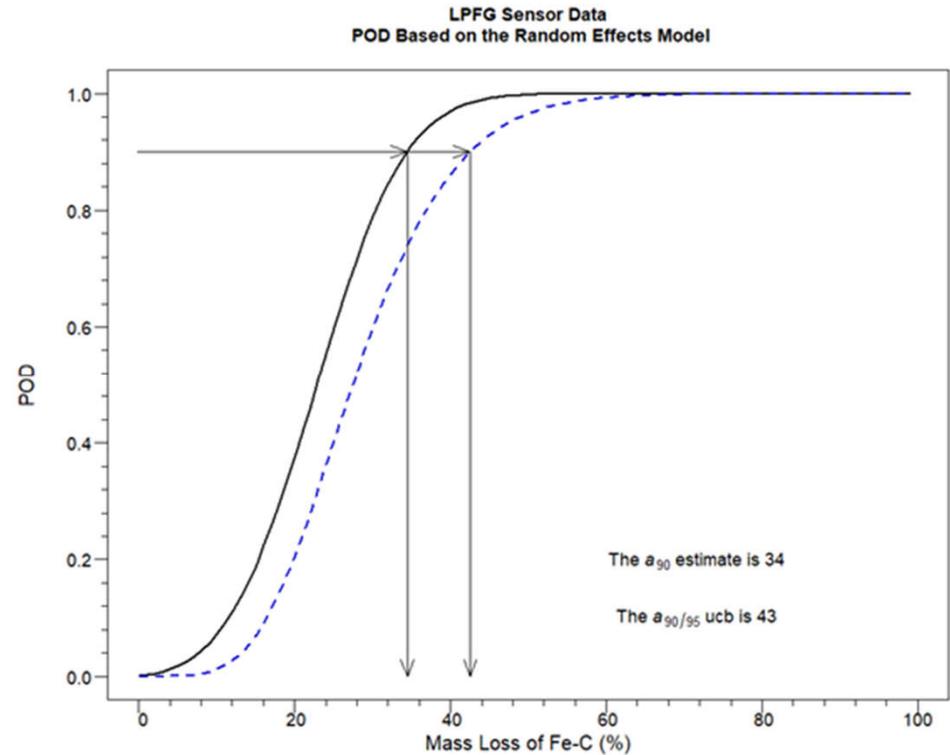
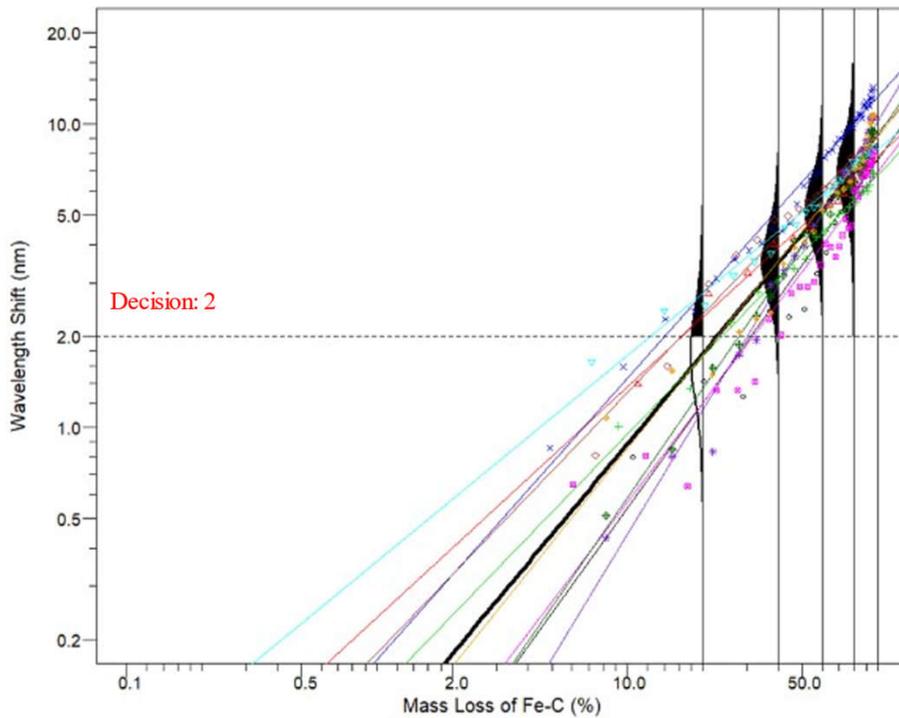
- Linear-x vs Linear-y



POD Analysis

- RPM

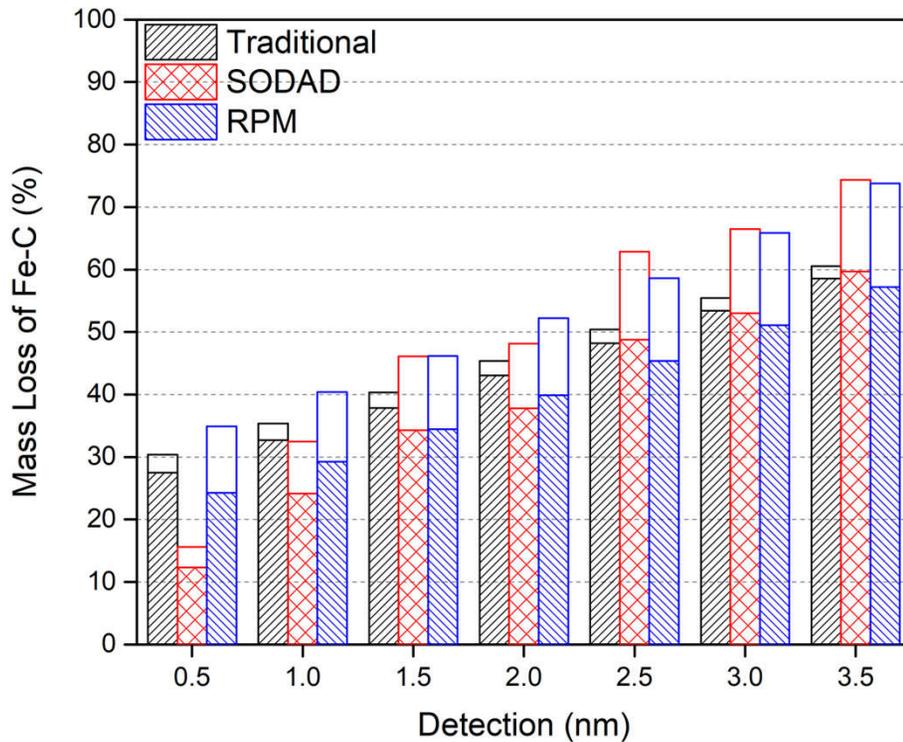
- Log-x vs Log-y



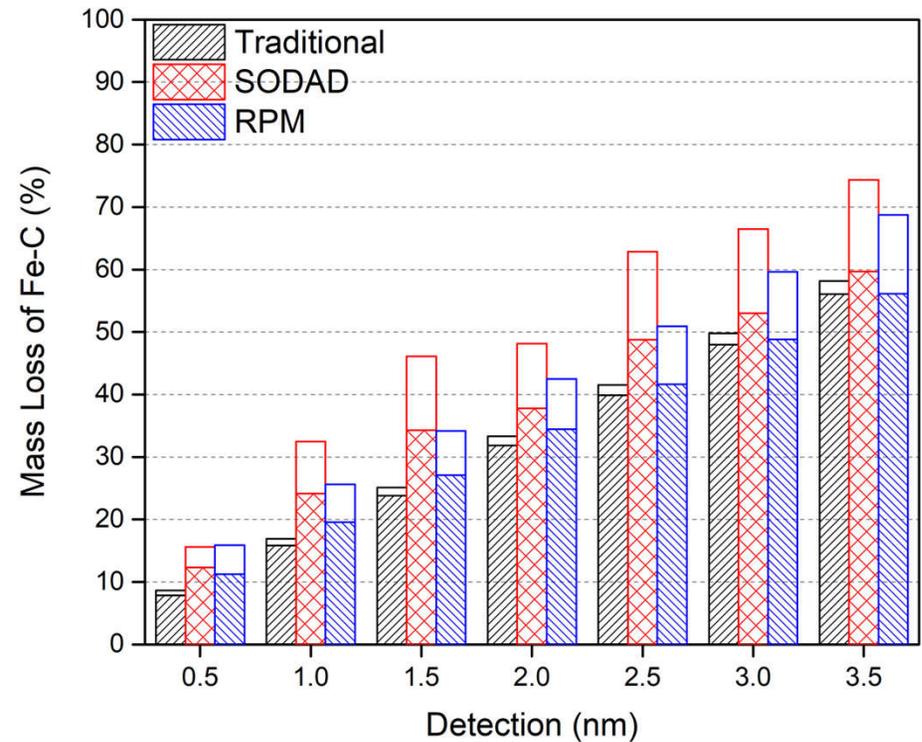
POD Analysis

- Comparison of Three Methods under Different Detection Thresholds

linear-x vs linear-y

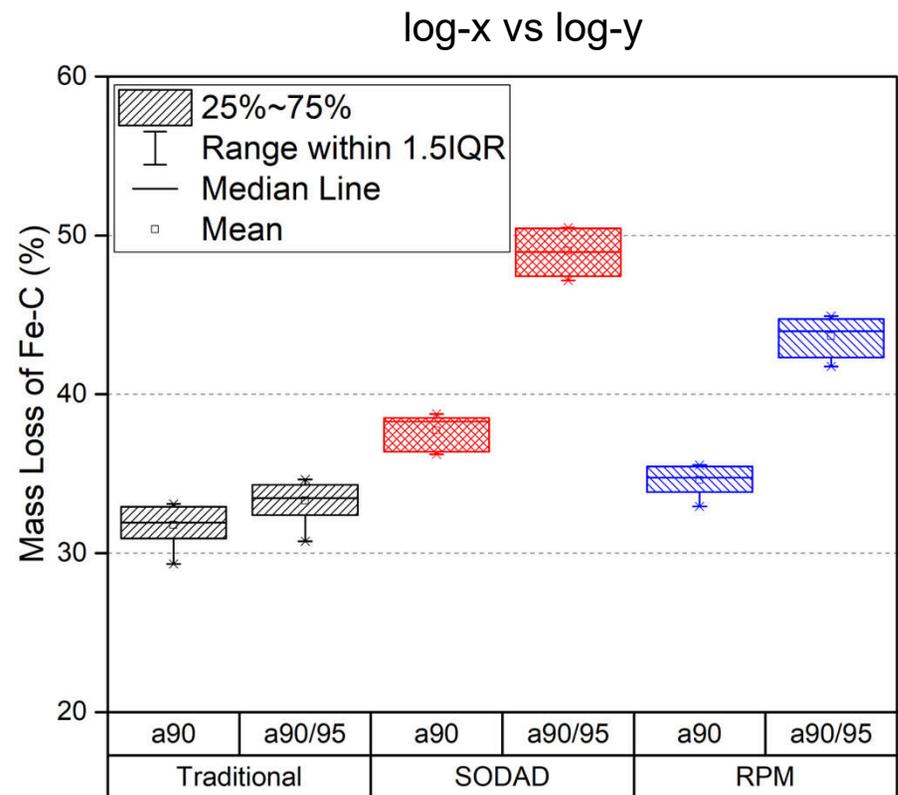
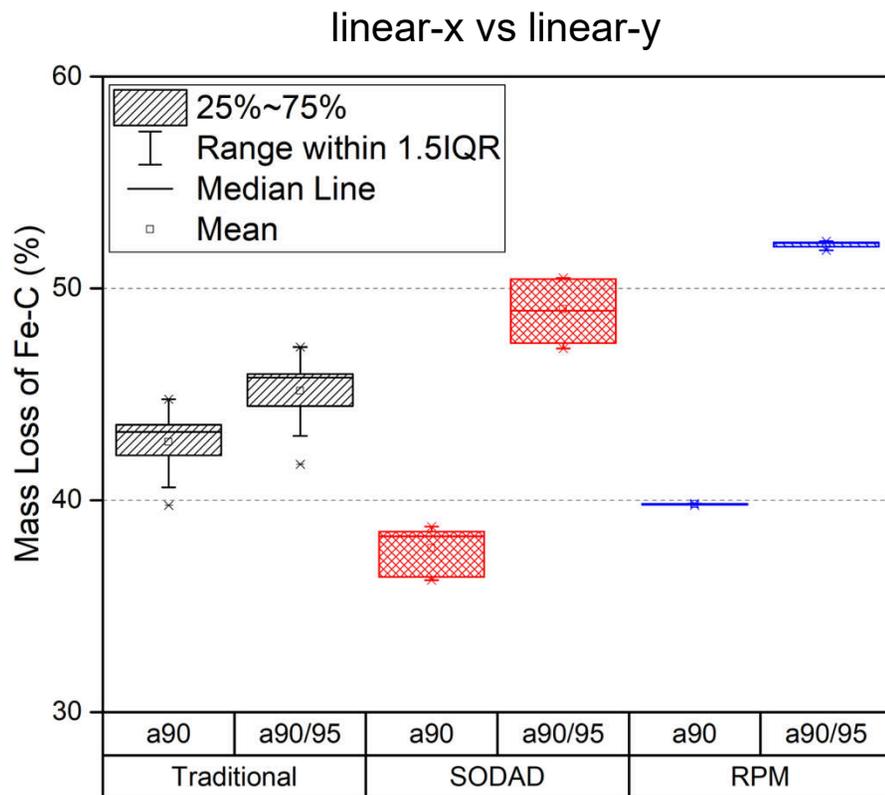


log-x vs log-y



POD Analysis

- Robustness of Three Methods Using Leave-one-out (LOO) 10-Fold Cross Validation



Detection threshold: 2 nm

Concluding Remarks

Conclusions

- A polynomial fit for the corrosion characteristic curve is acceptable since the coefficient of determination is 0.9996.
- The ranges of wavelength shift for various Fe-C coated LPFG sensors are different, but 70% of the sensors lie in a range of 6~10 nm.
- The concept of POD is successfully applied to the dataset obtained from Fe-C coated LPFG corrosion sensors.
- For all three methods, the a_{90} and $a_{90/95}$ increase as the detection threshold increases. However, the traditional and the RPM method shows a linear relationship, but the SODAD method does not.
- Given the detection threshold of 2 nm, the RPM method is more robust than the SODAD method since it takes full consideration of the difference between datasets from various sensors.

Acknowledgement

- Financial support for the INSPIRE UTC project is provided by the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (USDOT/OST-R) under Grant No. 69A3551747126 through INSPIRE University Transportation Center (<http://inspire-utc.mst.edu>) at Missouri University of Science and Technology.
- The content of this presentation is part of the Ying Zhuo's Ph.D. dissertation.
- The views, opinions, findings and conclusions reflected in this publication are solely those of the authors and do not represent the official policy or position of the USDOT or any State or other entity.

