University at Buffalo *The State University of New York*

Self-Sensing Systems and Smart Structures to Secure Safety

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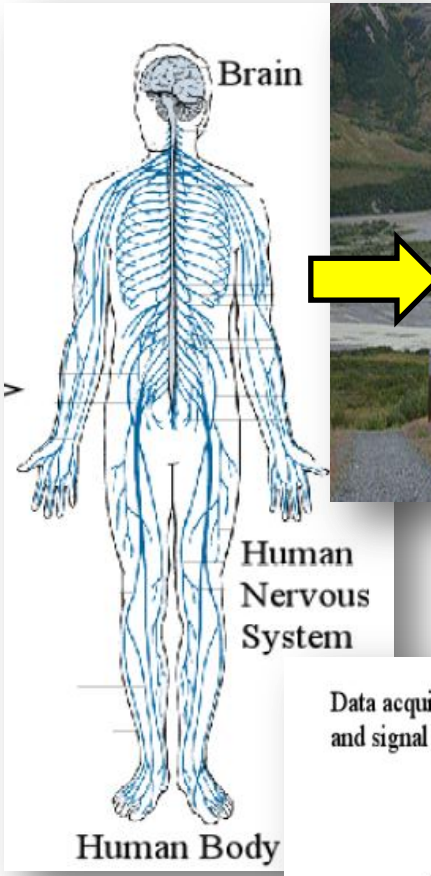
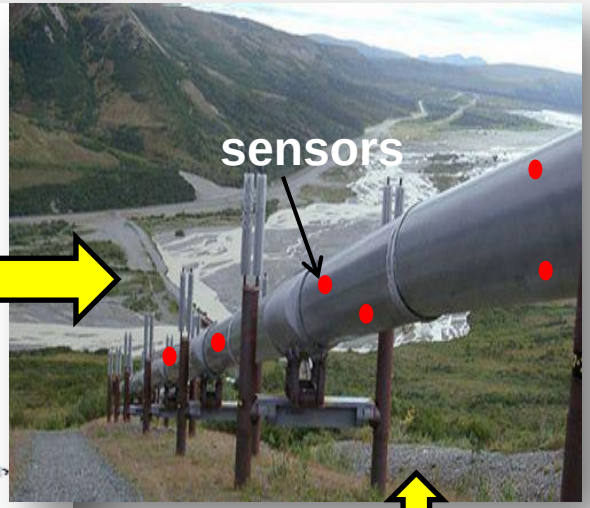
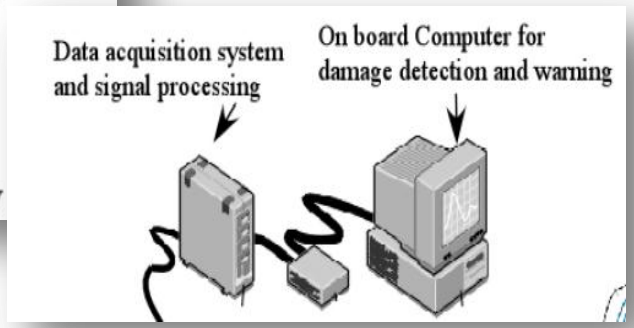
Overview:

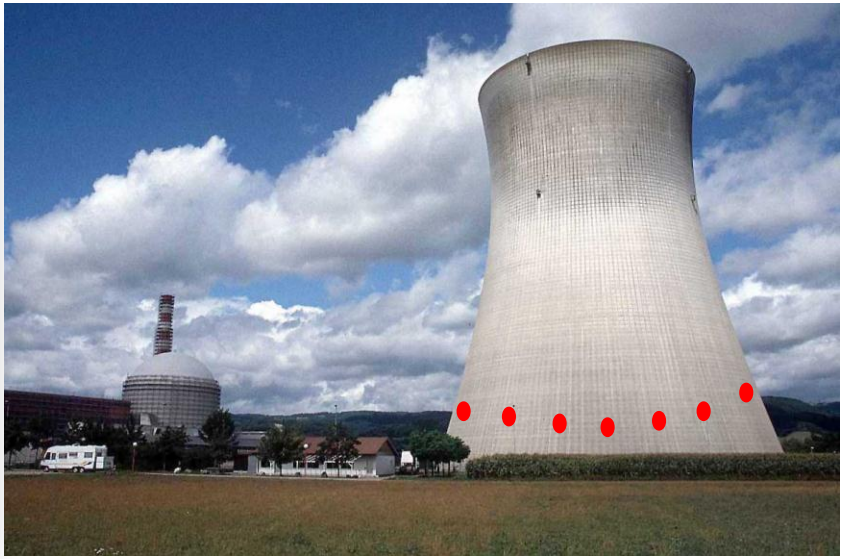
1) Motivation
2) Reference-free corrosion diagnosis in prestressed steel strands using GUW
3) Acoustic emission monitoring of concrete shear walls
4) Advanced visual inspection through fractal analysis of crack patterns
5) Complementary projects
6) Conclusions

Health Monitoring, a critical component of safe structures

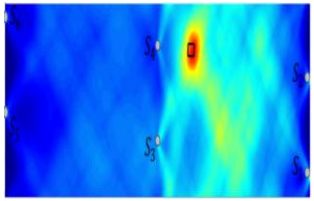








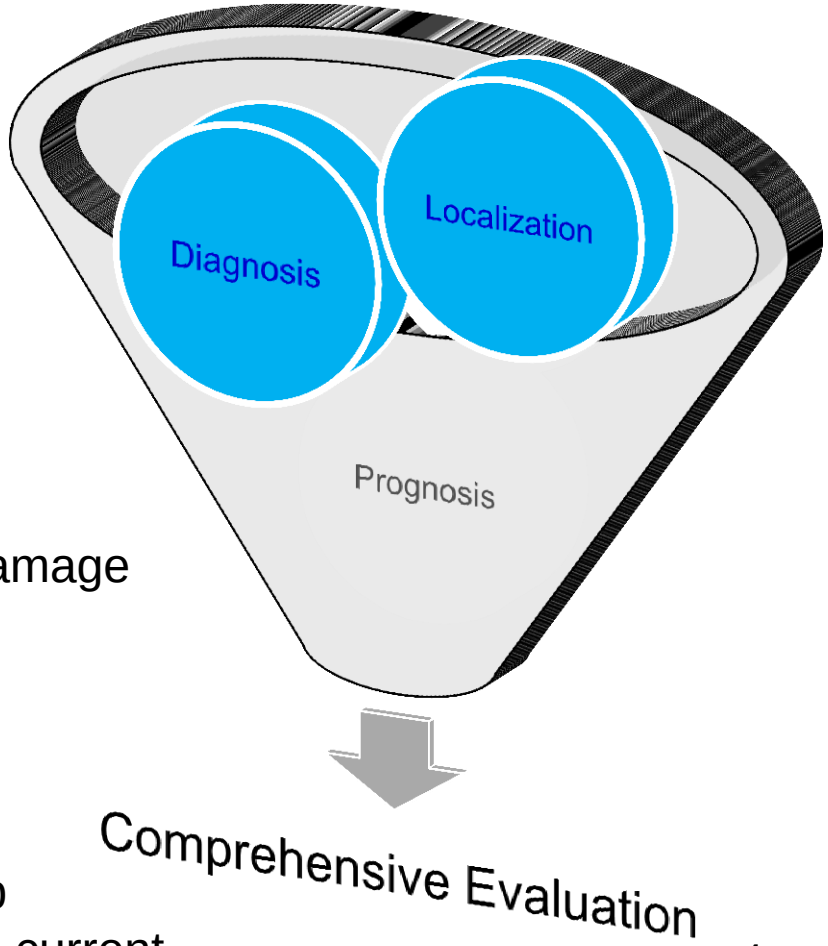
Steps for a comprehensive evaluation

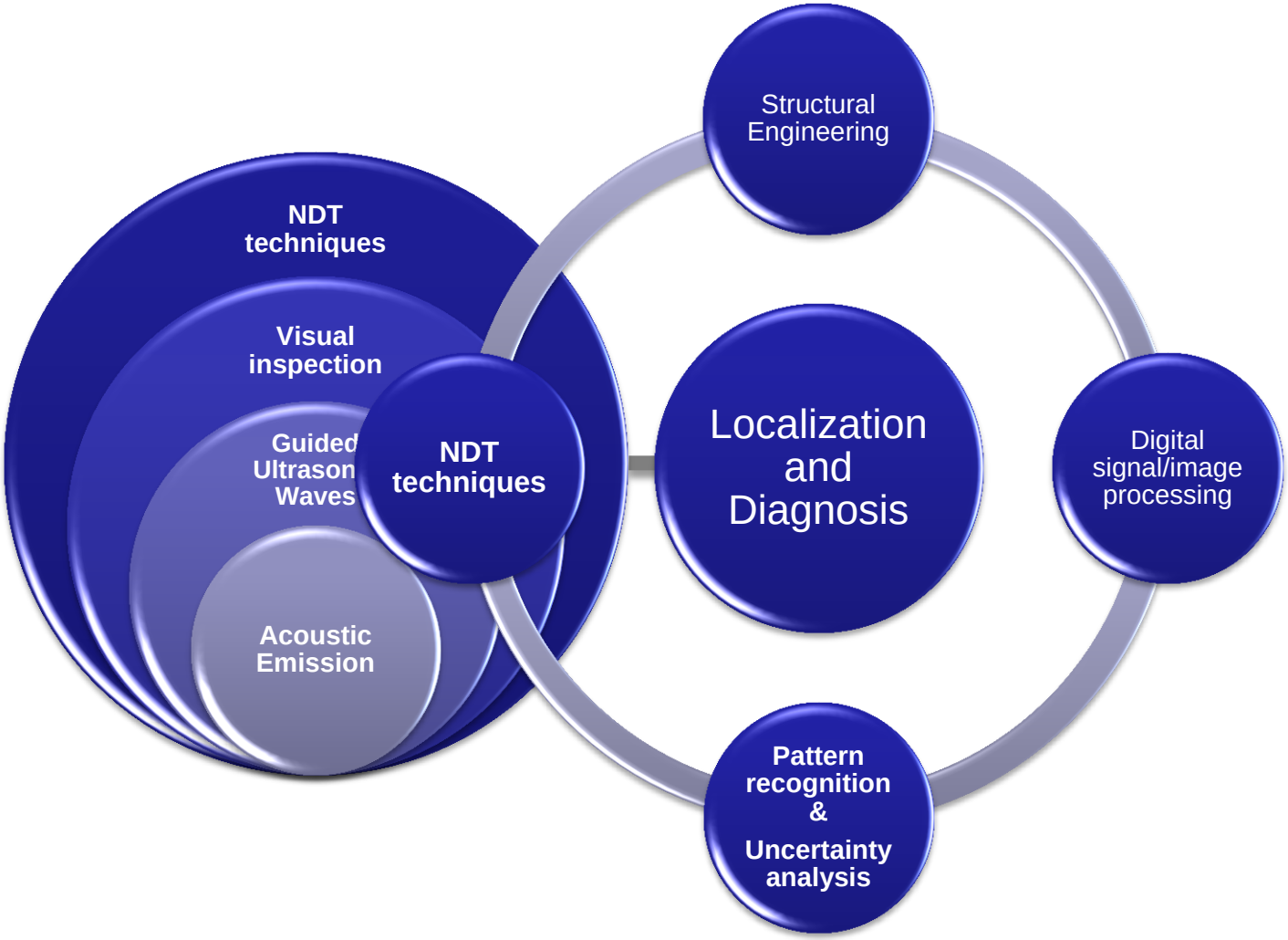


Localization
Highlighting the location of damage

Diagnosis
Identifying the nature, cause, or extent of damage

Prognosis
A prediction about how damage will develop and what will be the remaining life given the current damage state




NDT techniques
Visual inspection
Guided Ultrason Waves
Acoustic Emission
NDT techniques
Structural Engineering
Localization and Diagnosis
Digital signal/image processing
Pattern recognition & Uncertainty analysis

Overview:

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2) Reference-free corrosion diagnosis in prestressed steel strands using GUW
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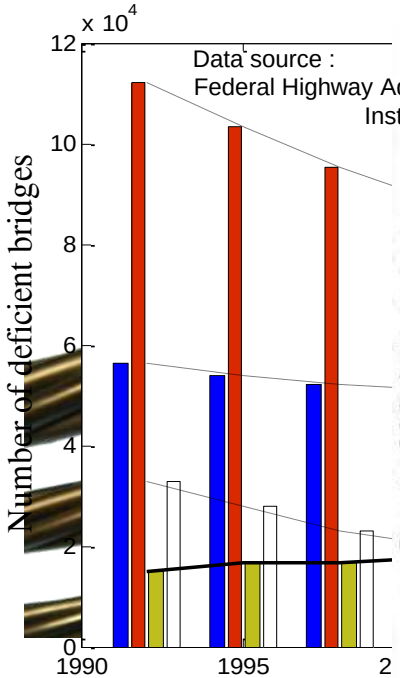
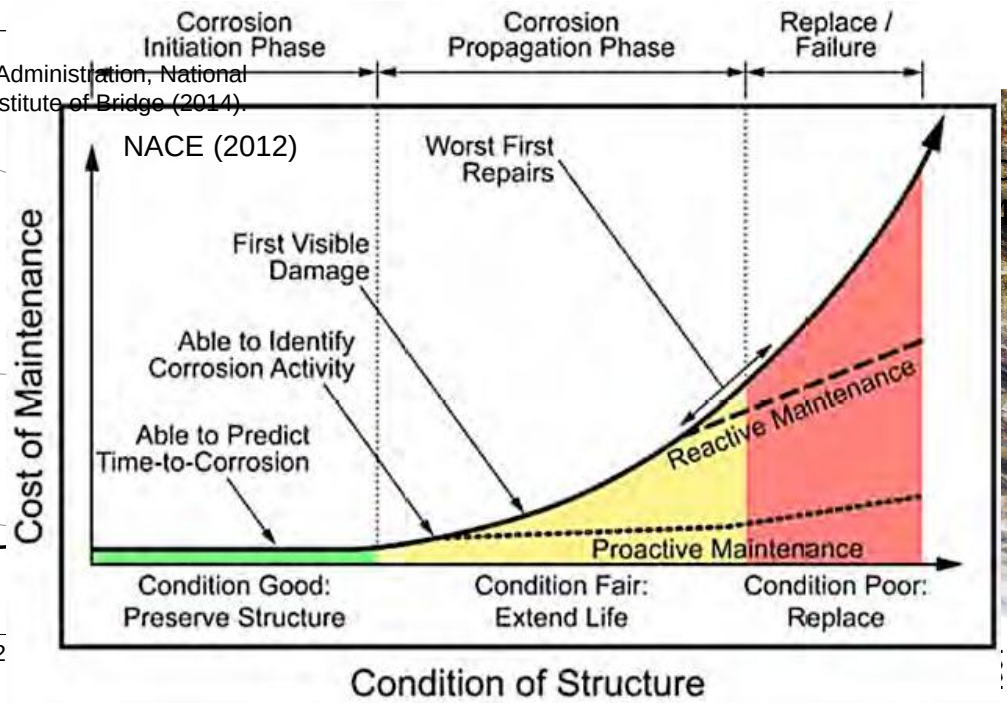
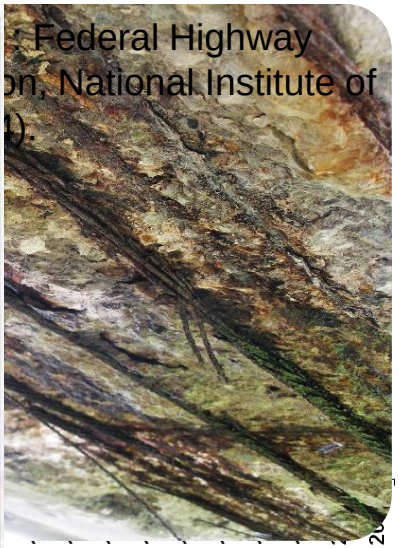
5) Complementary projects
6) Conclusions

- More than 25% of bridges built in USA are pre-stressed (e.g., OR 50%., FL 48%, WA 42%)
- PS strands are the main load-carrying components
- PS strands are prone to corrosion defects which may lead to loss of prestress (tendon failures in Hampshire 1967, Berlin 1980 , Wales 1985, Florida 1999 and 2000, North Carolina 2001)
- Considerable savings in bridge maintenance if repairs would be implemented in a timely manner.



Data source : Federal Highway Administration, National Institute of Bridge (2014).





: Federal Highway
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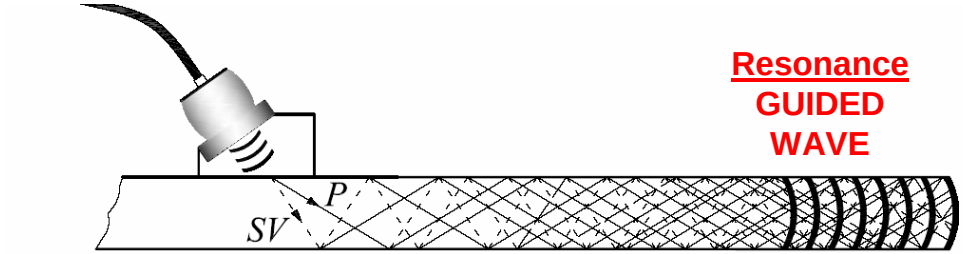
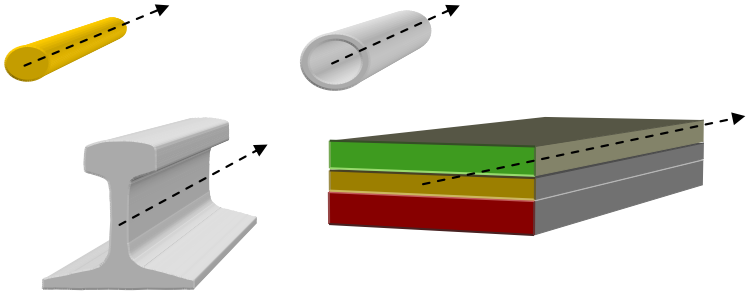
1956 - 1961 - 1966 - 1971 - 1976 - 1981 - 1986 - 1991 - 1996 - 2001 - 2

Guided Ultrasonic Waves (GUWs)



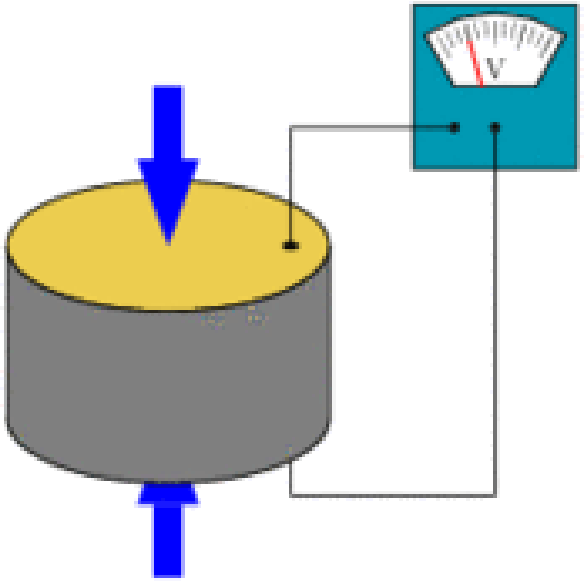
GUIDED WAVES: are stress waves generated from the constructive interference of Longitudinal and Shear bulk waves

WAVEGUIDE: Rods, Plates, Tubes...

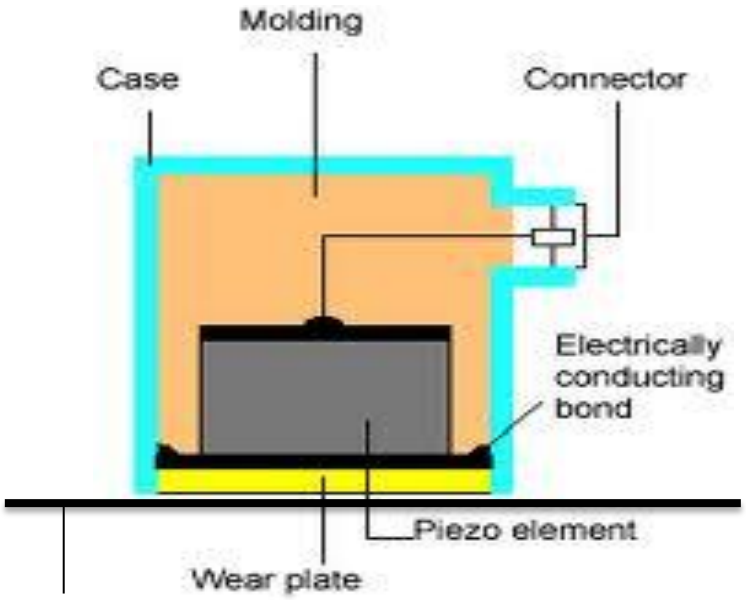


ADVANTAGES:

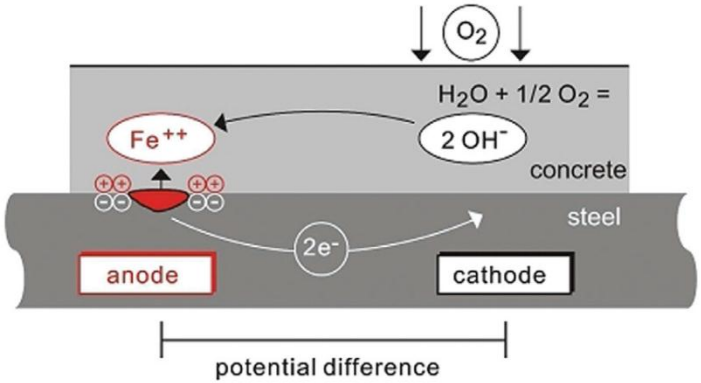
- The use of transducers that are permanently attached to the structural element to perform real-time SHM and routine inspection with the same sensing system,
- The ability to probe a large area of the structure, locating cracks and notches from only a few monitoring points
- The capability to detect both active cracks and pre-existing cracks by toggling between the modes of “passive” acoustic emission testing and “active” ultrasonic testing.

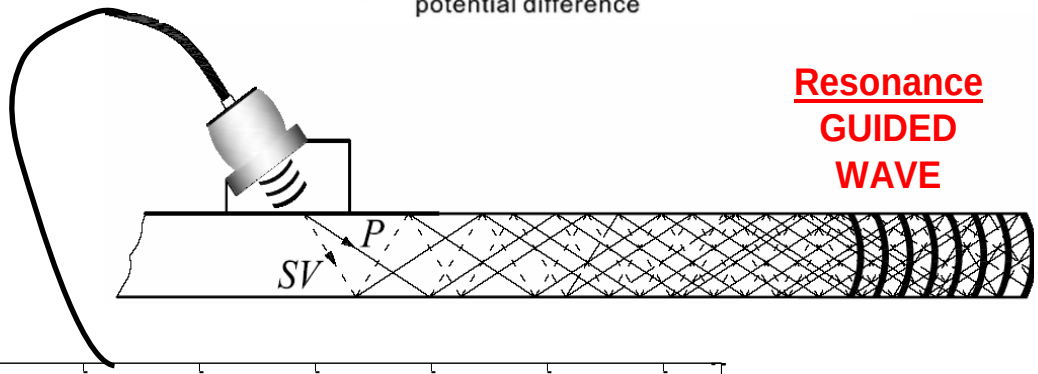


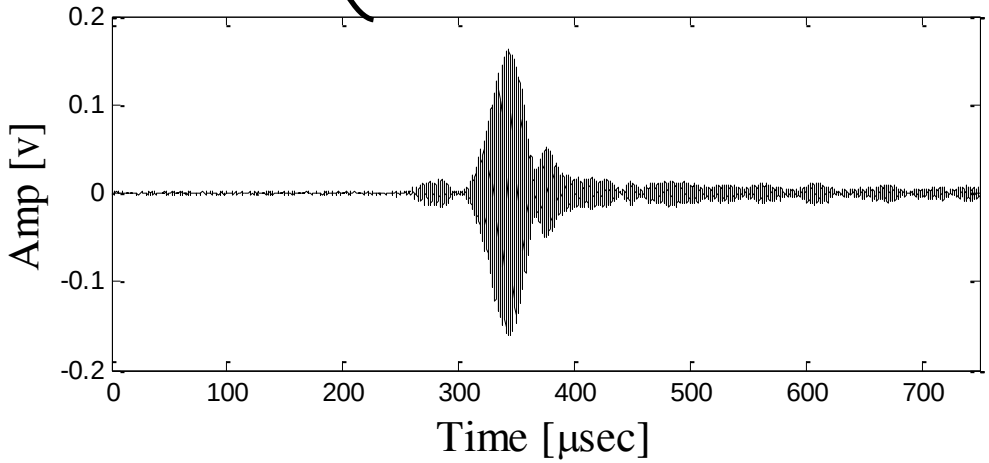
piezoelectric material

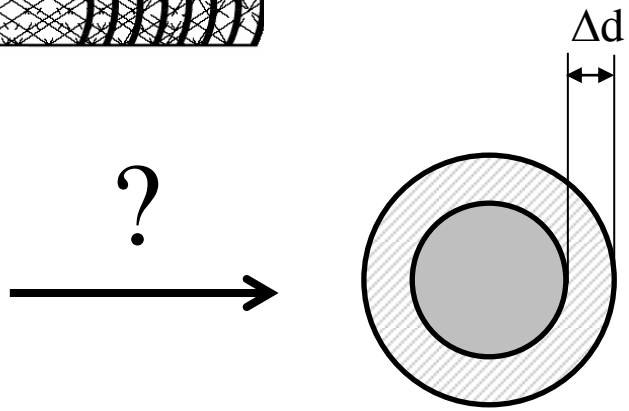


Material surface









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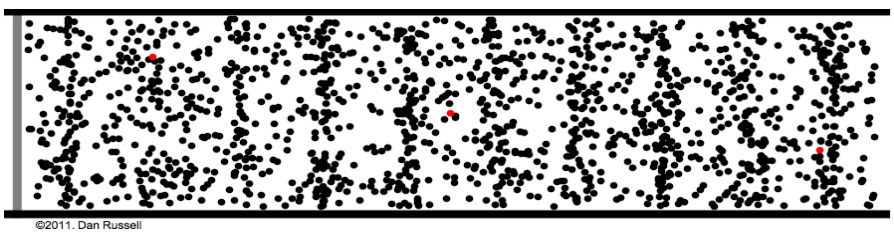
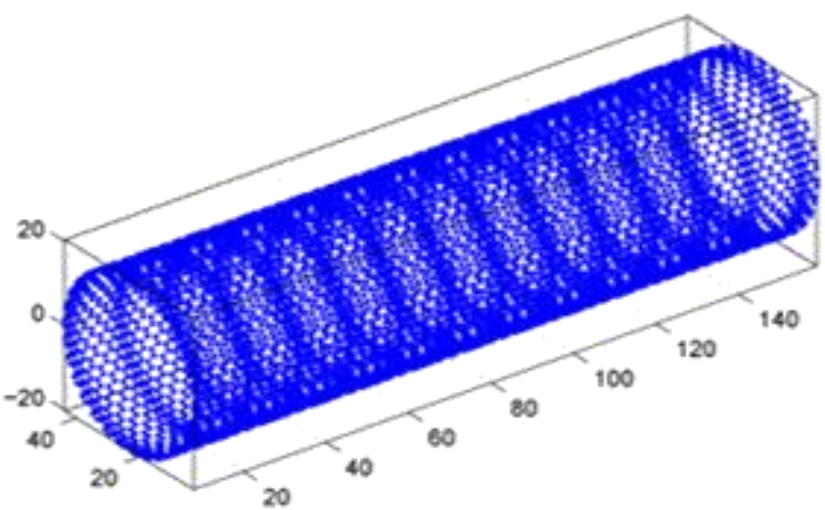
Numerical Modeling

Pochhammer-Chree vibrations in cylindrical waveguides (1876, 1889)

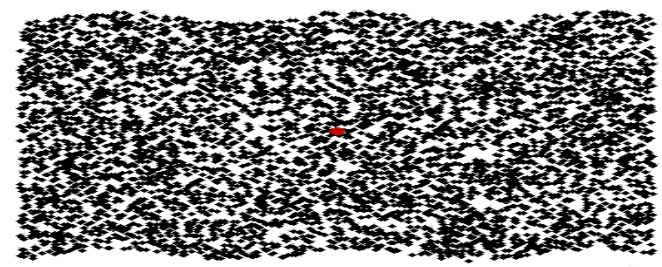
$$\begin{cases} (\lambda+2\mu)\dfrac{\partial\phi}{\partial r}-\dfrac{2\mu}{r}\dfrac{\partial\omega_z}{\partial\theta}+2\mu\dfrac{\partial\omega_\theta}{\partial z}=\rho\dfrac{\partial^2 u_r}{\partial t^2}; \\ (\lambda+2\mu)\dfrac{1}{r}\dfrac{\partial\phi}{\partial\theta}-2\mu\dfrac{\partial\omega_r}{\partial z}+2\mu\dfrac{\partial\omega_z}{\partial r}=\rho\dfrac{\partial^2 u_\theta}{\partial t^2}; \\ (\lambda+2\mu)\dfrac{\partial\phi}{\partial z}-\dfrac{2\mu}{r}\dfrac{\partial(r\omega_\theta)}{\partial r}+2\mu\dfrac{\partial\omega_r}{\partial\theta}=\rho\dfrac{\partial^2 u_z}{\partial t^2} \end{cases} \xrightarrow[\text{modes}]{\text{Displacement}} \begin{cases} \text{Longitudinal} \\ \text{Flexural} \\ \text{Torsional} \end{cases}$$

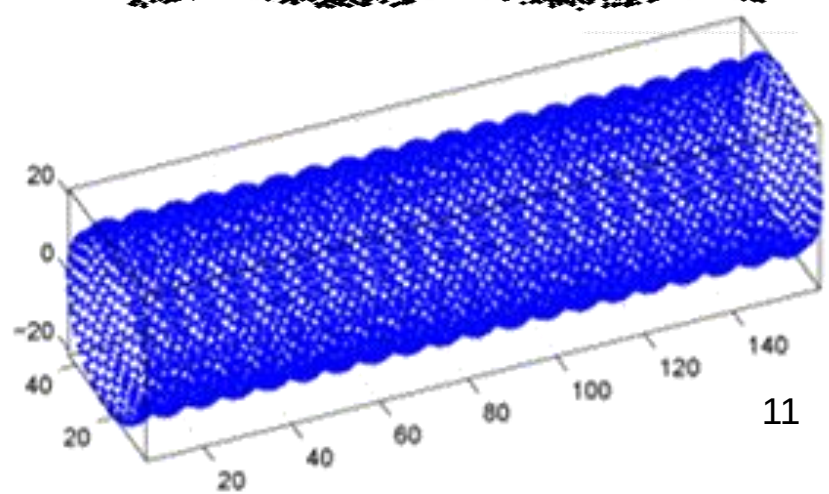
Longitudinal



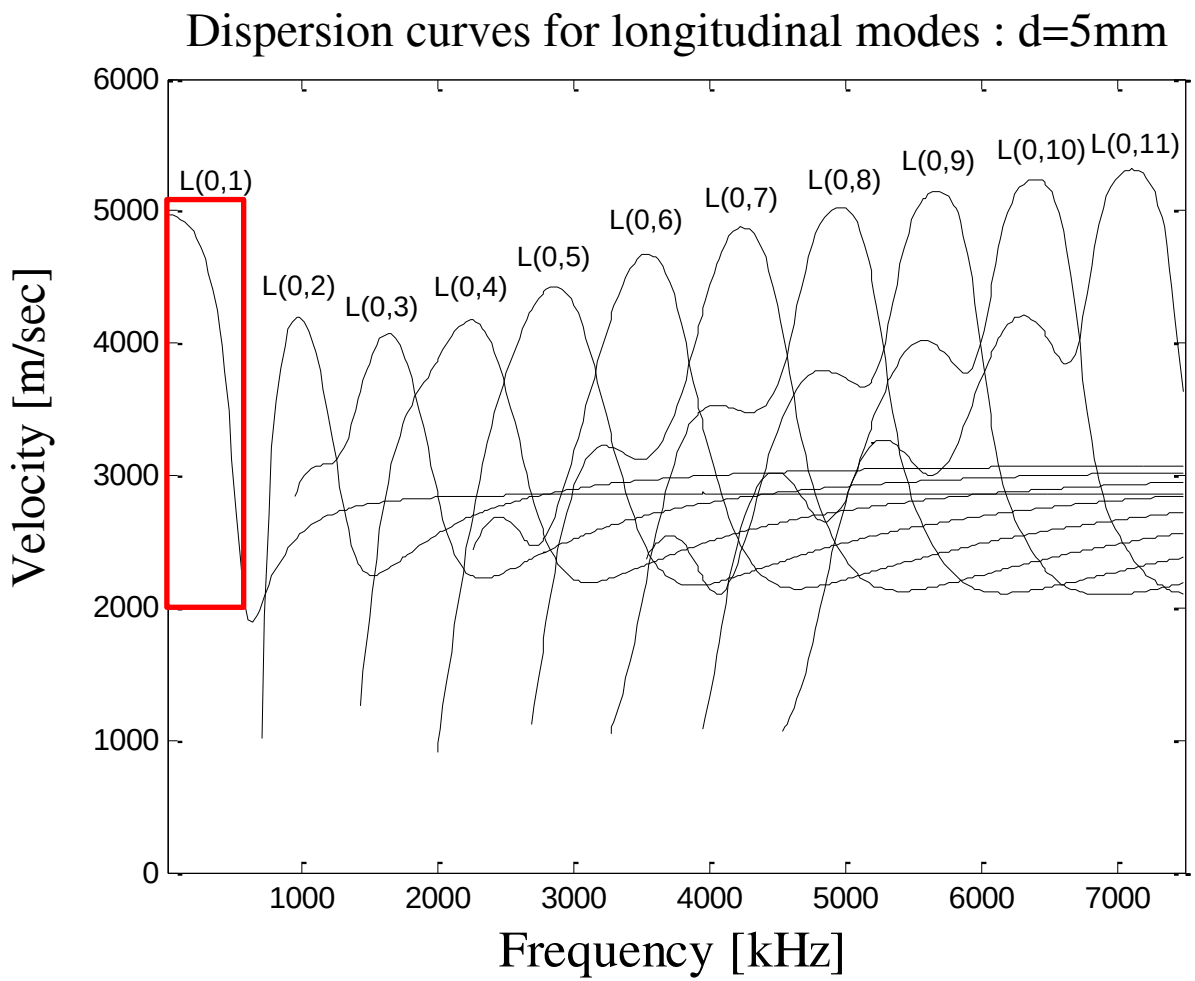


Flexural





Numerical Modeling



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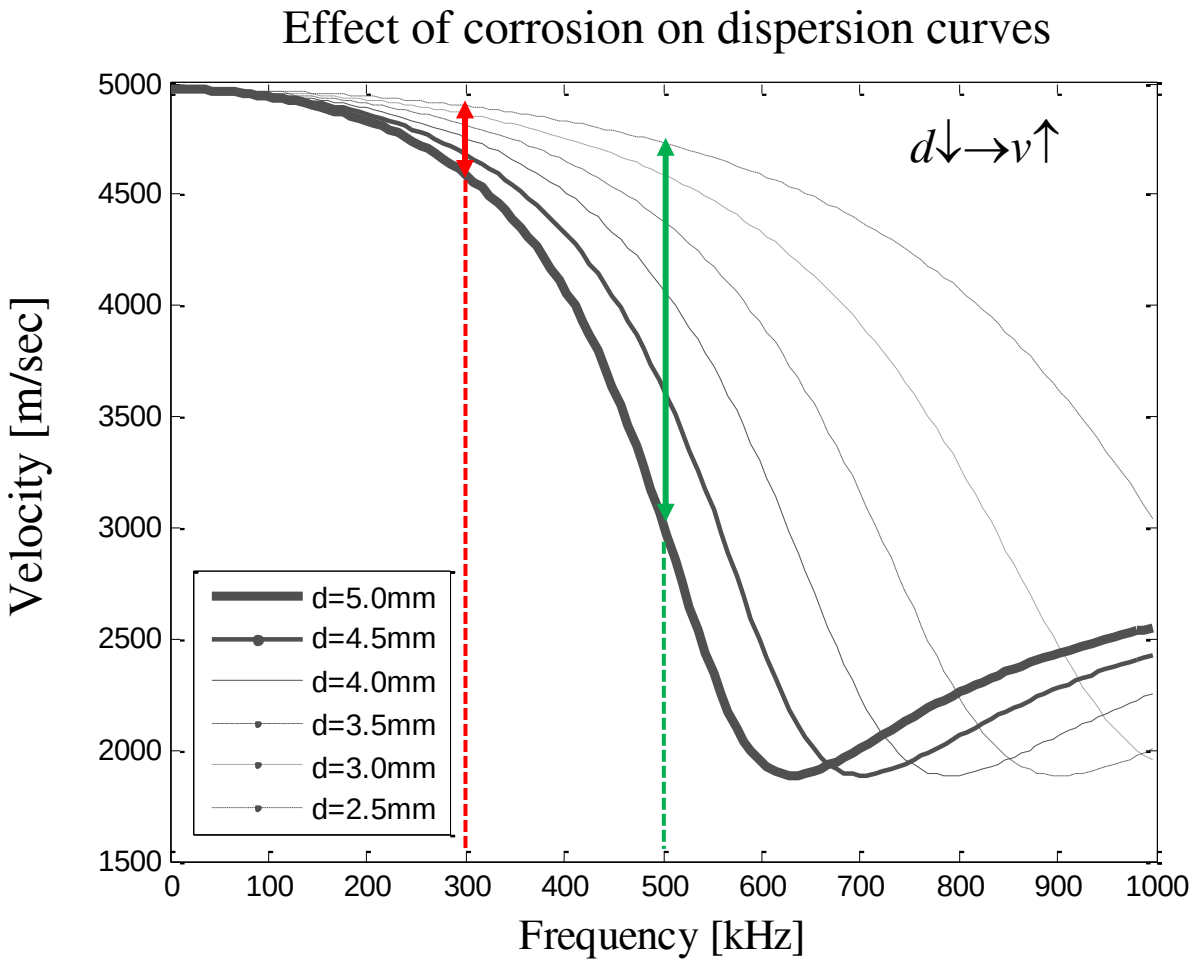
Numerical Modeling



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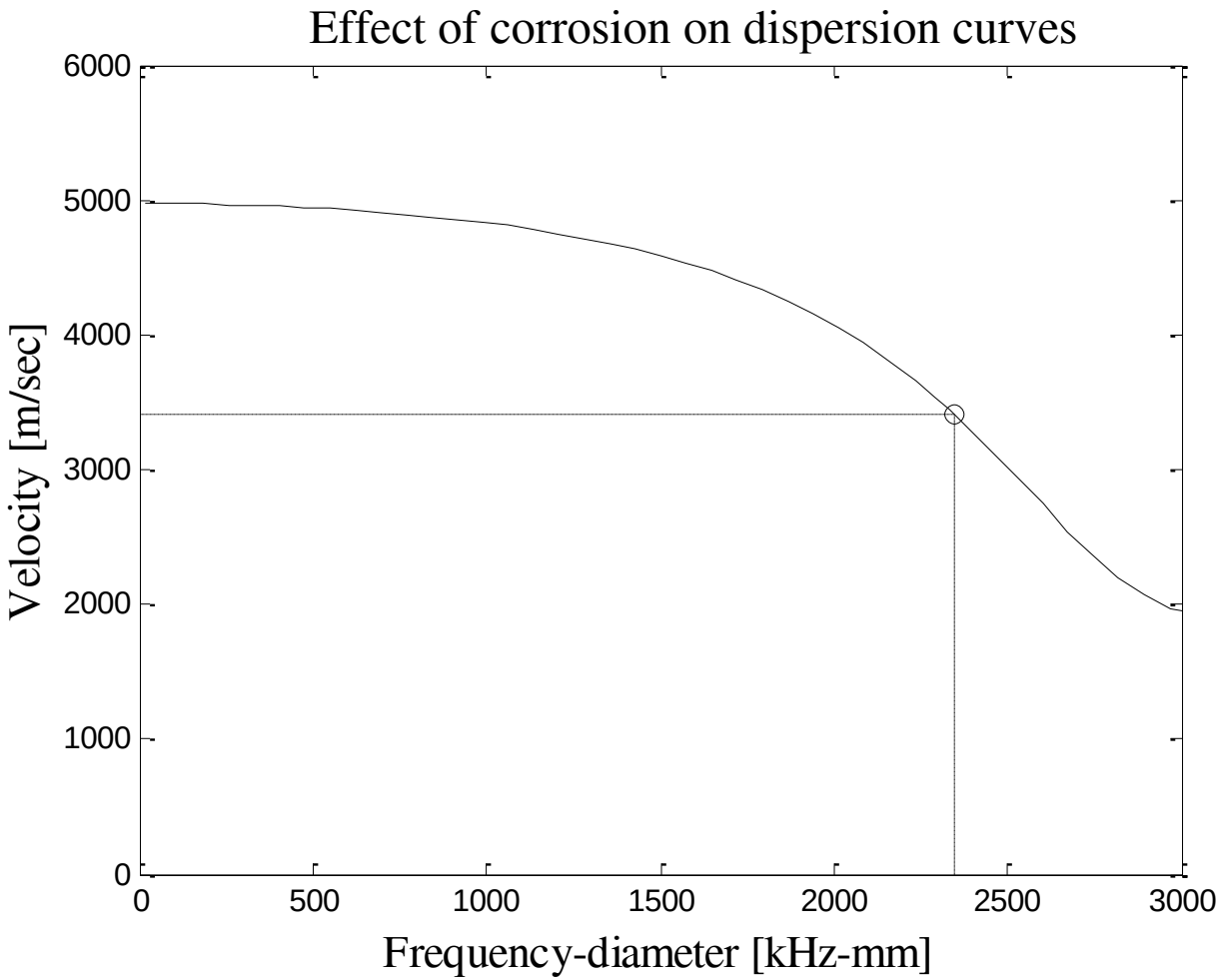

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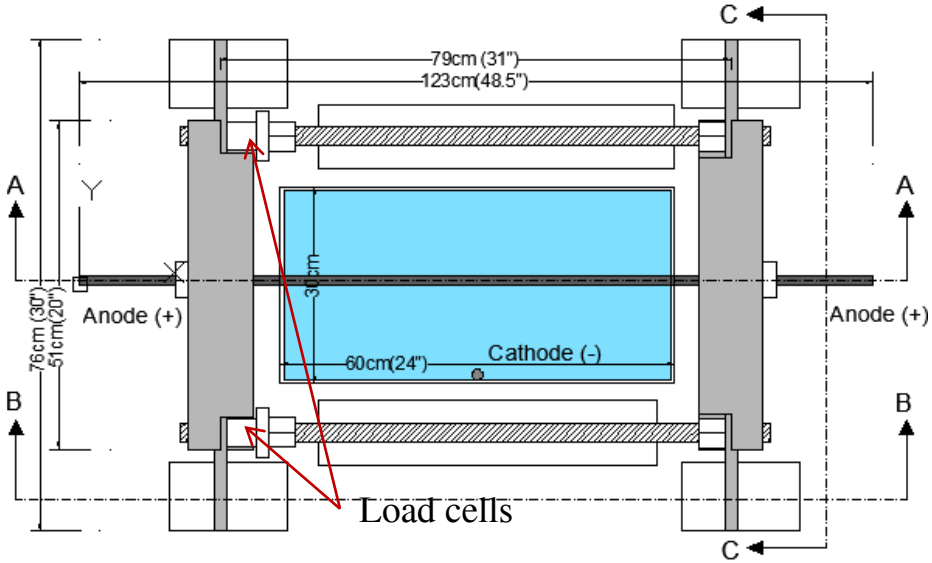
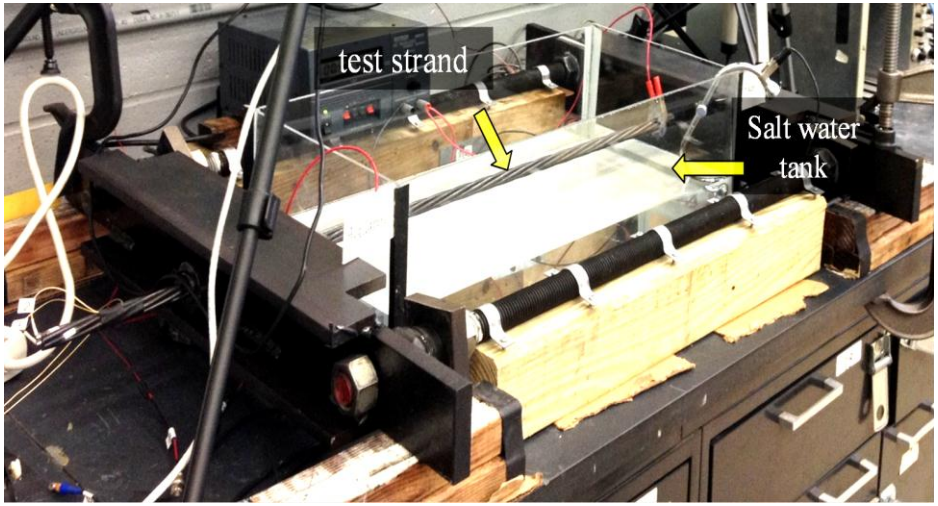
Experiment





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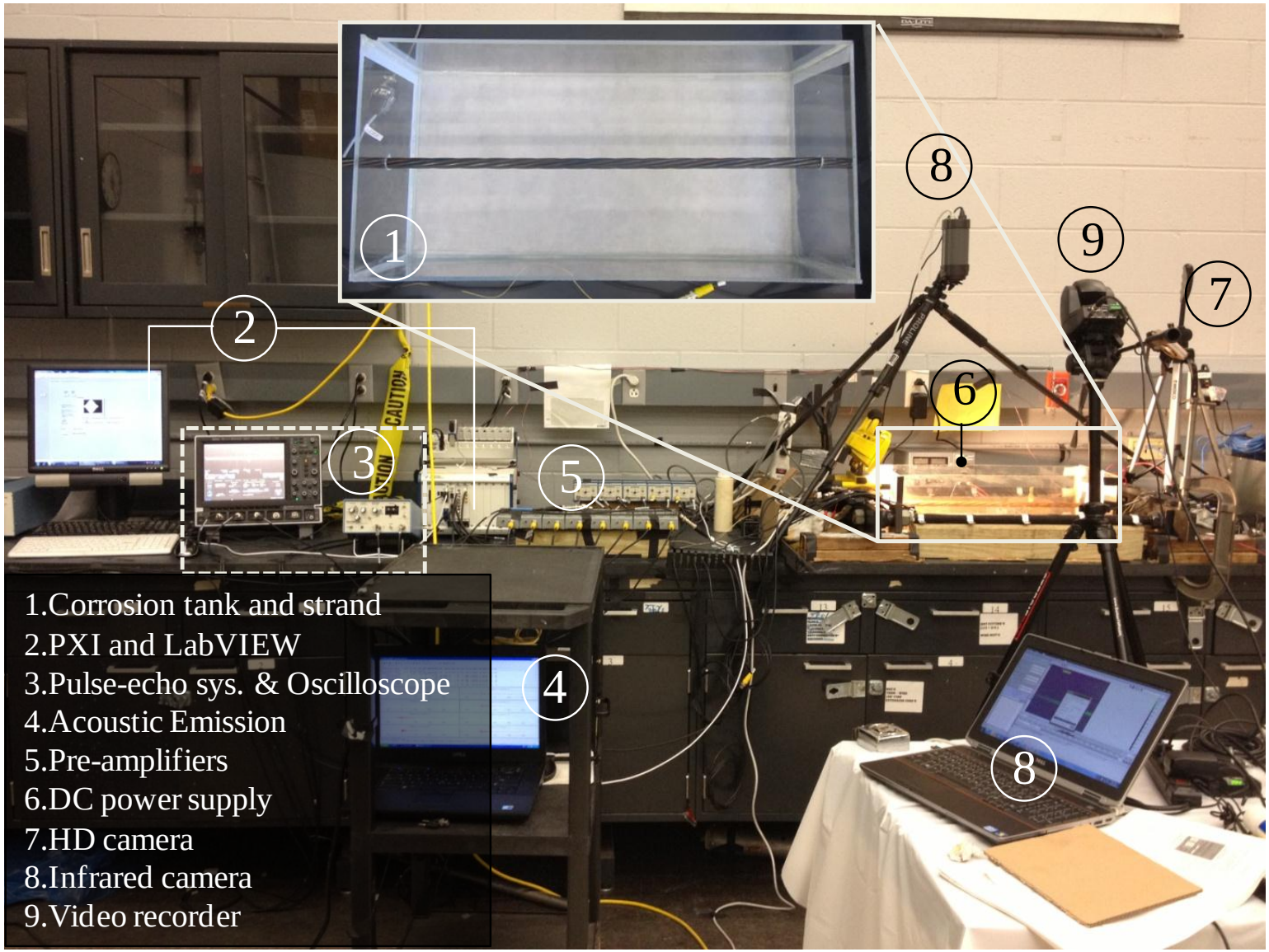
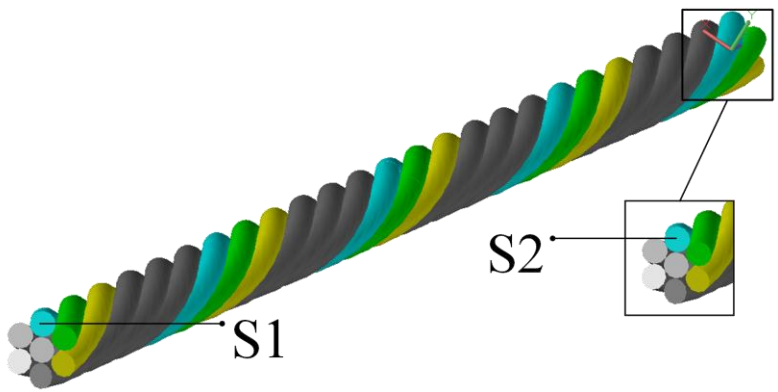
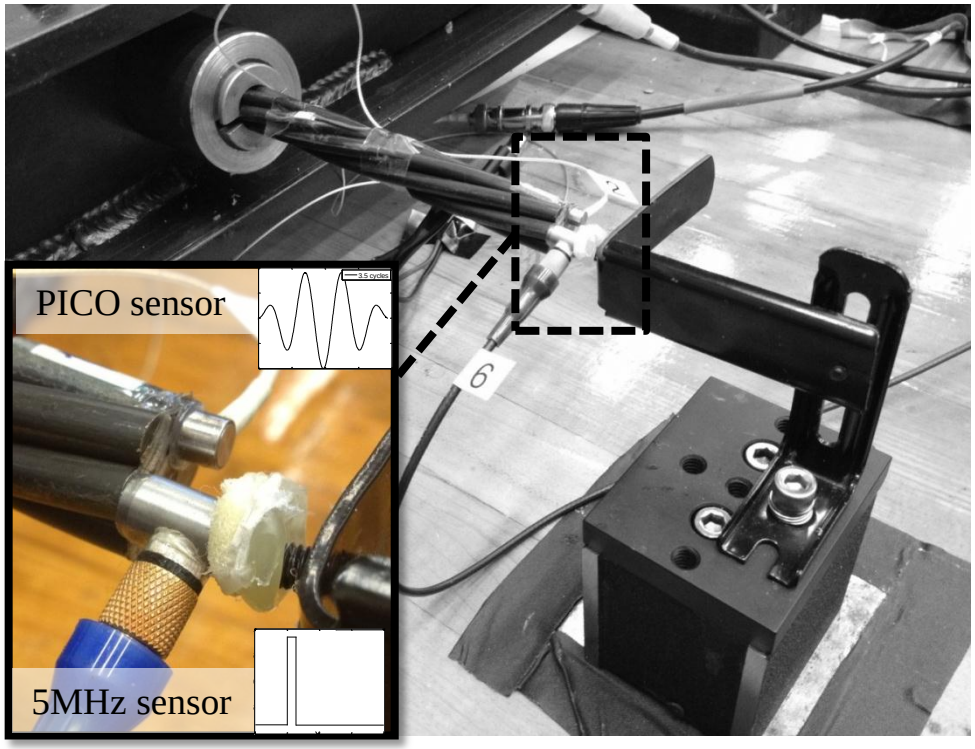


A Farhidzadeh (2014), Application of Pattern Recognition Algorithms and Nondestructive Evaluation Techniques for the Structural Health Monitoring of Civil Structures, PhD dissertation, Department of Civil, Structural, and Environmental Engineering, University at Buffalo, Buffalo, NY

Sensor layout: Pitch-catch configuration





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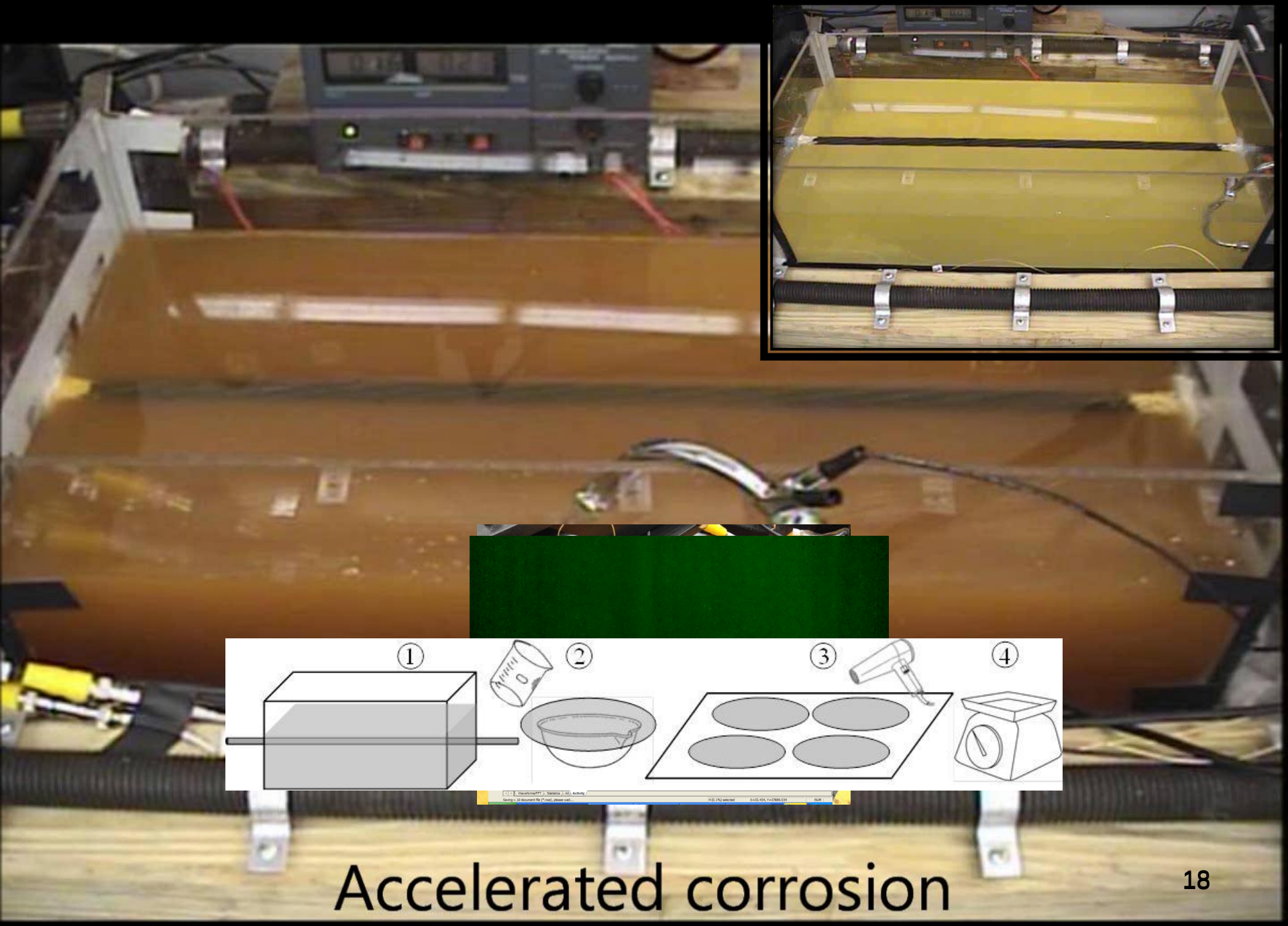


Accelerated corrosion

Visual Inspection, load and mass loss monitoring

No corrosion (Mass loss = 0.0%)

Light corrosion (Mass loss = 0.19%)

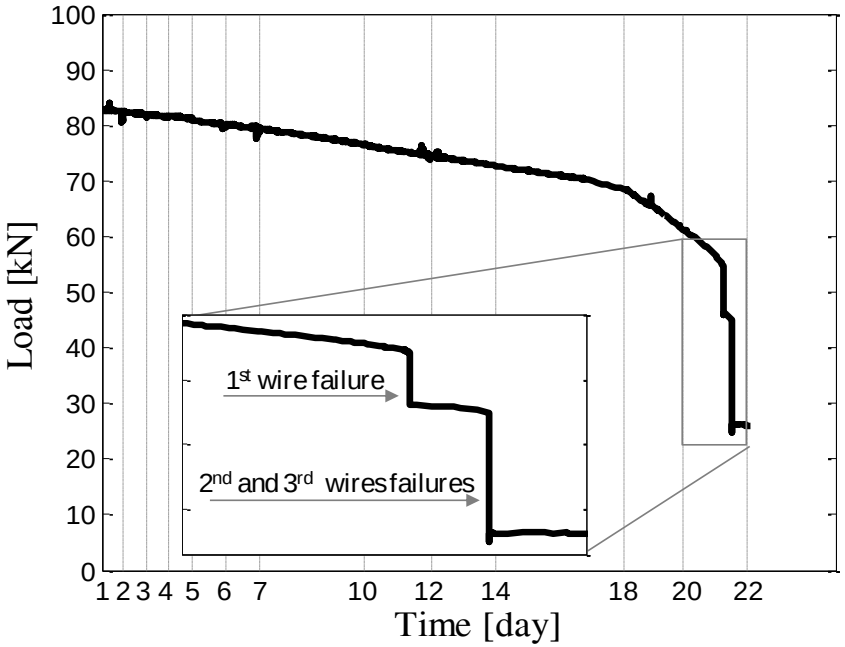
Pitting (Mass loss = 1.26%)

Heavy Pitting (Mass loss = 2.72%)

Cross section loss (Mass loss = 8.38%)

Fracture (Mass loss = 21.34%)

Wire breakage



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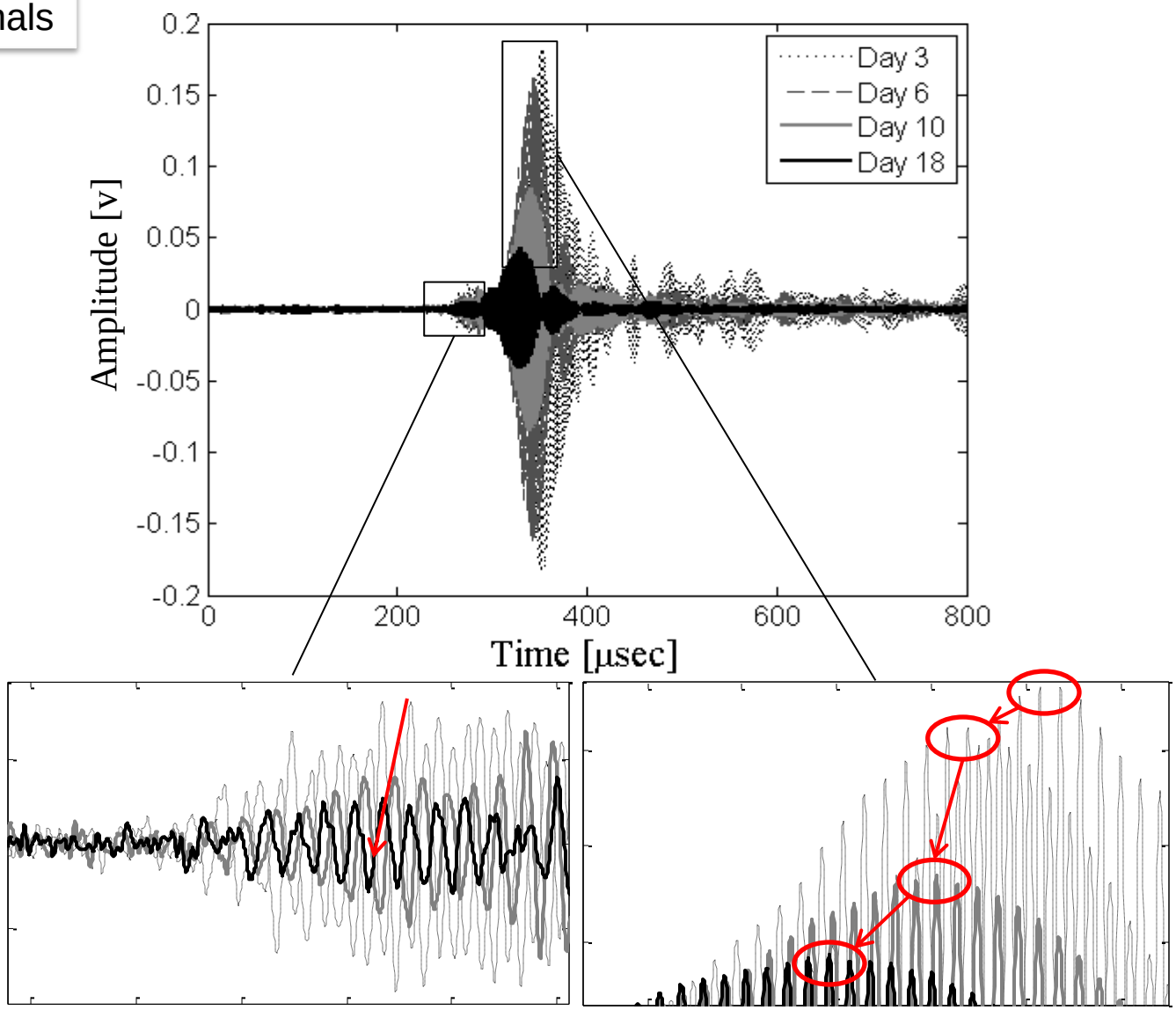
Ultrasonic signals



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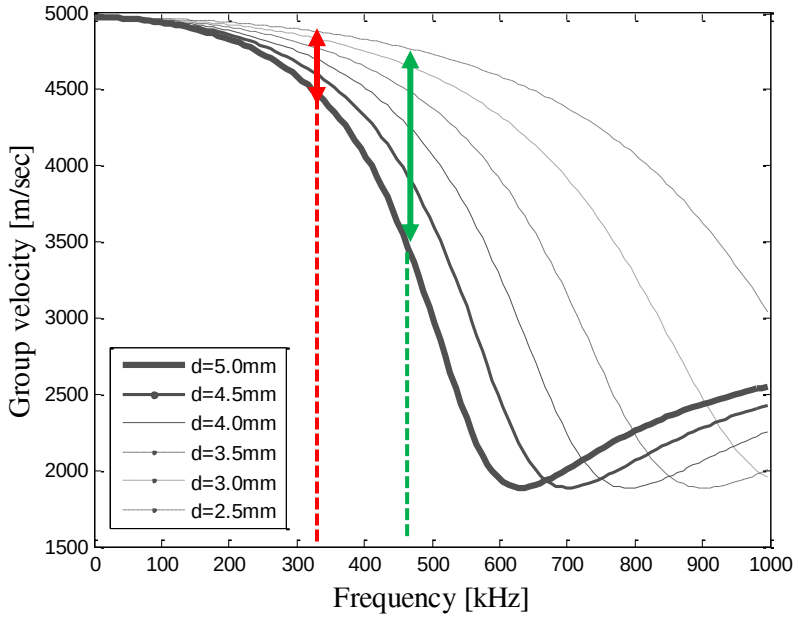

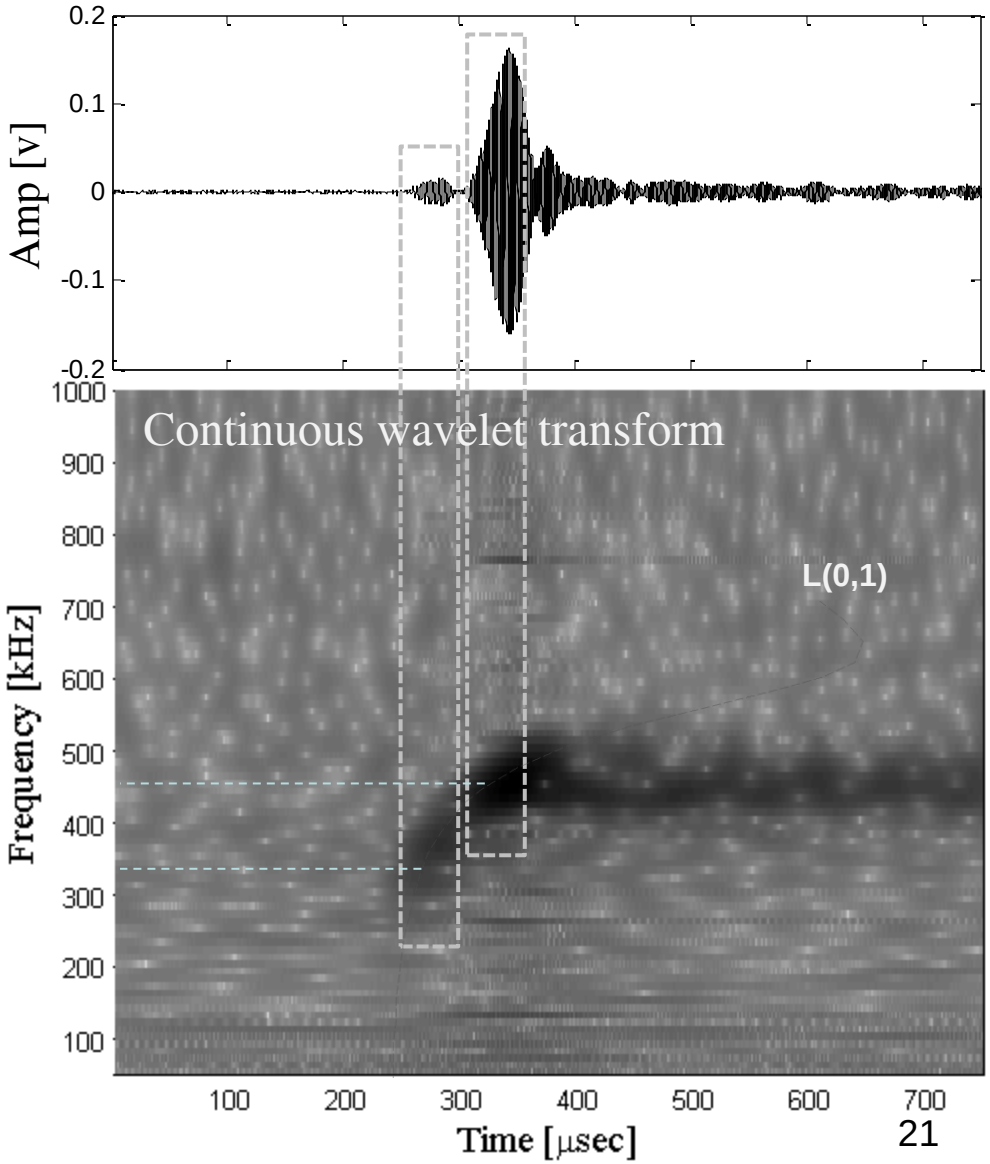

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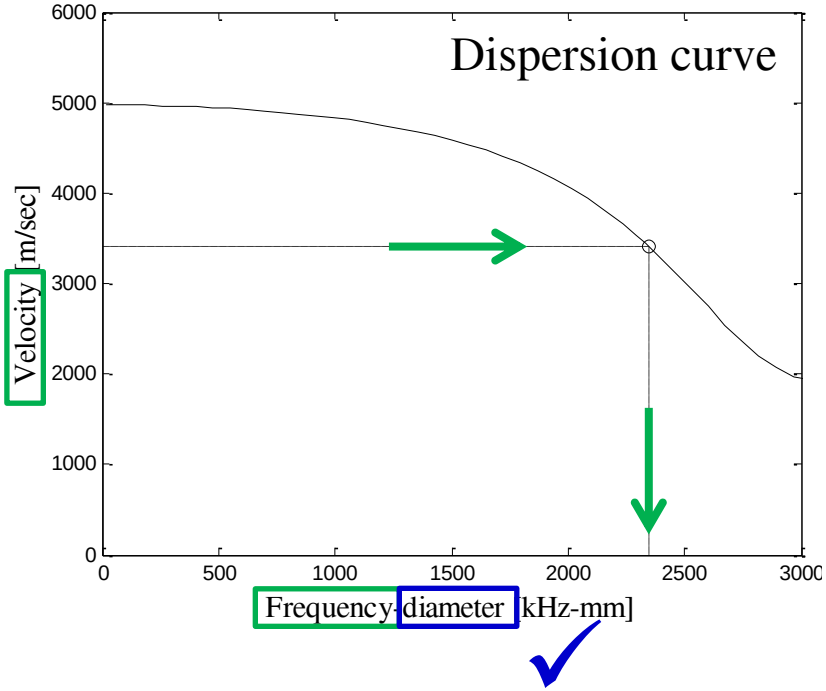

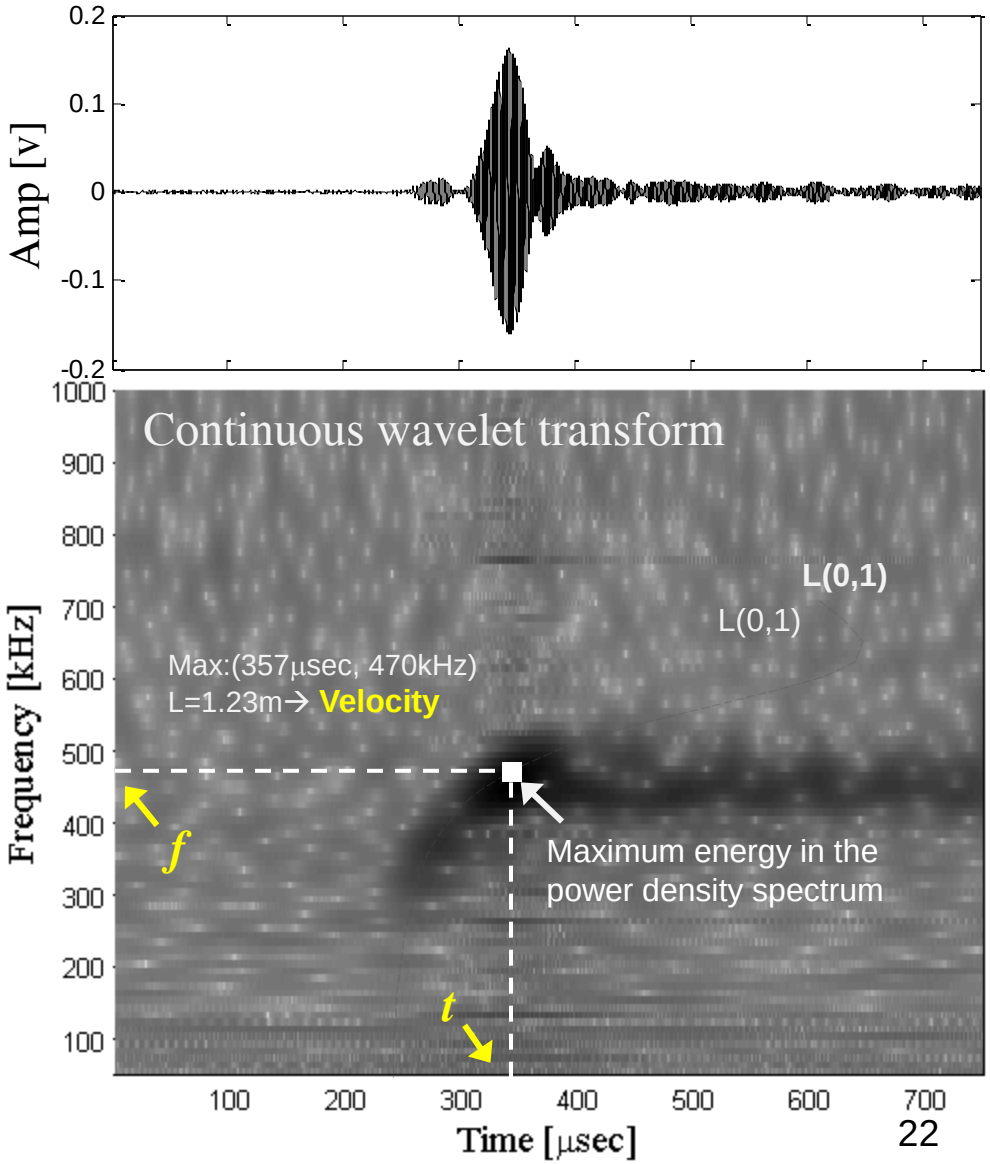

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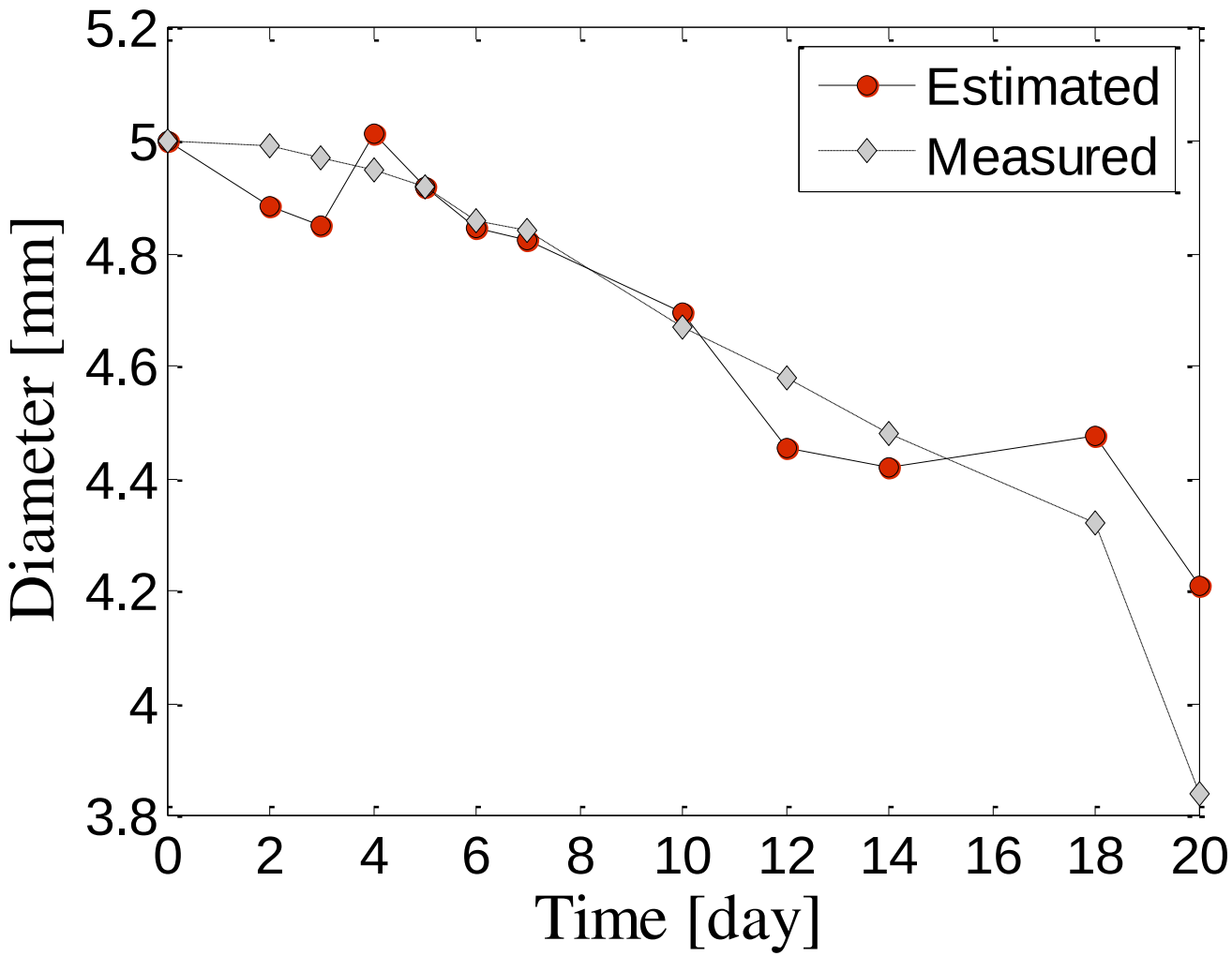
Diameter estimation



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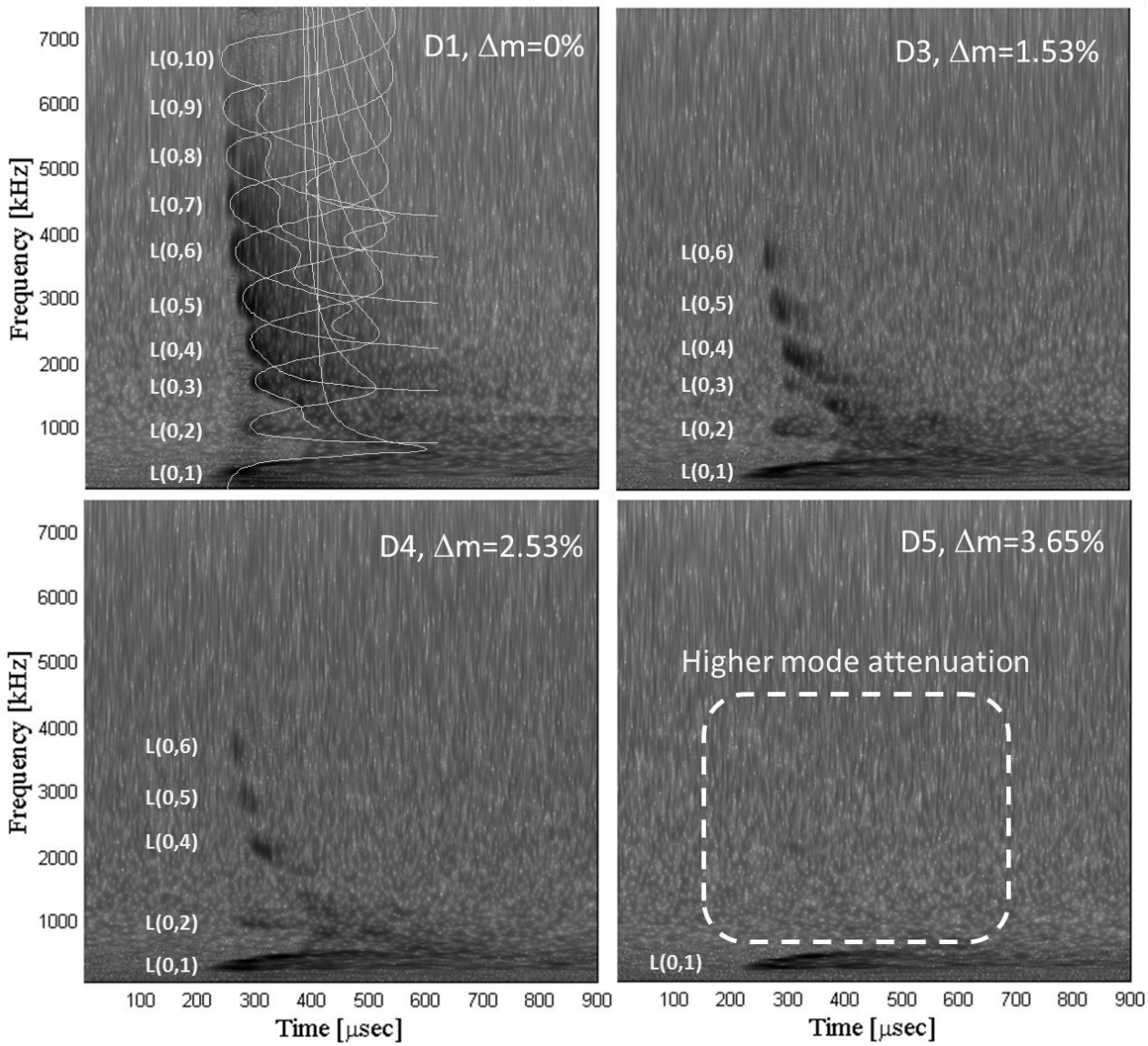
Attenuation



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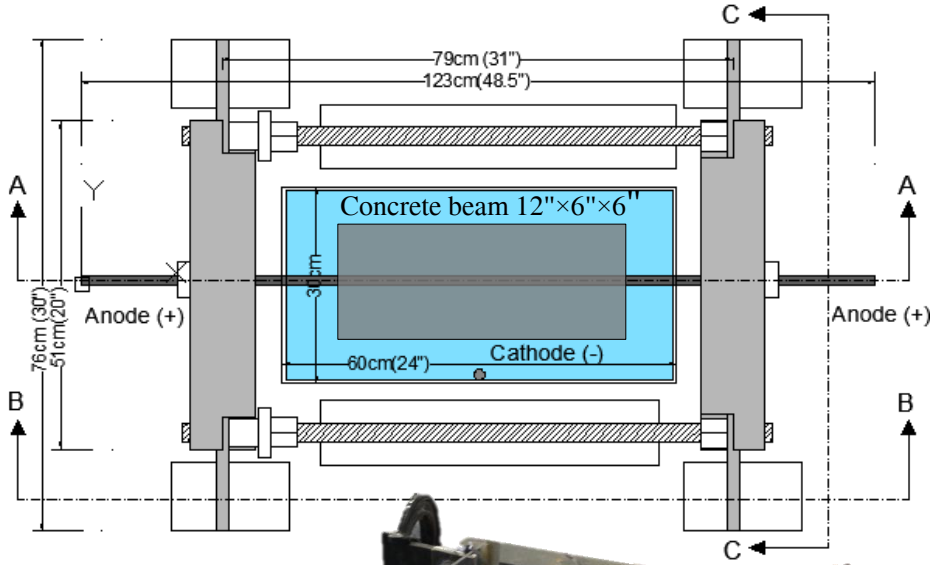
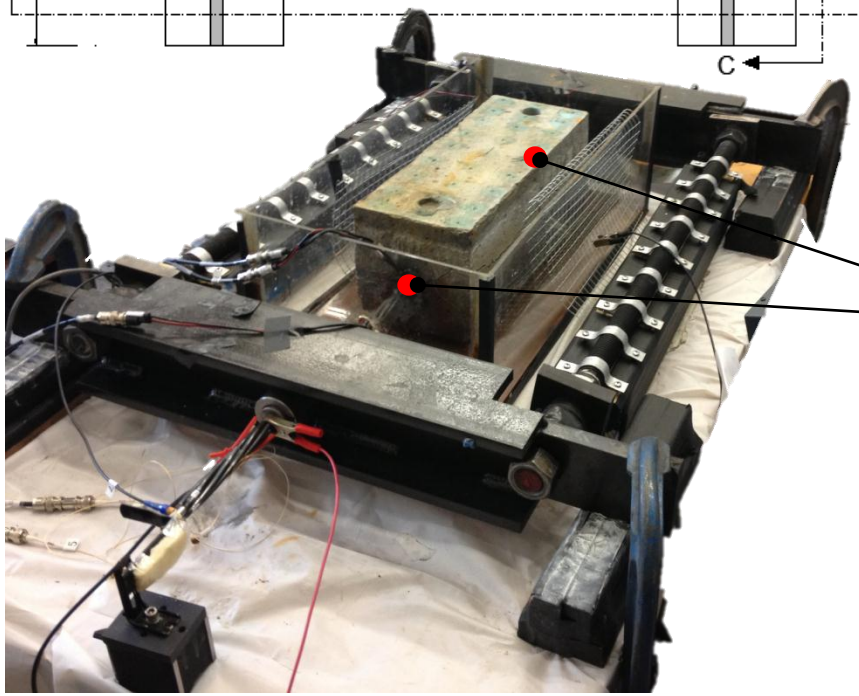
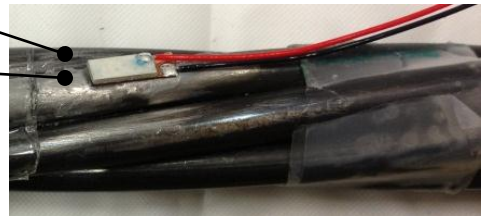
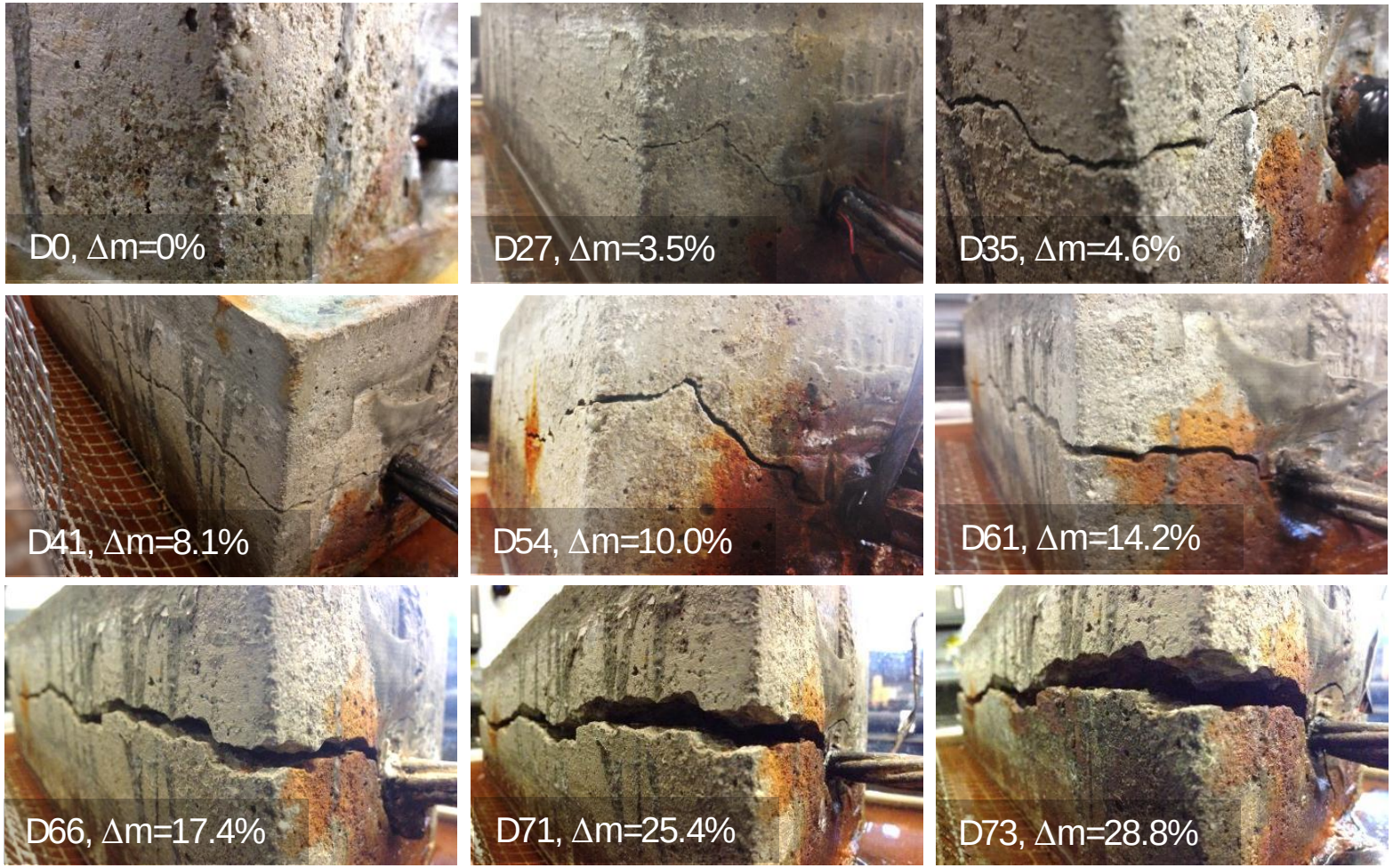
Specimen 2


C
79cm (31")
123cm(48.5")
A
Y
Concrete beam 12"×6"×6"
30cm
Anode (+)
76cm (30")
51cm(20")
60cm(24")
Cathode (-)
B
C

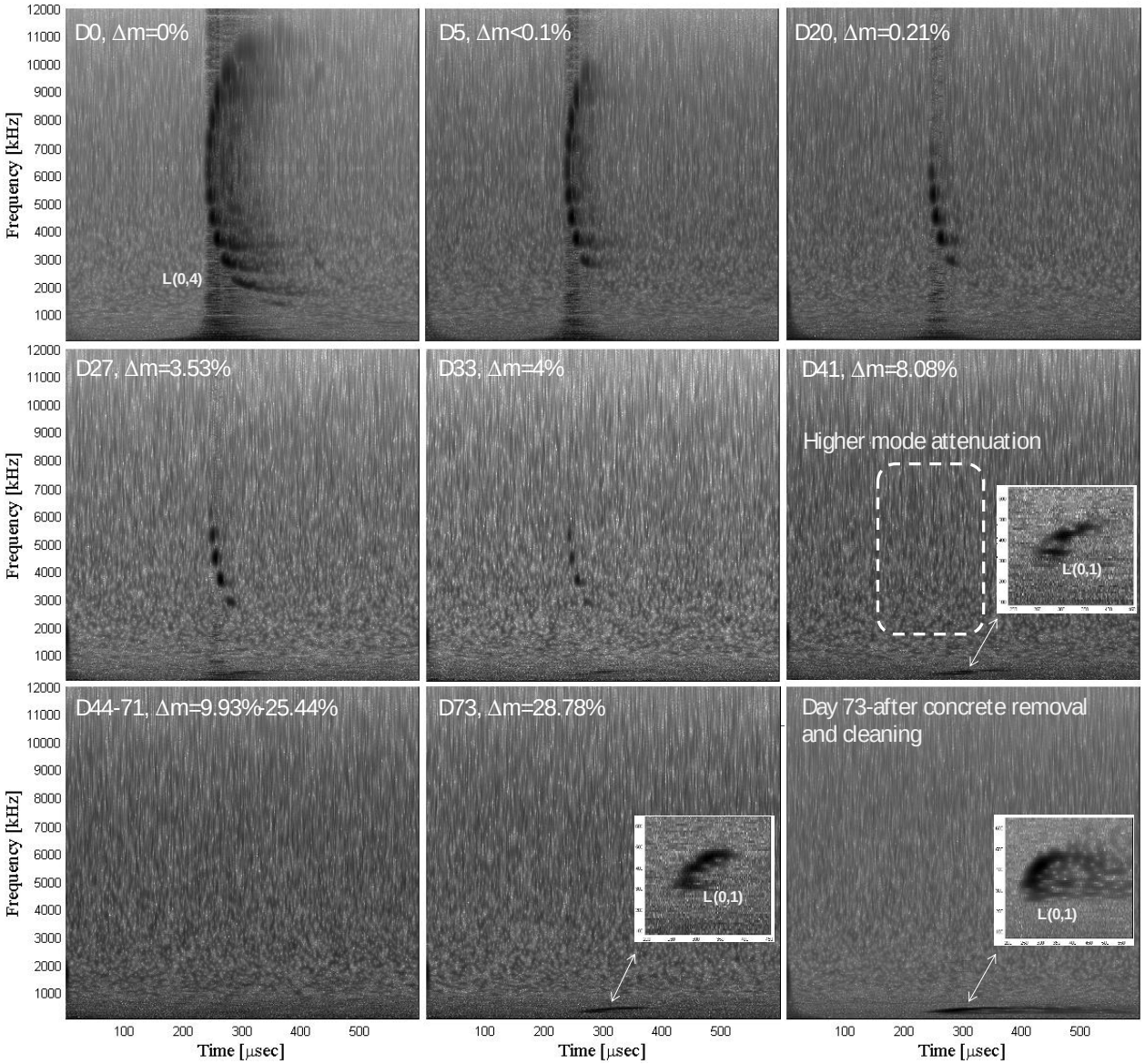




Visual inspection

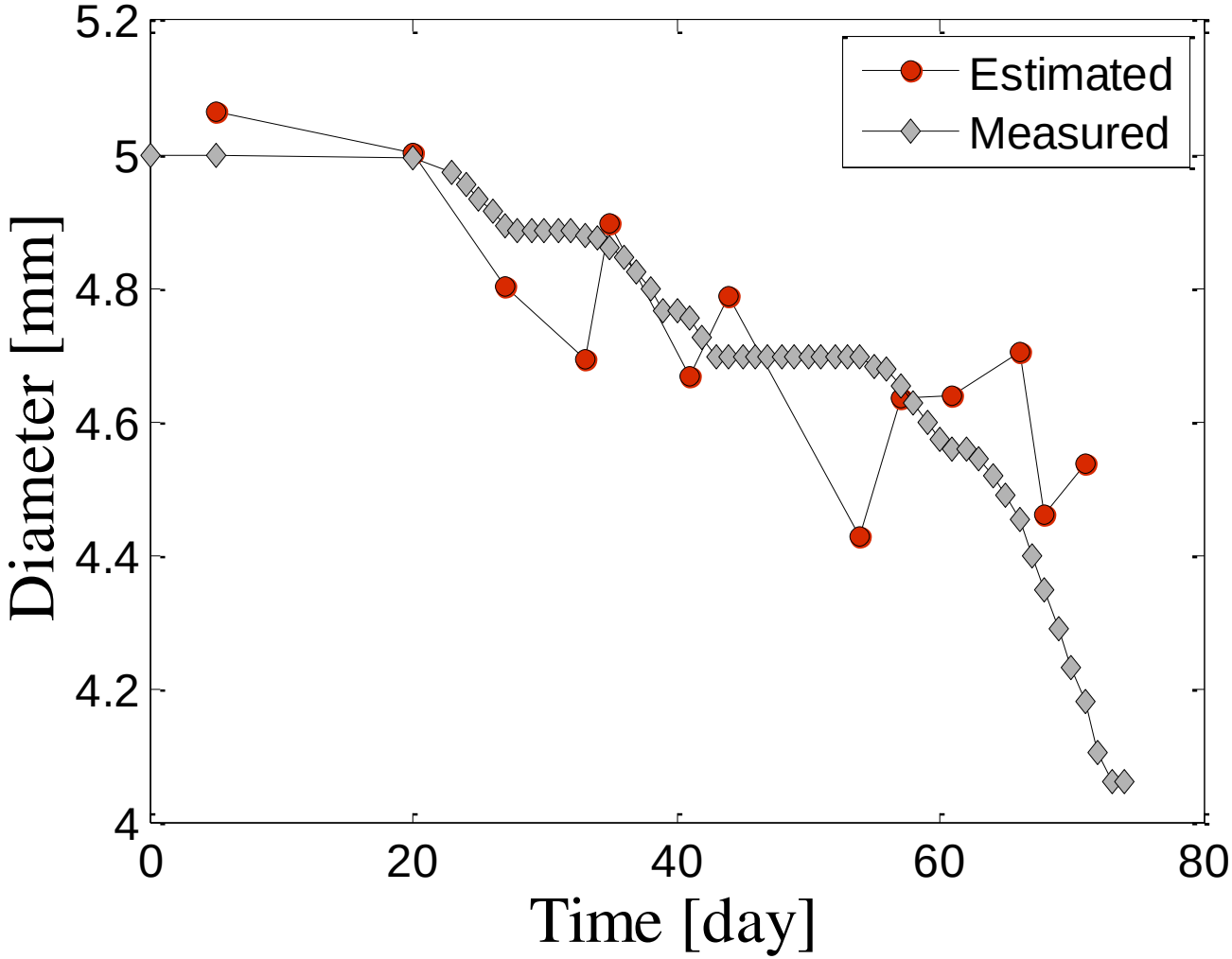


Attenuation



Visual inspection

Specimen 2


Estimated
Measured
Diameter [mm]
Time [day]
5.2
5
4.8
4.6
4.4
4.2
4
0
20
40
60
80

Overview:

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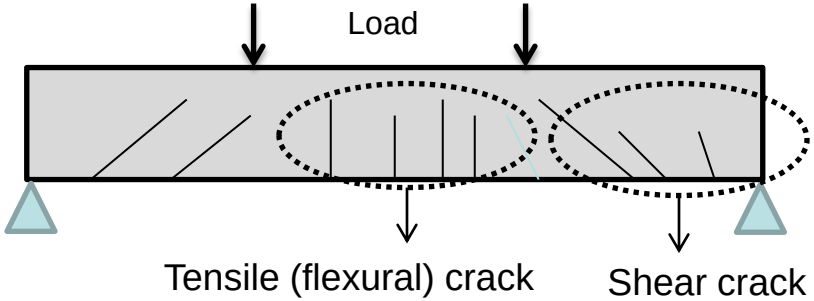
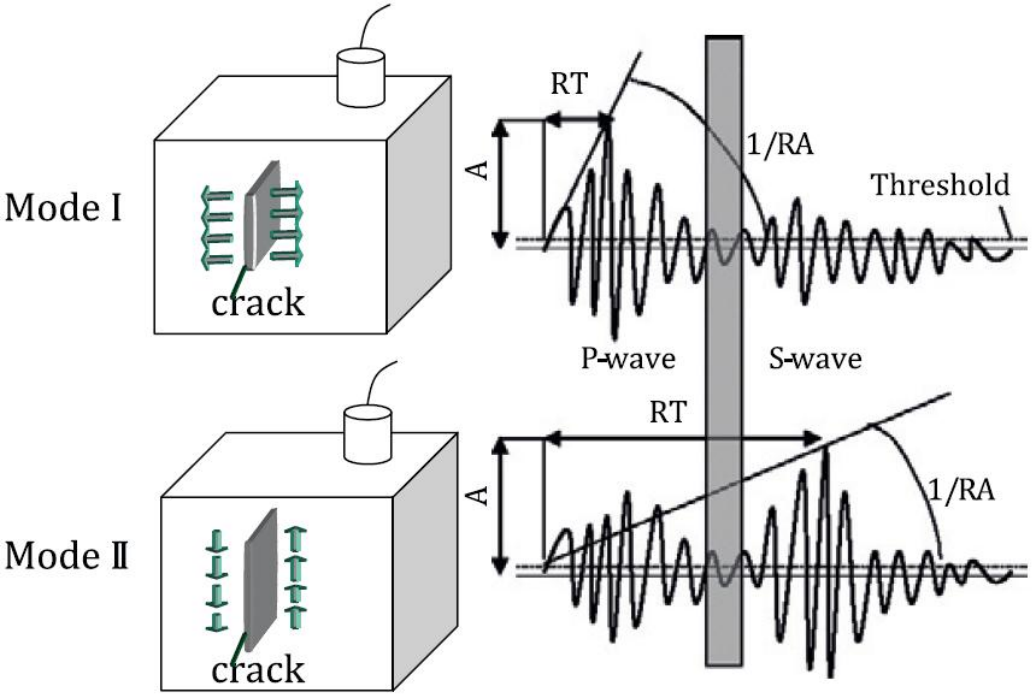
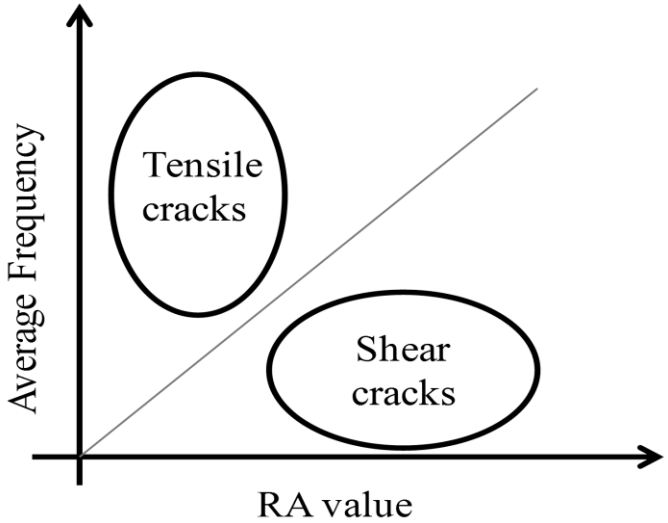
Acoustic Emission (AE)

Crack mode identification



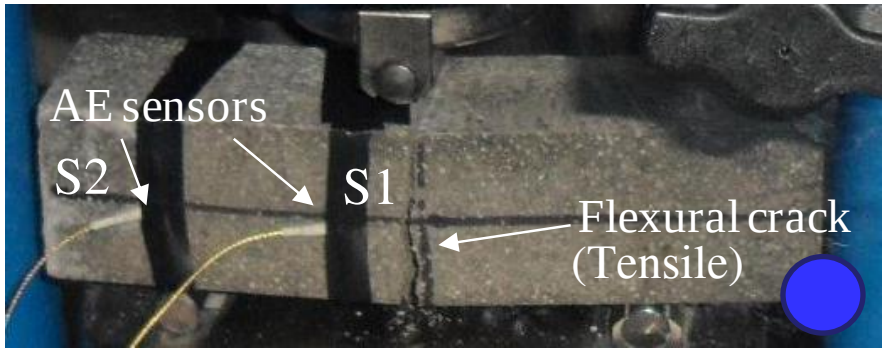


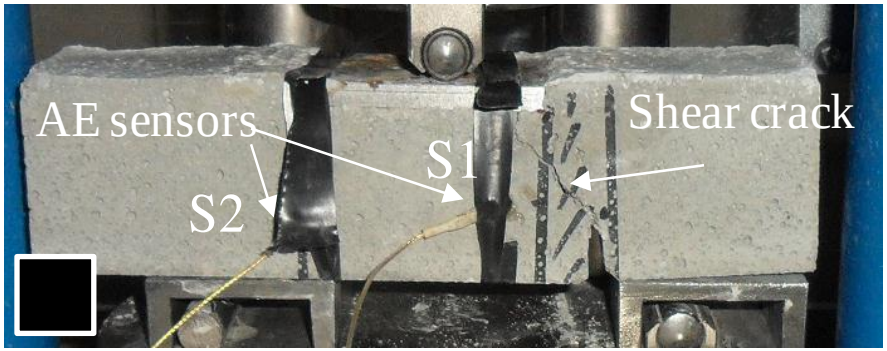
Aggelis, D G, et al (2012), Ohtsu , M (2010)

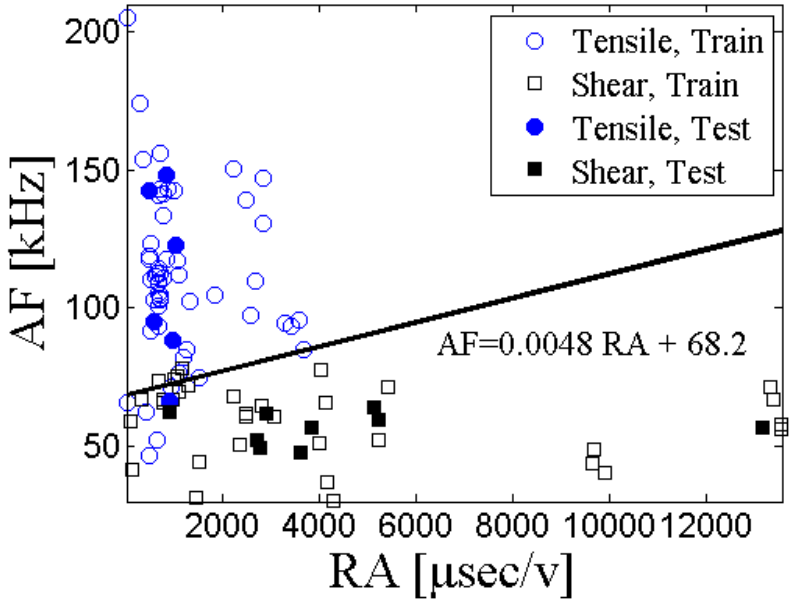


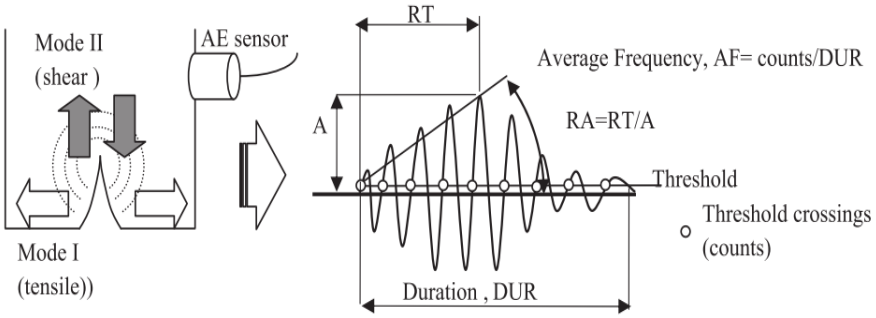
Japan Construction and Material Standard (JCMS)

Crack mode identification





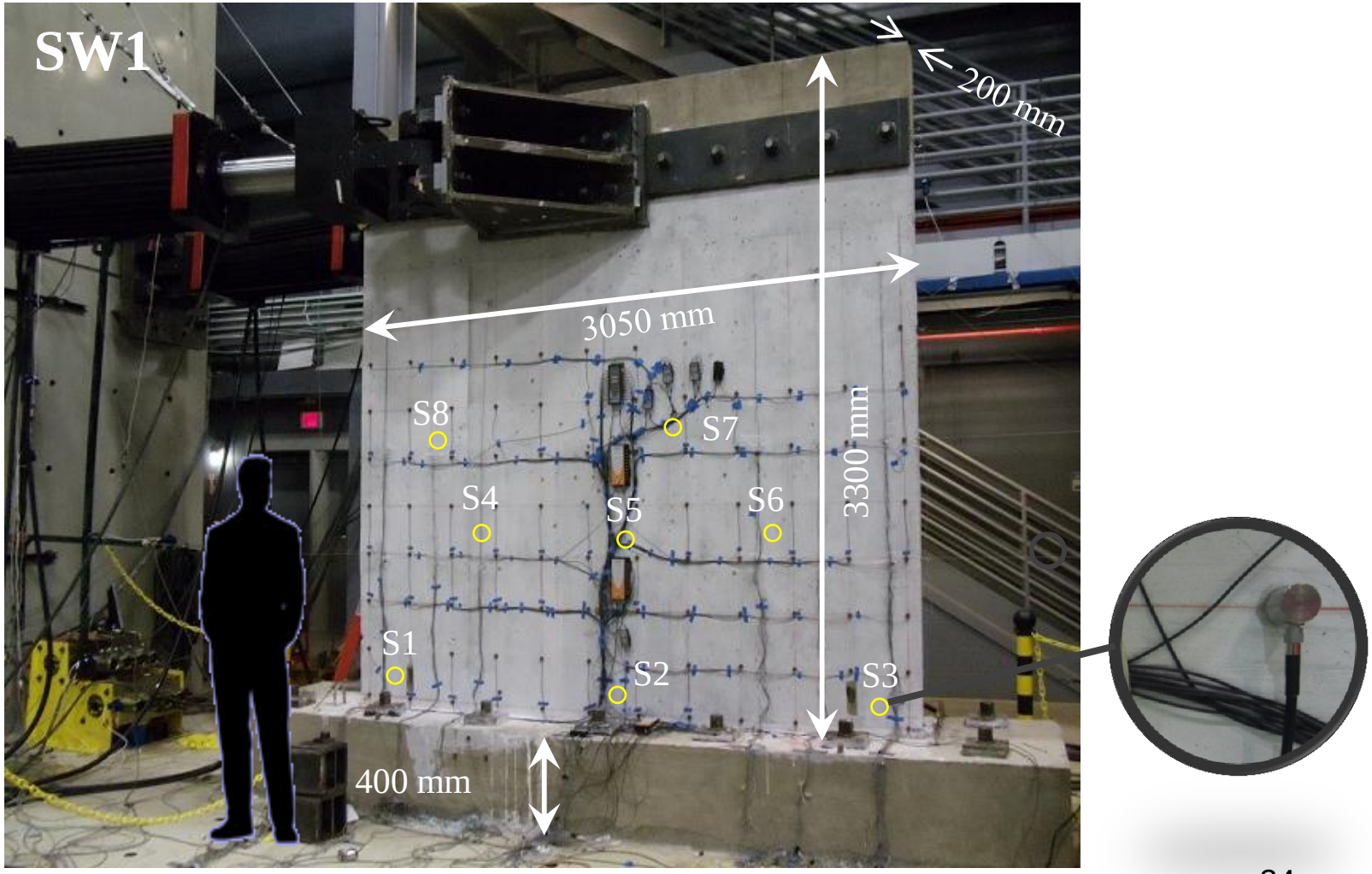




AF = (Counts) / Duration

RA = (Rise time) / (Peak Amplitude)

A. Farhidzadeh, A. C. Mpalaskas, T. E. Matikas, et al, (2014), Fracture Mode Identification in Cementitious Material using Supervised Pattern Recognition of Acoustic Emission Features, Construction and Building Materials, 67: 129-138.



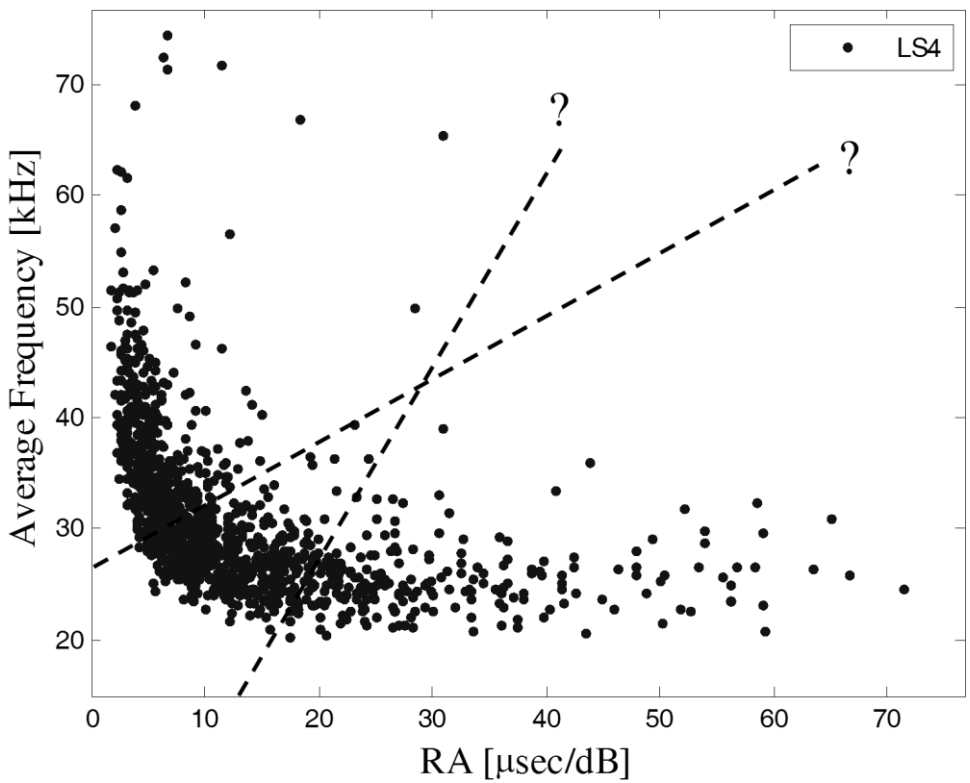
A. Farhidzadeh, S. Salamone, P. Singla, (2012), "A Probabilistic Approach …", *J Intelligent Material Systems and Structures*, 24 (14), 1722-1735.

The open questions:

"What is the best discriminant line?"

"Is the decision boundary a line?"

"Is there really two clusters?"



A. Farhidzadeh, S. Salamone, P. Singla, (2012), "A Probabilistic Approach …", *J Intelligent Material Systems and Structures*, 24 (14), 1722-1735.

Gaussian Mixture Model (GMM) is a parametric probability density function represented as a weighted sum of M component Gaussian densities.

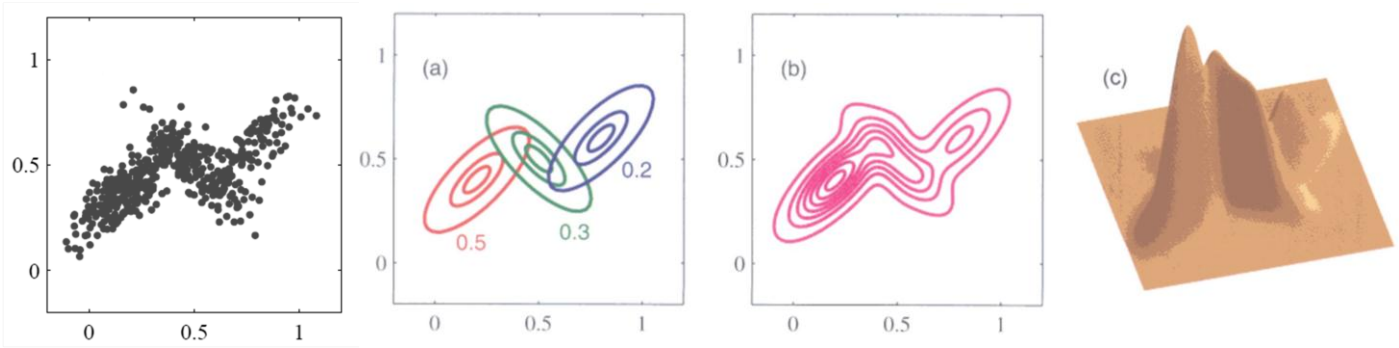
$$p(\vec{x} \mid \lambda) = \sum_{i=1}^{M} \omega_i \mathcal{N}_i (\vec{x} \mid \vec{\mu}_i, \Sigma_i) \qquad \text{i=1, ..., M,}$$

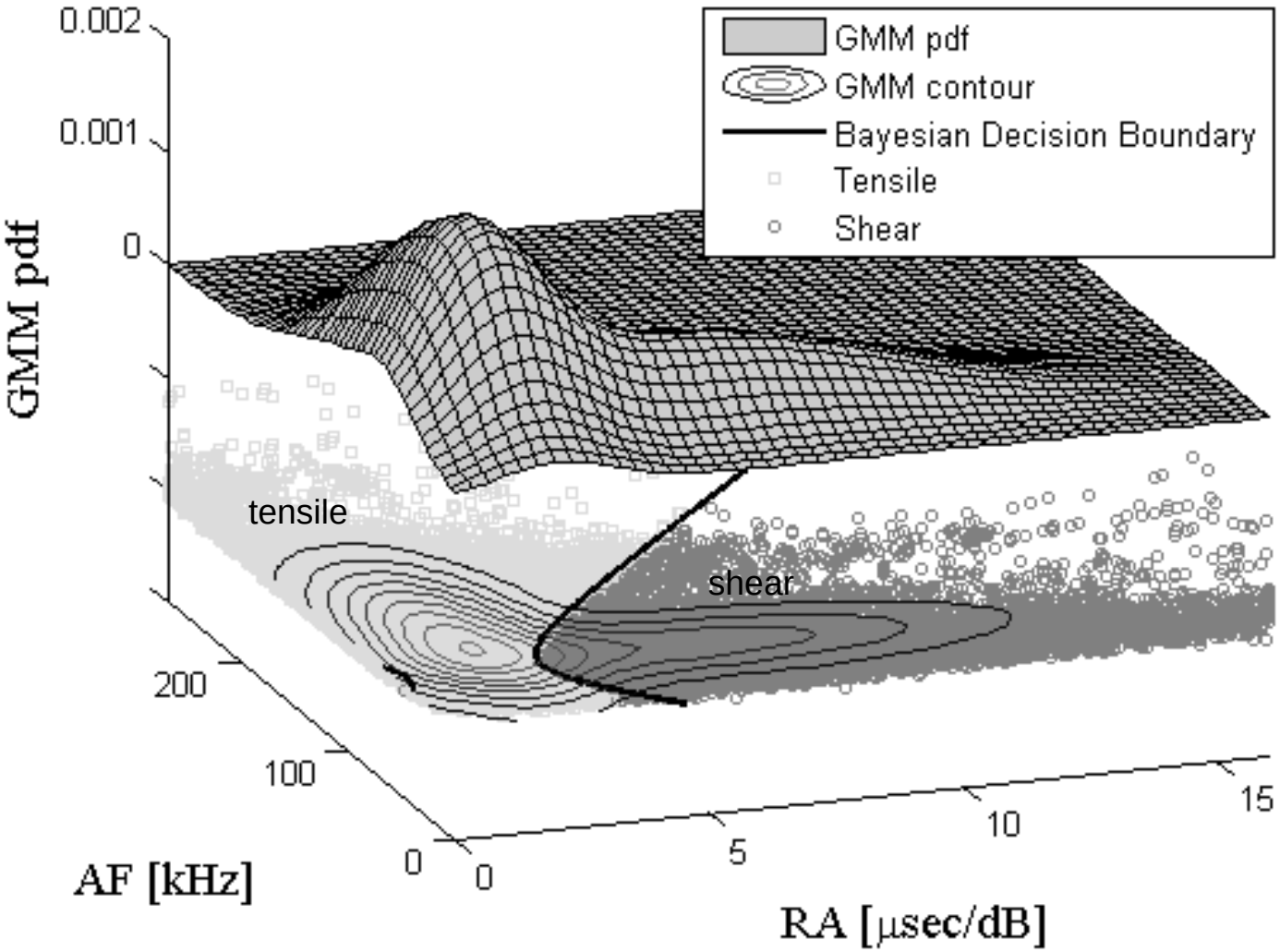
$\vec{x}$: D-dimensional feature (observation) vector, in this study

$\lambda = \{\omega_i, \vec{\mu}_i, \Sigma_i\}, \quad i = 1, \ldots, M$ Model Parameters, weight, mean, covariance

ω_i : mixture weights

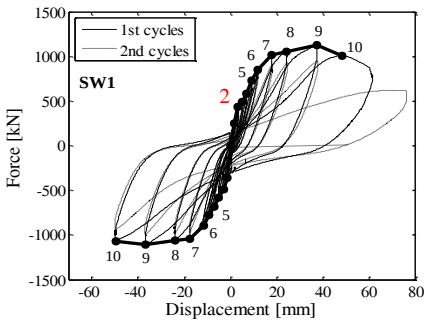
$\mathcal{N}_i (\vec{x} \mid \vec{\mu}_i, \Sigma_i)$: unimodal component Gaussian (Normal) densities

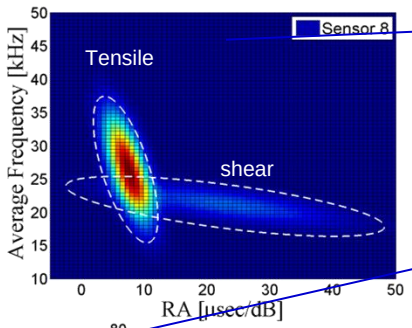


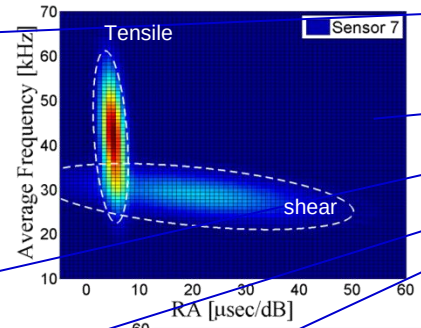


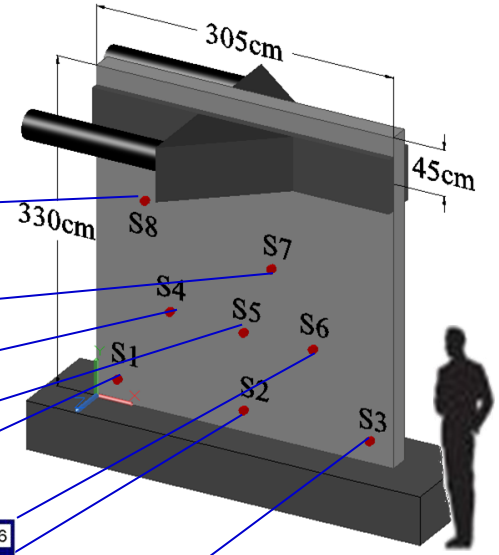
A. Farhidzadeh, S. Salamone, P. Singla, (2012), "A Probabilistic Approach …", *J Intelligent Material Systems and Structures*, 24 (14), 1722-1735.

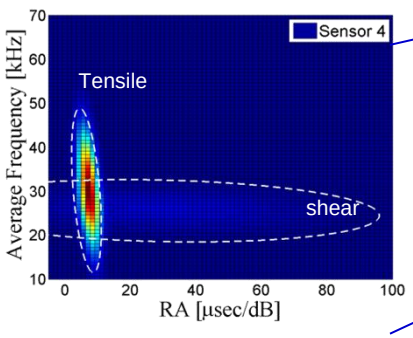
Load step 2

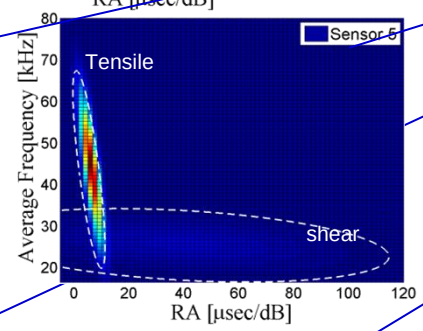


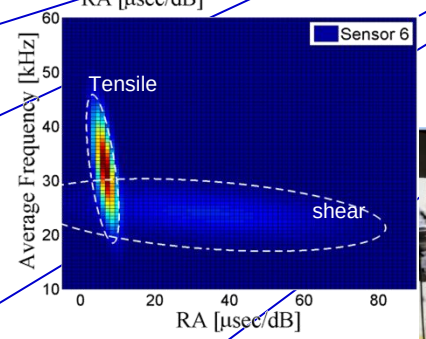


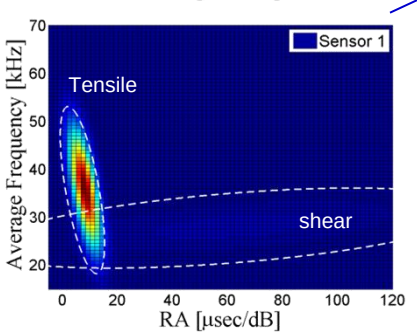


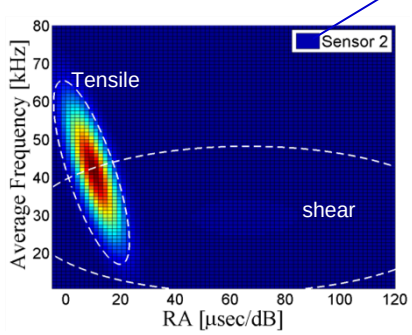


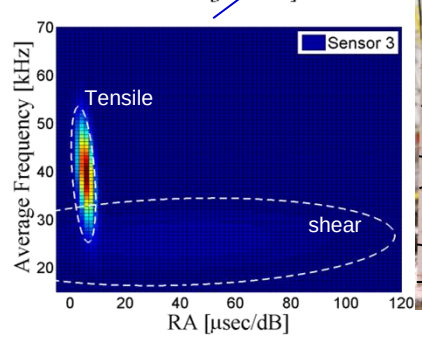


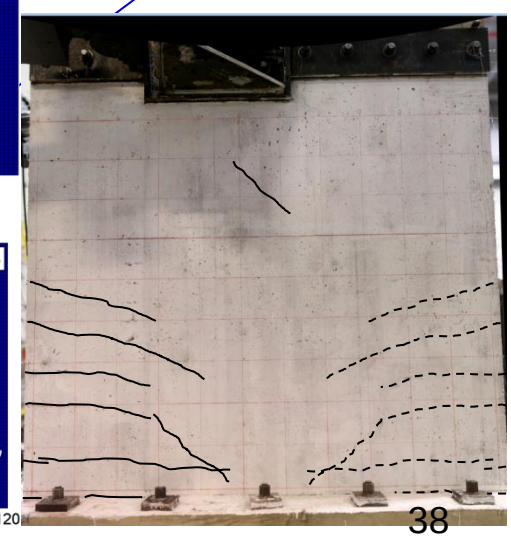






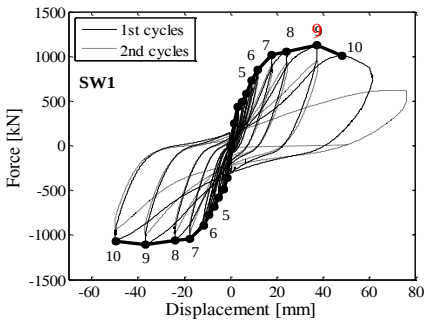


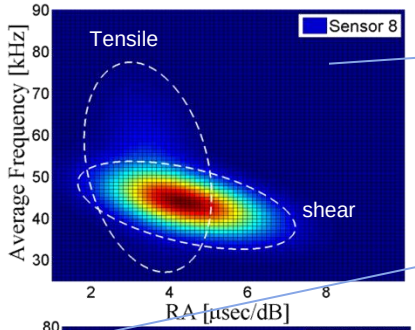


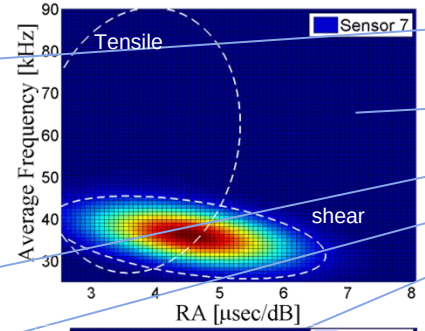


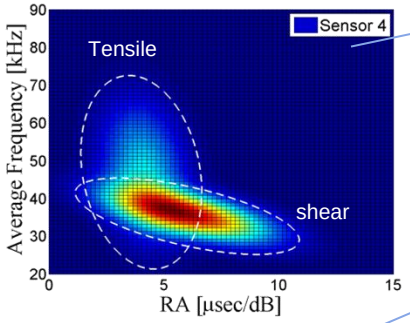
A. Farhidzadeh, S. Salamone, P. Singla, (2012), "A Probabilistic Approach …", *J Intelligent Material Systems and Structures*, 24 (14), 1722-1735.

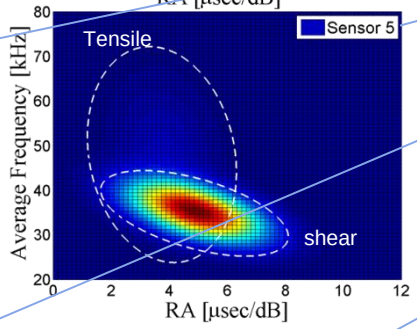
Load step 9

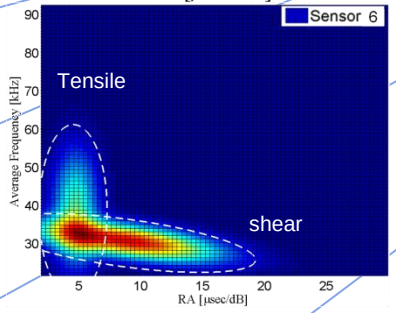


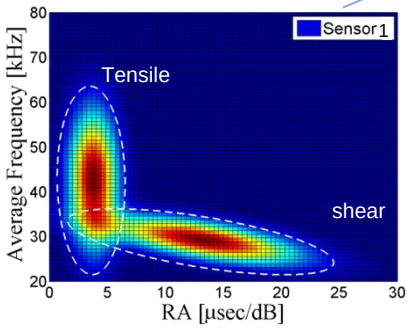


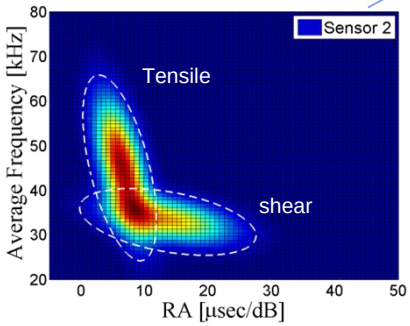


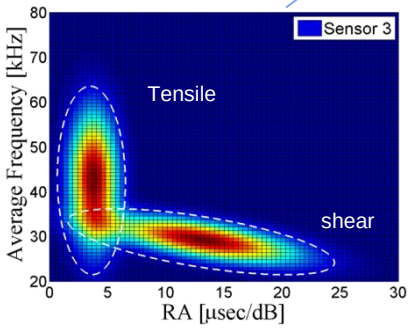


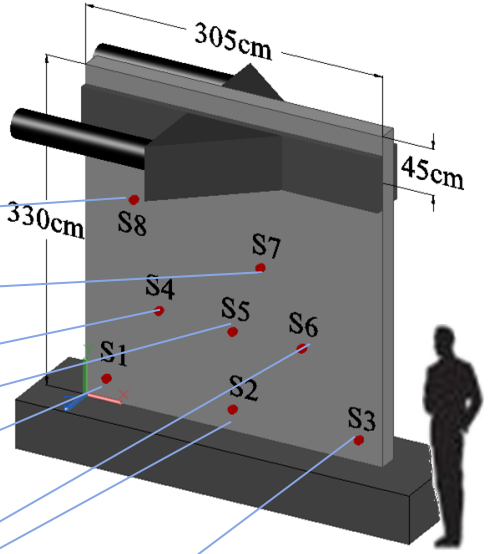


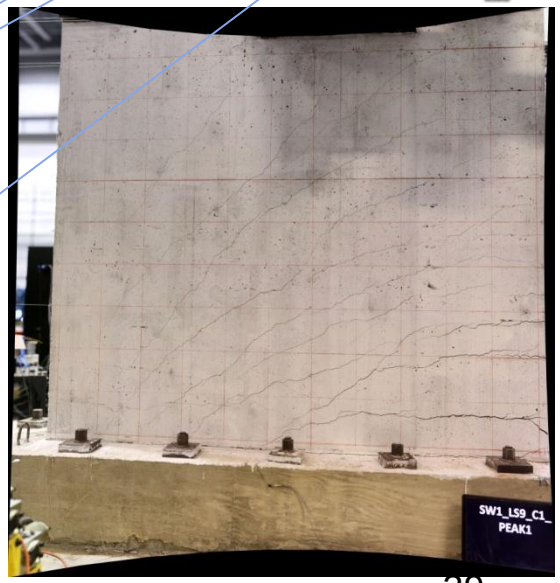




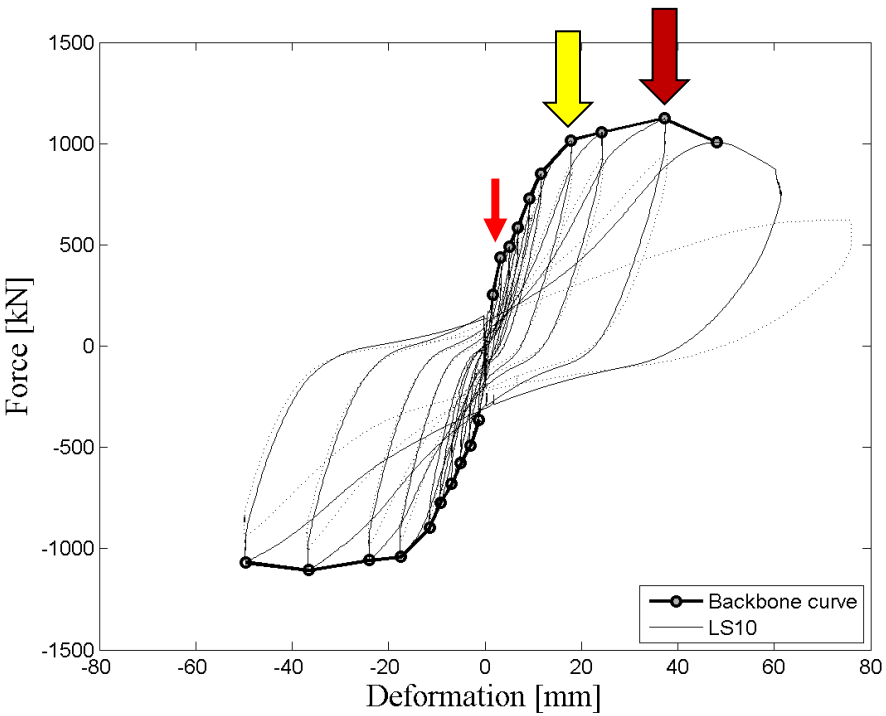


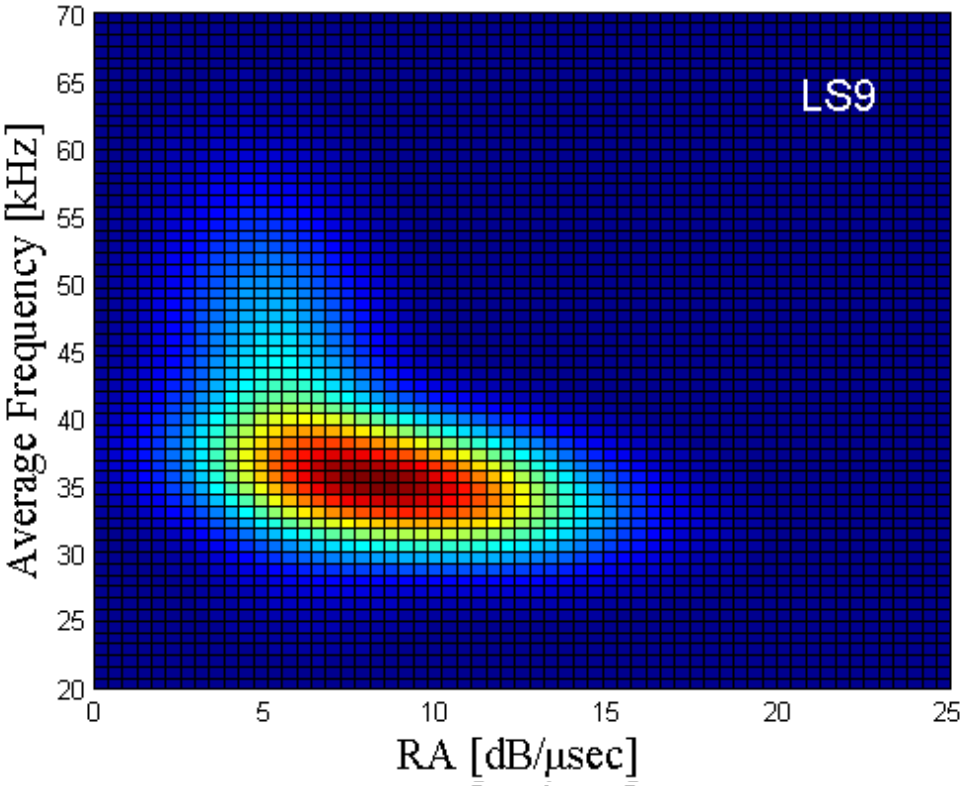




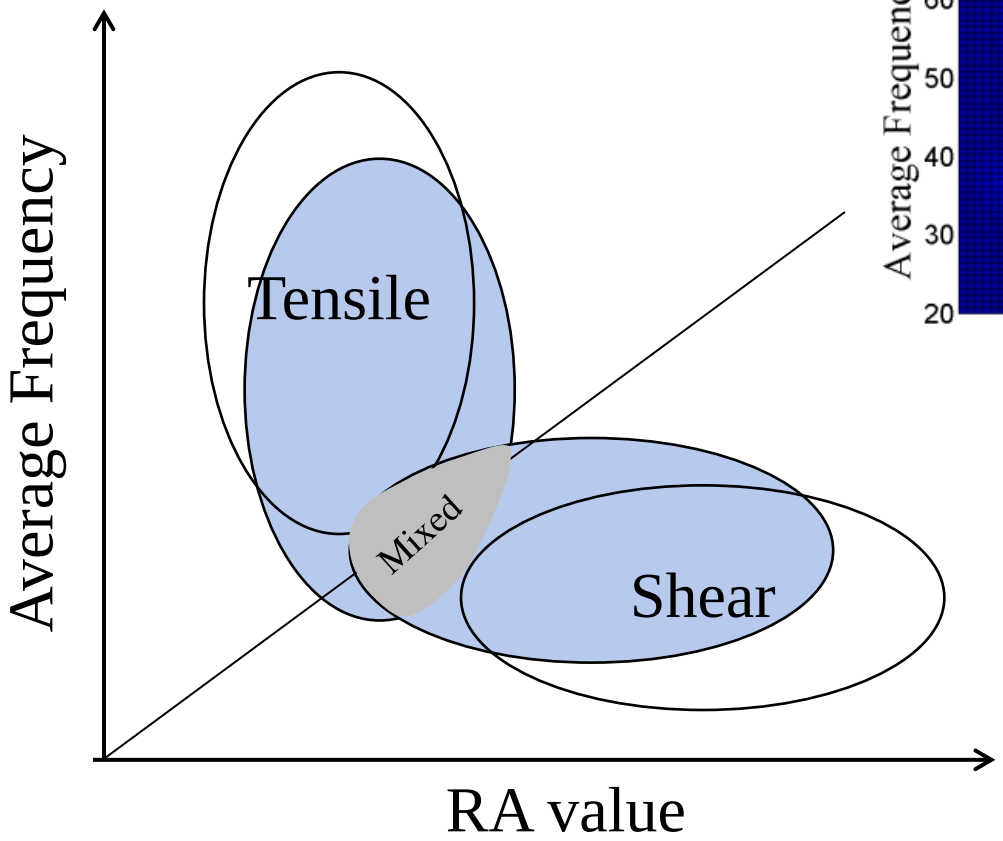


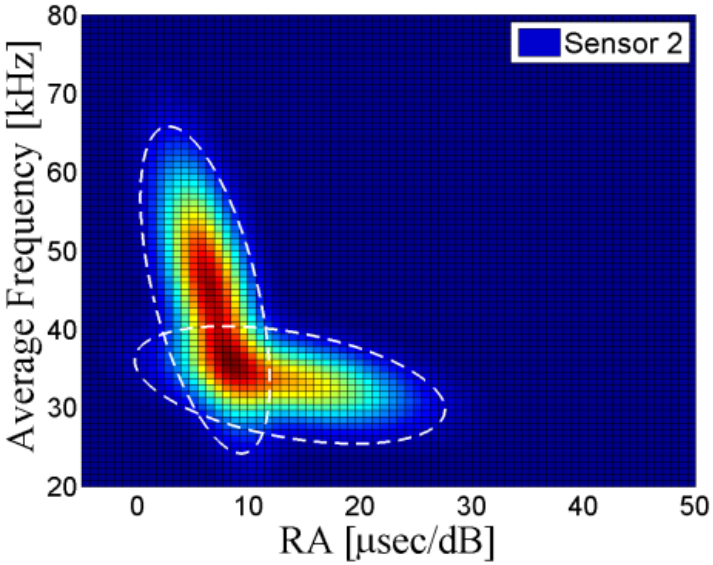
A. Farhidzadeh, S. Salamone, P. Singla, (2012), "A Probabilistic Approach …", *J Intelligent Material Systems and Structures*, 24 (14), 1722-1735.





A. Farhidzadeh, S. Salamone, P. Singla, (2012), "A Probabilistic Approach …", *J Intelligent Material Systems and Structures*, 24 (14), 1722-1735.



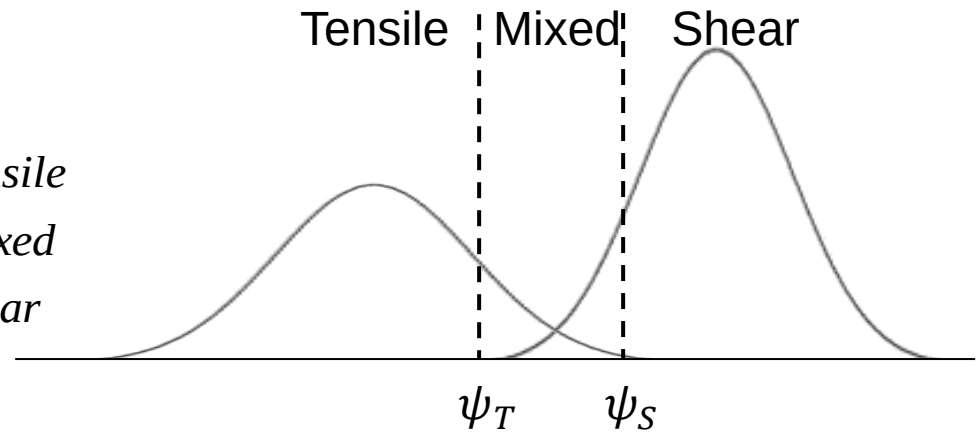


Japan Construction and Material Standard (2003)

A Farhidzadeh et al., (2013) Gaussian mixture modeling of acoustic emissions for structural health monitoring of reinforced concrete structures, SPIE Smart Structures/NDE, doi:10.1117/12.2008705

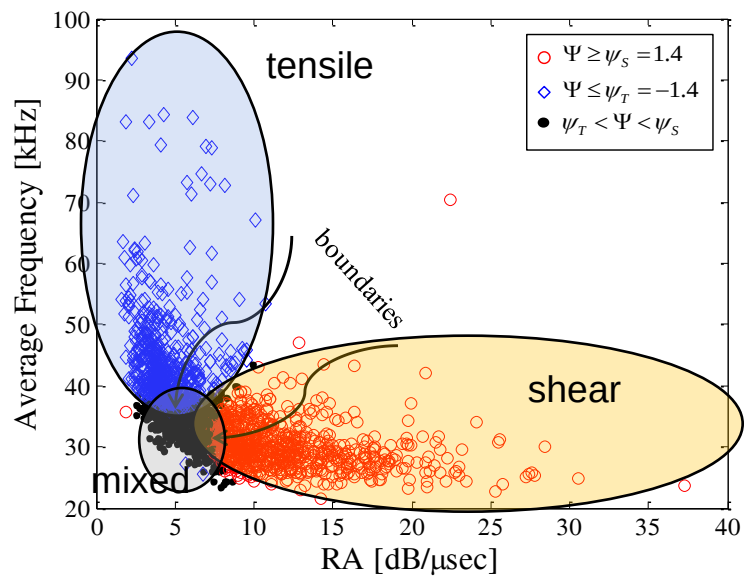
Likelihood Ratio Test

$$\Psi = -2\ln\frac{P(X\mid\lambda_1)}{P(X\mid\lambda_2)} \rightarrow \begin{cases} \Psi \le \psi_T & \rightarrow Tensile \\ \psi_T < \Psi < \psi_S & \rightarrow Mixed \\ \Psi \ge \psi_S & \rightarrow Shear \end{cases}$$



$$\frac{P(X\mid\lambda_1)}{P(X\mid\lambda_2)} = 2 \rightarrow \psi_T = -1.4$$

$$\frac{P(X\mid\lambda_1)}{P(X\mid\lambda_2)} = \frac{1}{2} \rightarrow \psi_S = 1.4$$



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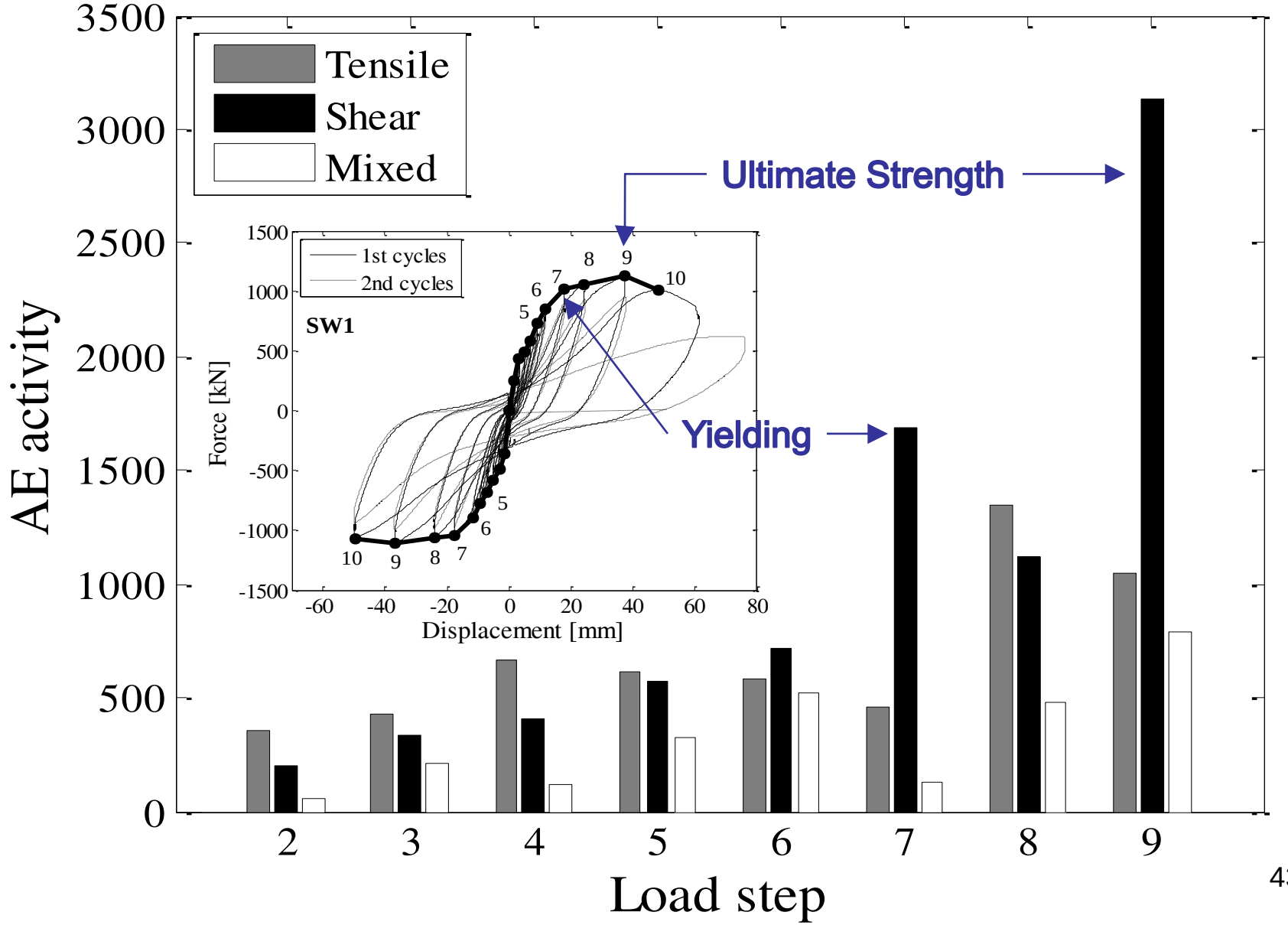

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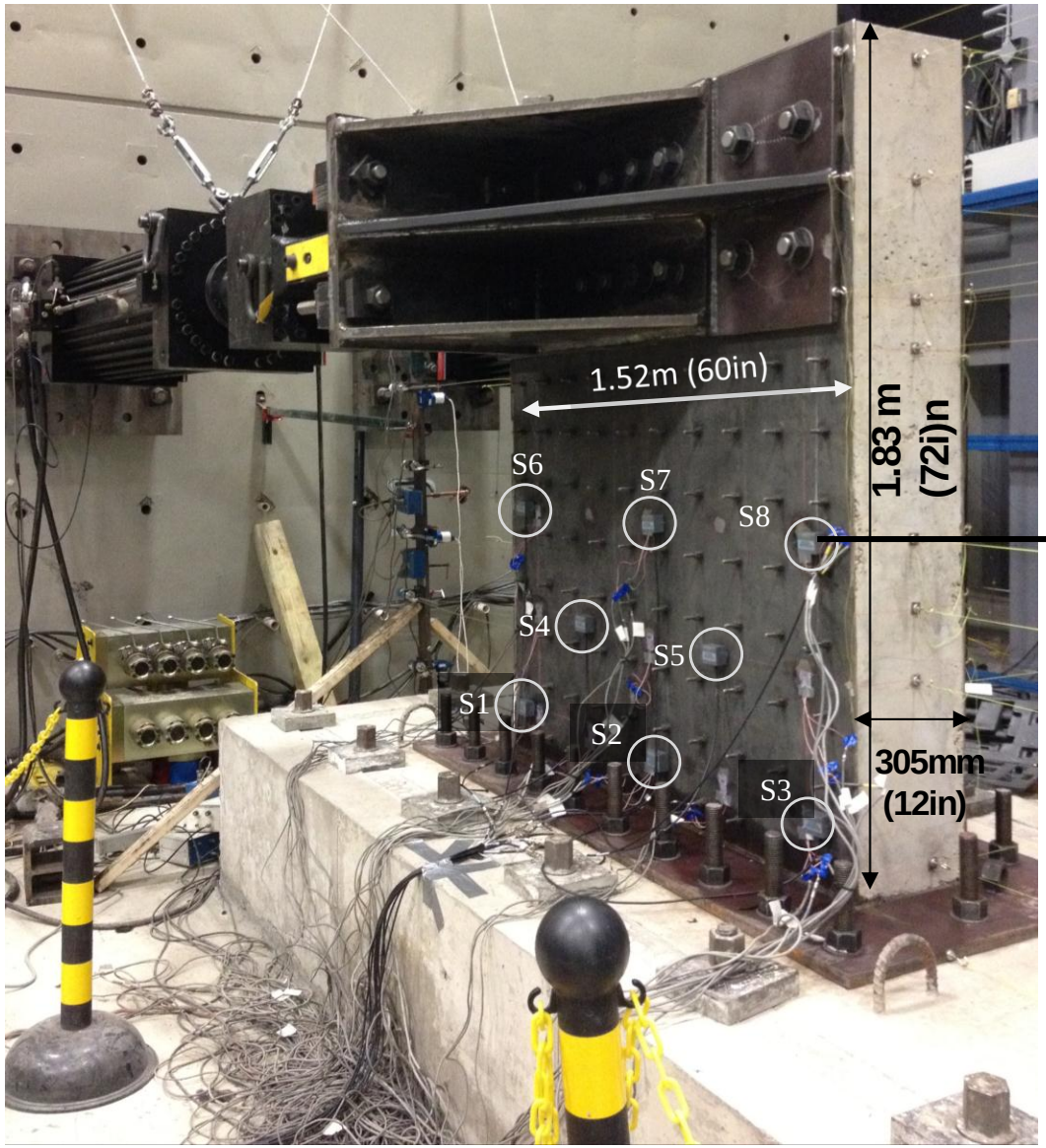
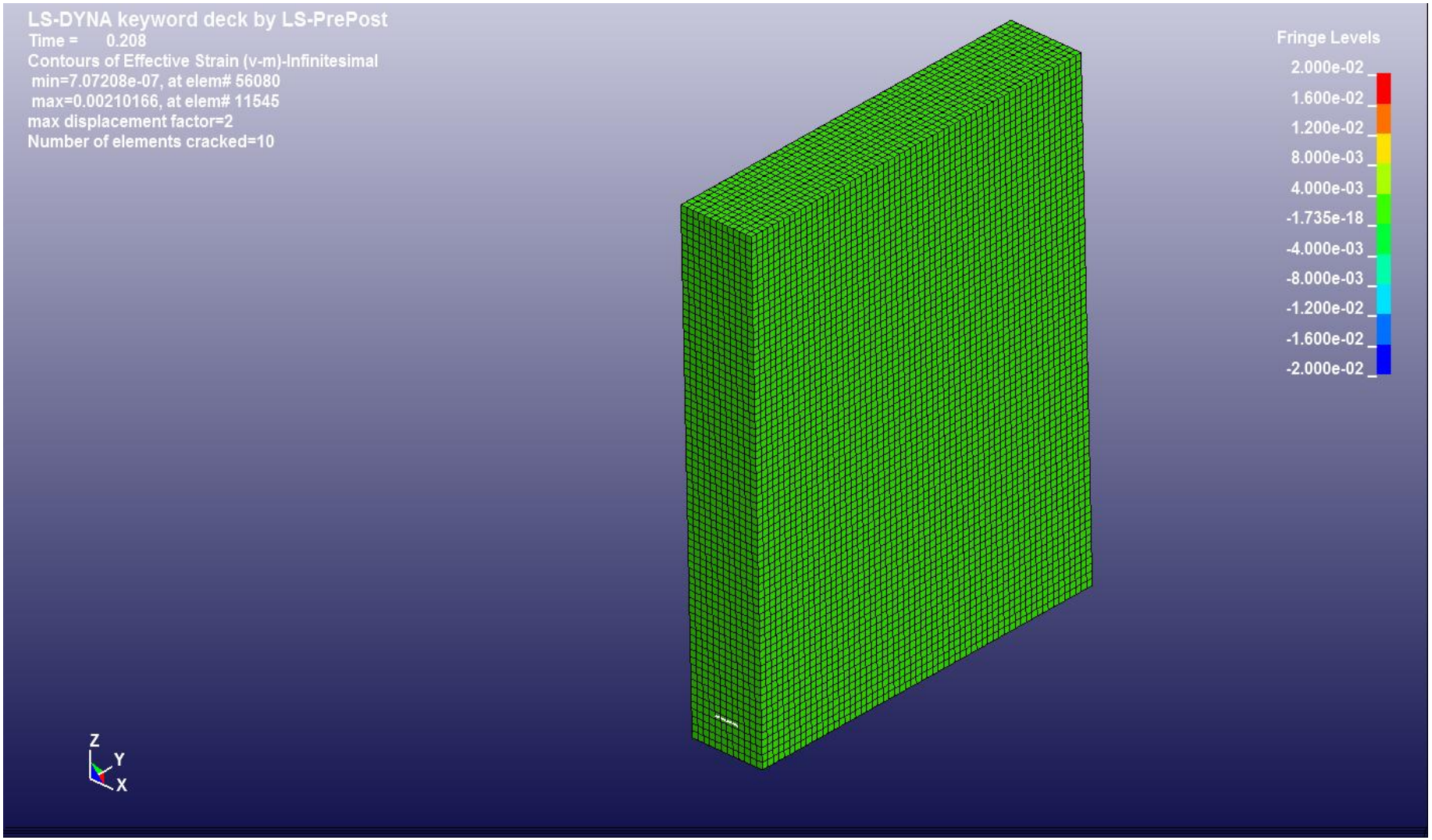


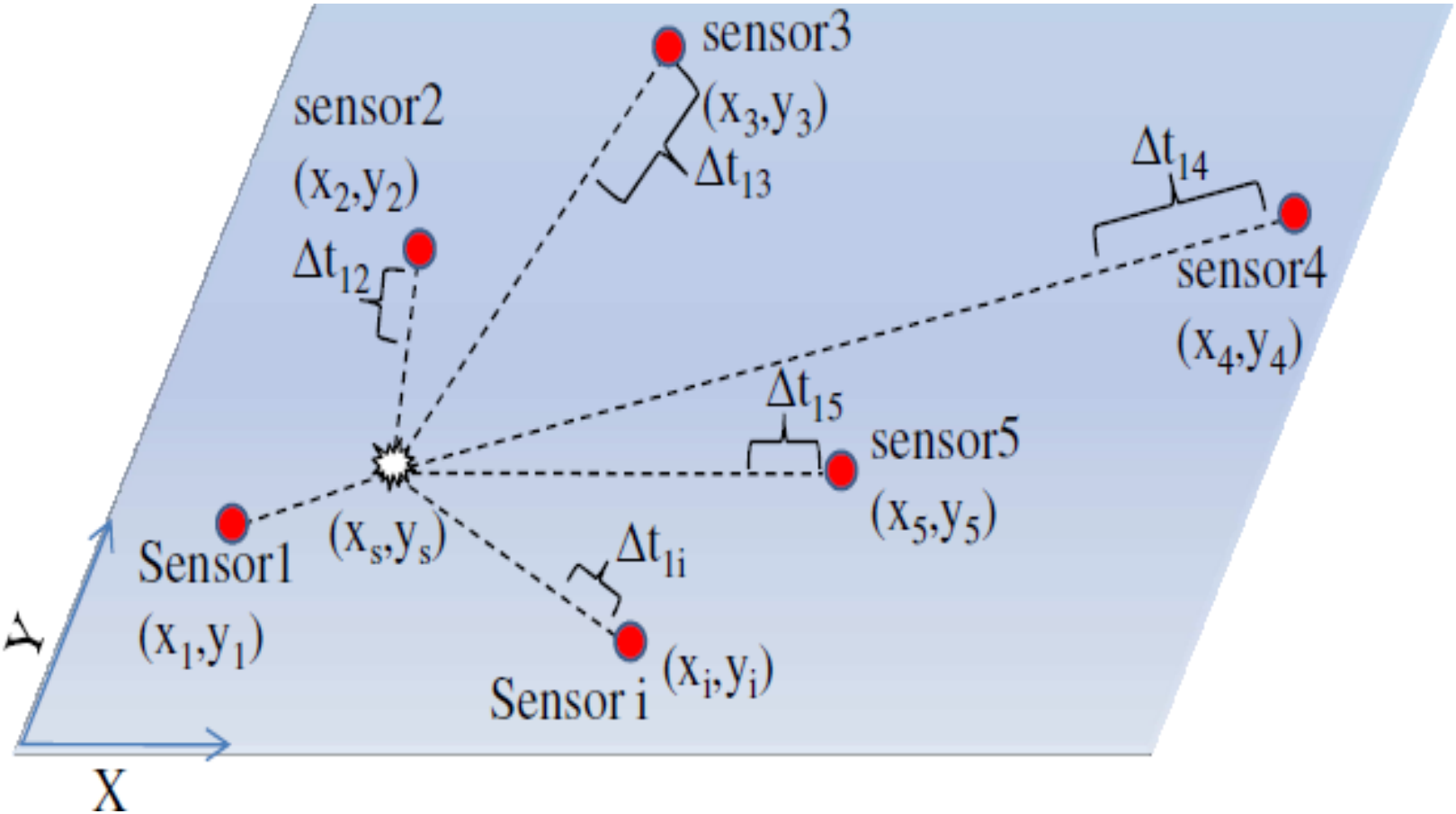
A. Farhidzadeh, S. Epackachi, S. Salamone, A. Whittaker, (2014), Bayesian Decision and Mixture Models for Multi-scale Damage Interrogation in Composite Shear Walls Using Acoustic Emission, to be submitted to an ASCE Journal

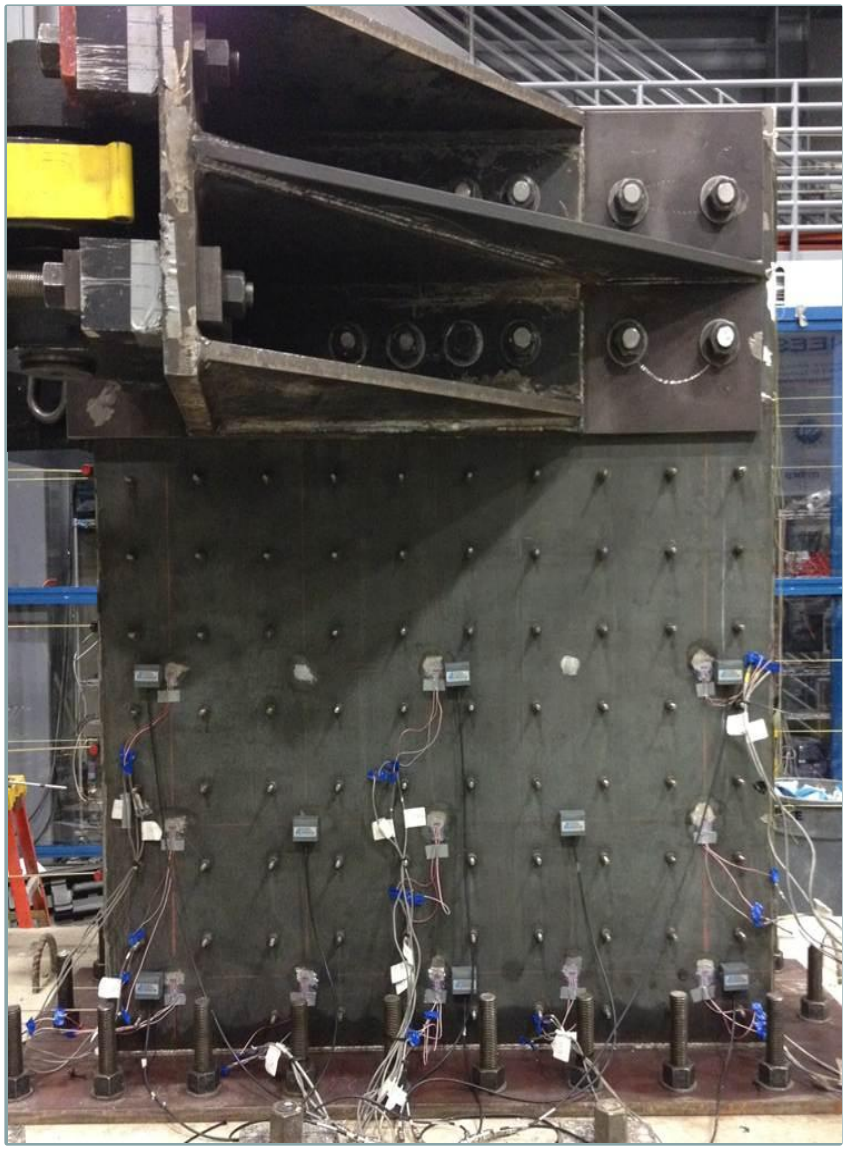
Numerical modeling of damage



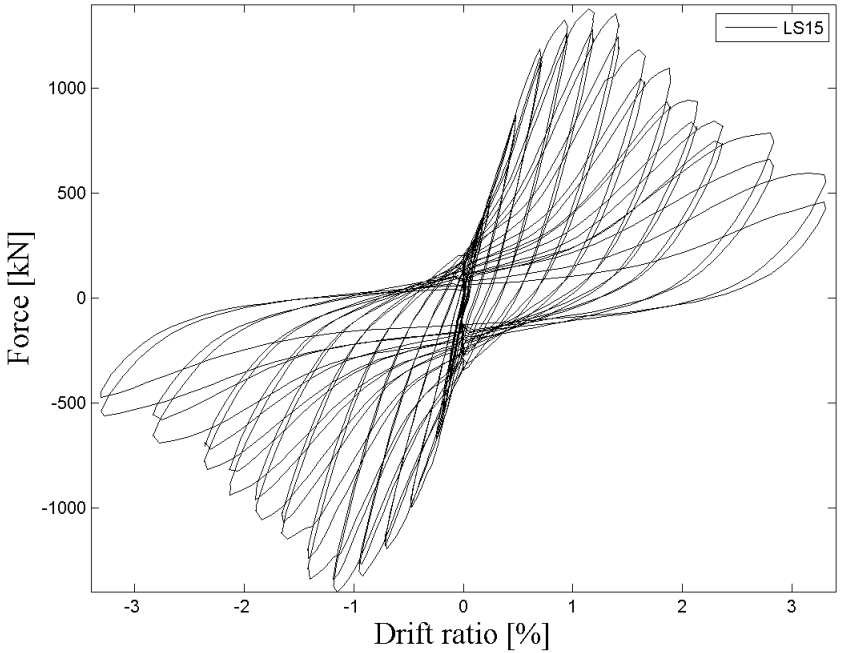
S. Epackachi (2014)

Damage localization using acoustic emission





Acoustic Imaging



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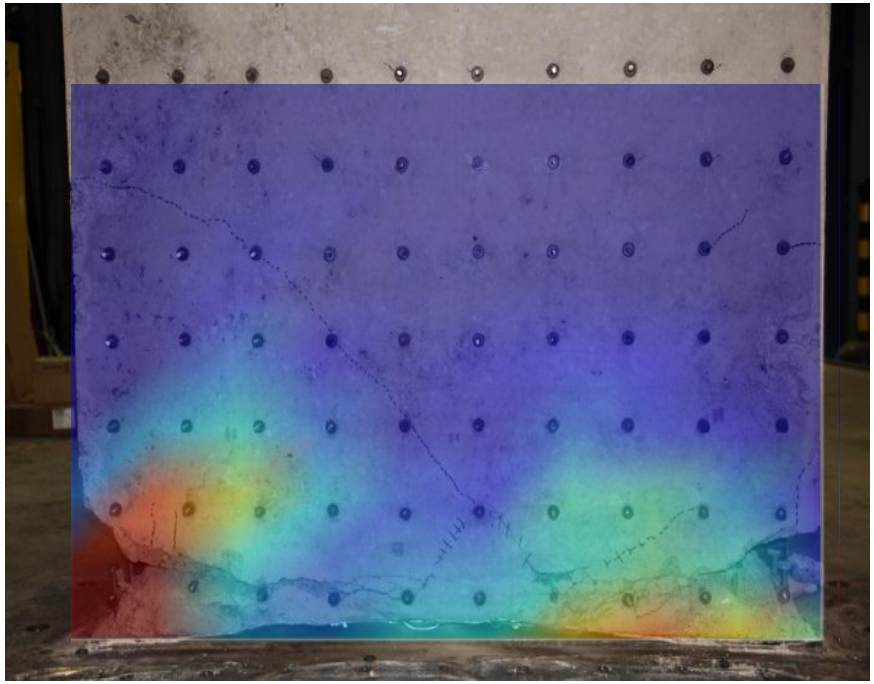

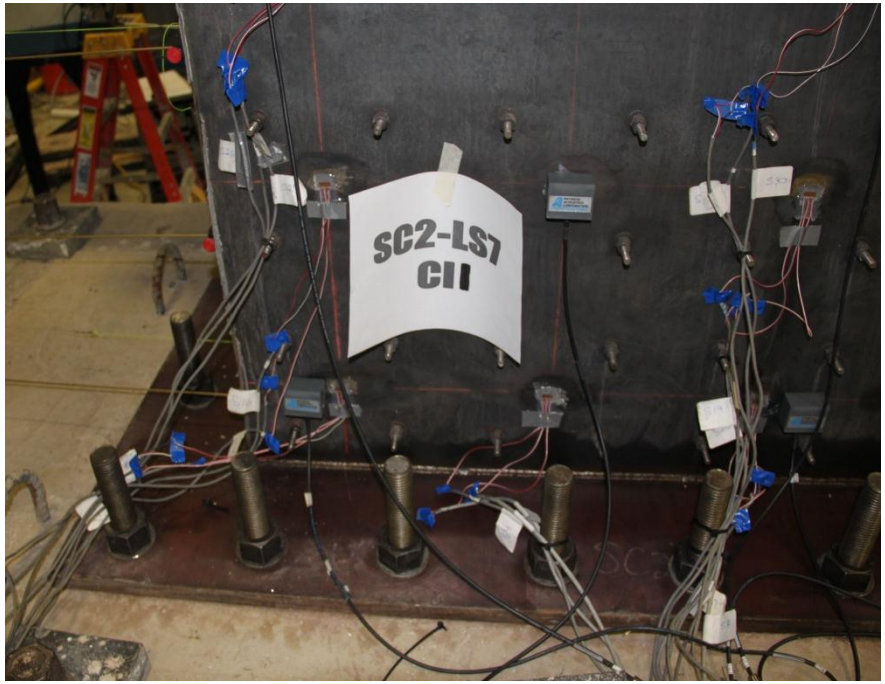

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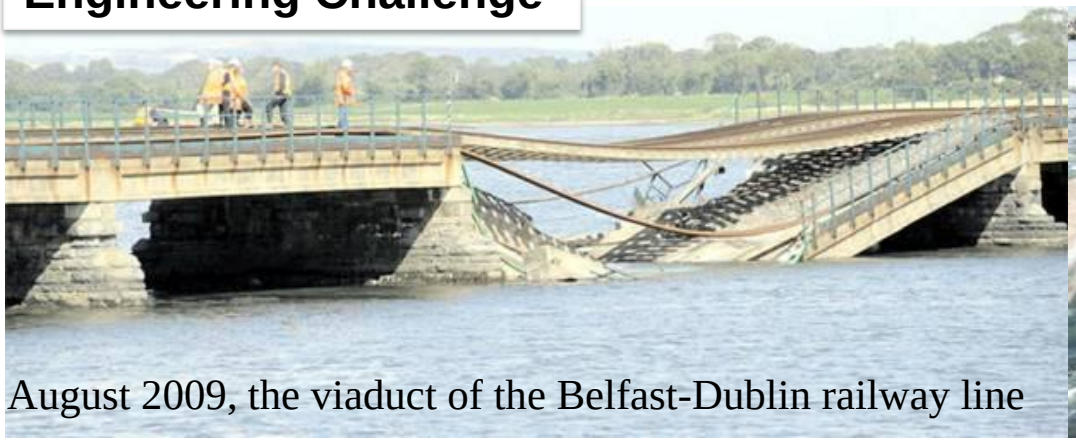
Overview:

1) Motivation
2) Reference-free corrosion diagnosis in prestressed steel strands using GUW
3) Acoustic emission monitoring of concrete shear walls
4) Advanced visual inspection through fractal analysis of crack patterns
5) Complementary projects
6) Conclusions

Engineering Challenge

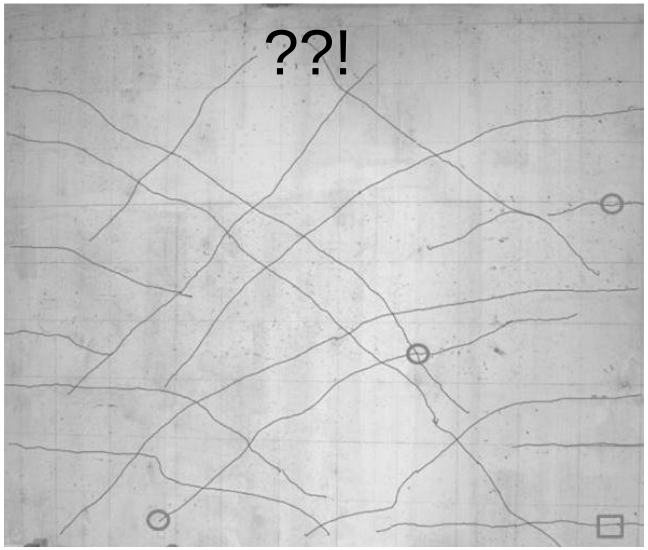


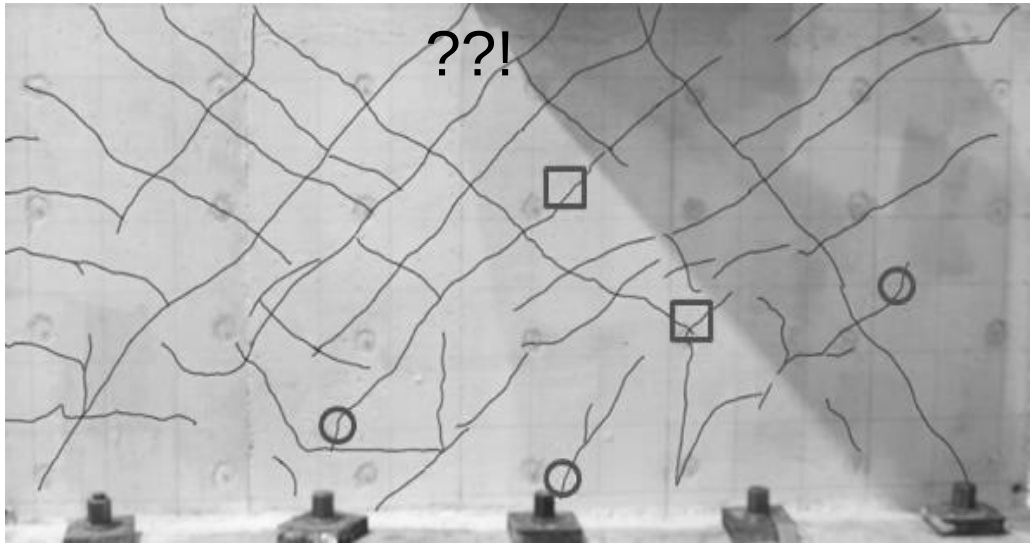
August 2009, the viaduct of the Belfast-Dublin railway line

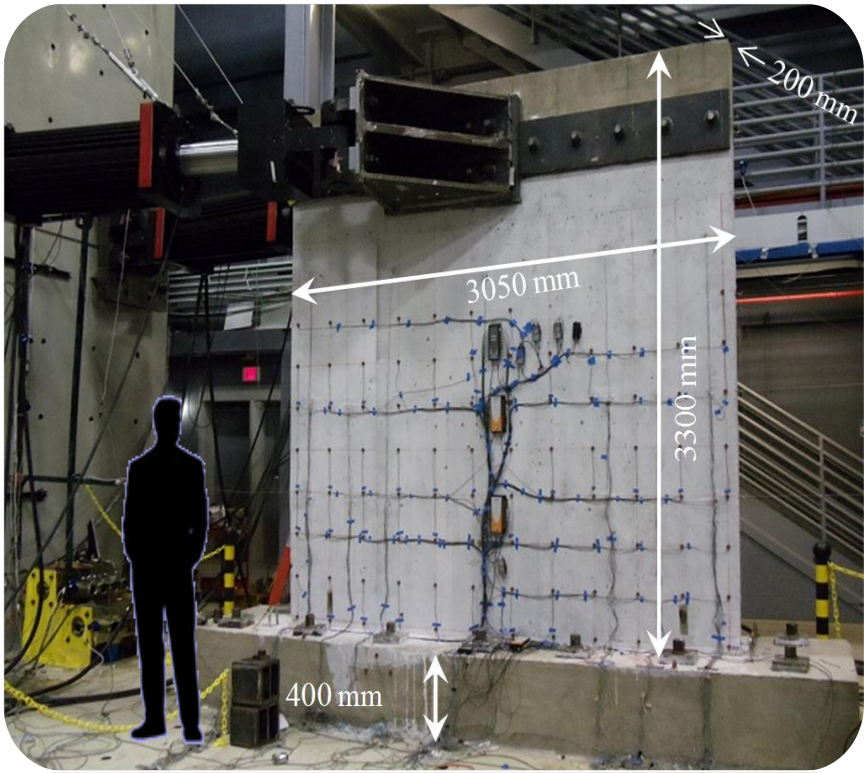
1st EQ:
Sep 2010, M=7.1

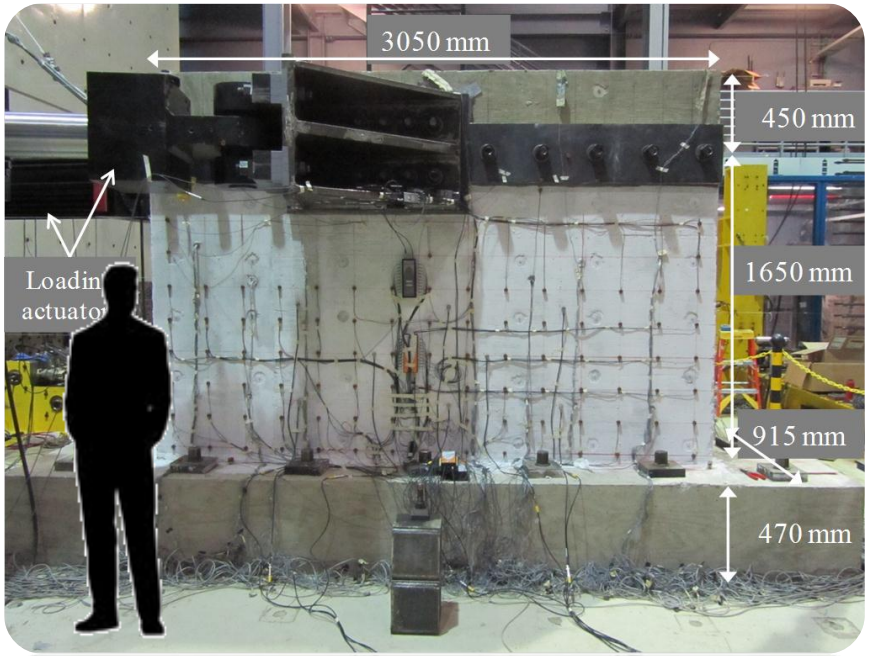
2nd EQ:
Feb 2011, M=6.3

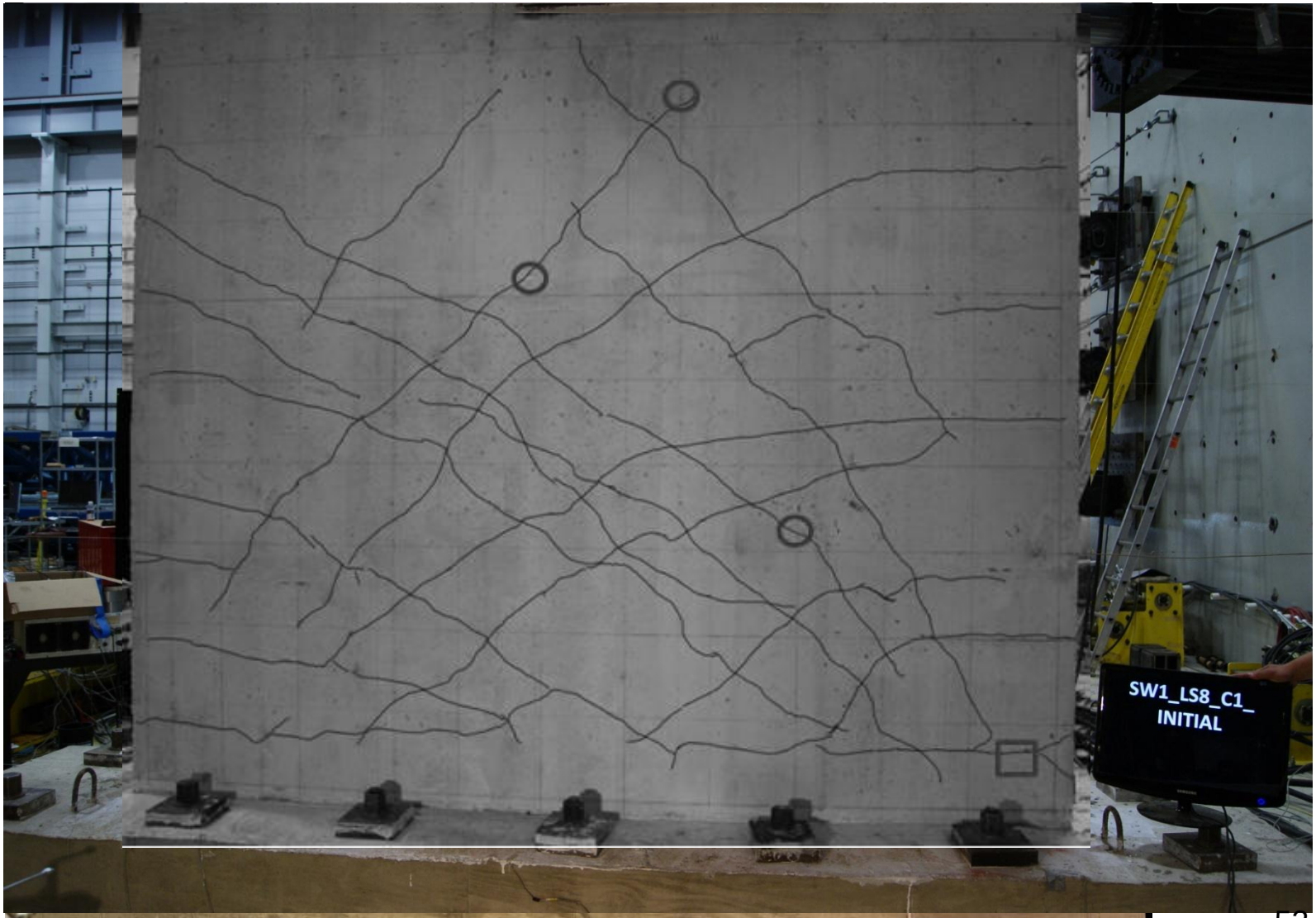
Canterbury television building, Christchurch, New Zealand 2011

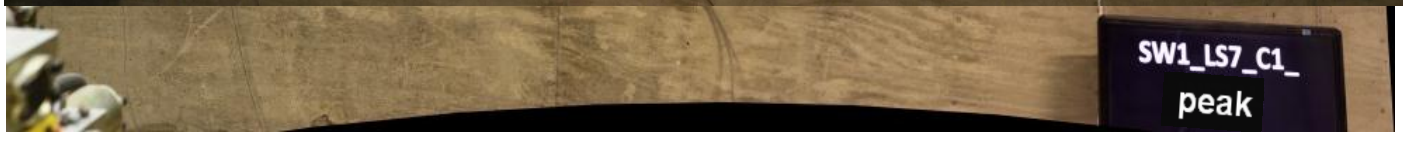





200 mm
3050 mm
3300 mm
400 mm

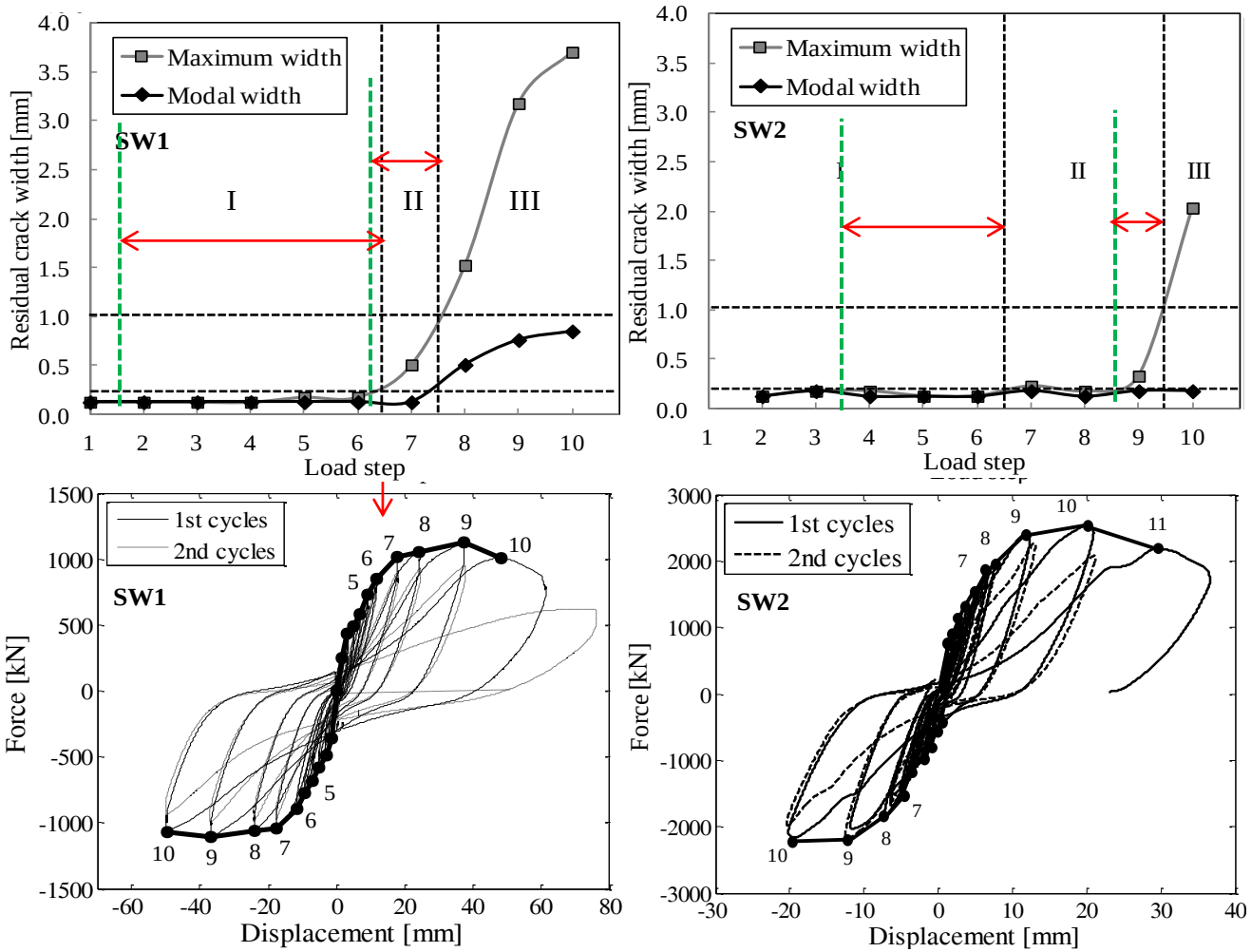

3050 mm
450 mm
1650 mm
915 mm
470 mm


SW1_LS8_C1_
INITIAL


SW1_LS7_C1_
peak

Damage grade assessment based on International Atomic Energy Agency guidebook (IAEA)

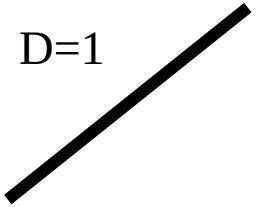
	<0.2 mm	Hairline, Non-structural	slight	No
	0.2 mm~1.0 mm	Medium, structural	moderate	Yes
	>1.0 mm	Wide, structural	Critical	Yes



A. Farhidzadeh, et al (2013), Damage assessment of reinforced concrete structures using fractal analysis of residual crack patterns, *Experimental Mechanics*, 53(2):1607–1619.

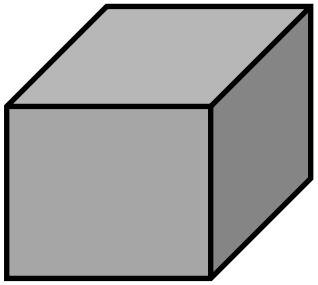
Euclidean dimension

D=1

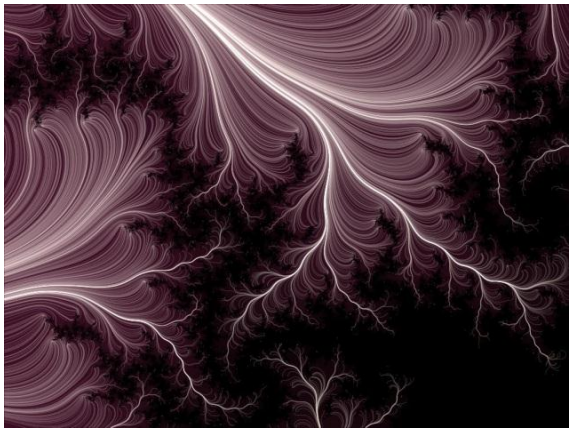


D=2

D=3



The term "Fractal" was first introduced by Mandelbrot in 1975 to indicate objects whose complex geometry cannot be characterized by an integer dimension.



Electrical Flow

Tree branches

Romanesque broccoli

A fractal dimension is a ratio providing a statistical index of complexity comparing how detail in a pattern changes with the scale at which it is measured.

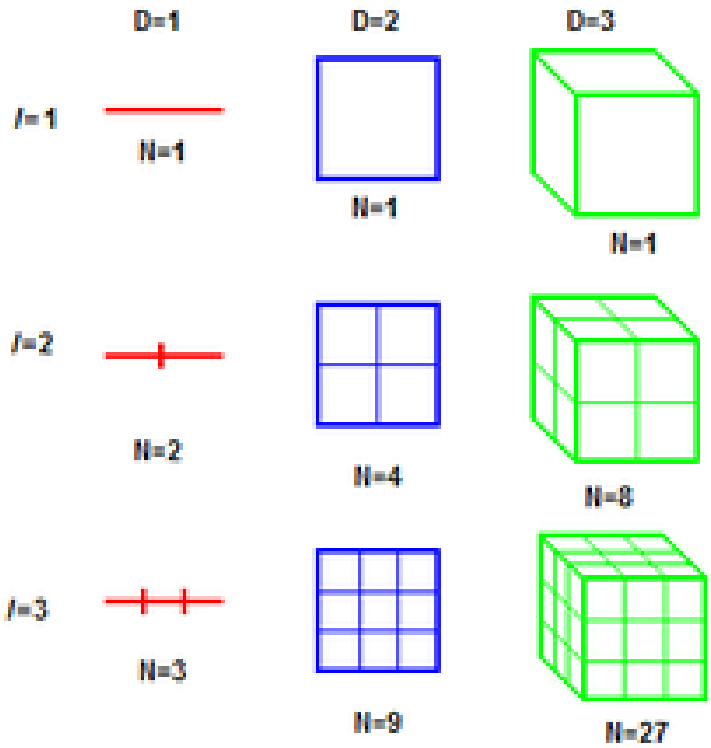
Intuitive example for understanding Fractal dimension:

$$N \propto \epsilon^{-D}$$

N: the number of new sticks

ϵ: scaling factor

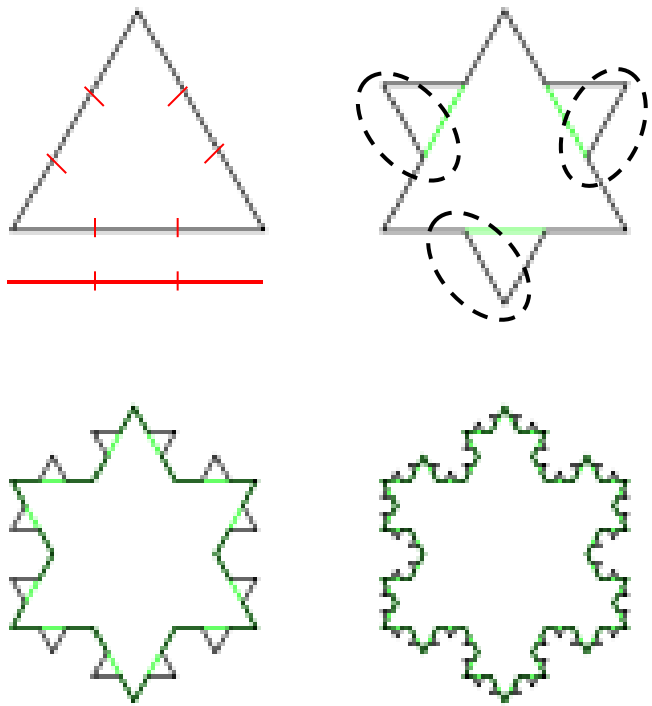
D: Fractal dimension



$1=1^{-1}$

$2=(1/2)^{-1}$

$3=(1/3)^{-1}$



N=3+3×1/3=4

ϵ =1/3

$$N = \epsilon^{-D}$$

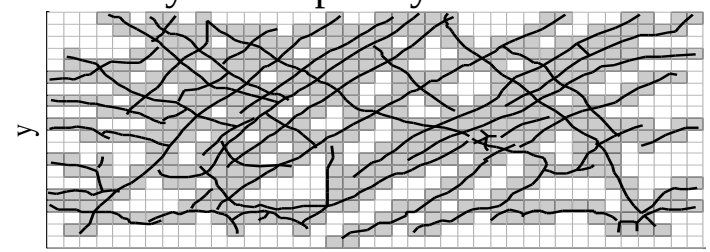
$$\log_\epsilon N = -D = \log \frac{N}{\log \epsilon}$$

$$D = 1.2619$$

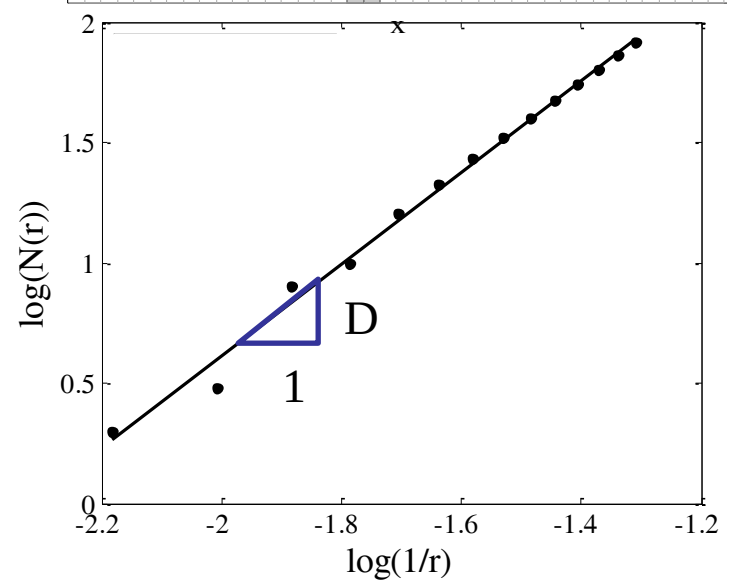
The first four iterations of the Koch snowflake

Box counting algorithm:

The object is covered with a collection of square boxes, and the number of elements of a given size *r* is counted to see how many of them are necessary to completely cover the object *N(r)*.



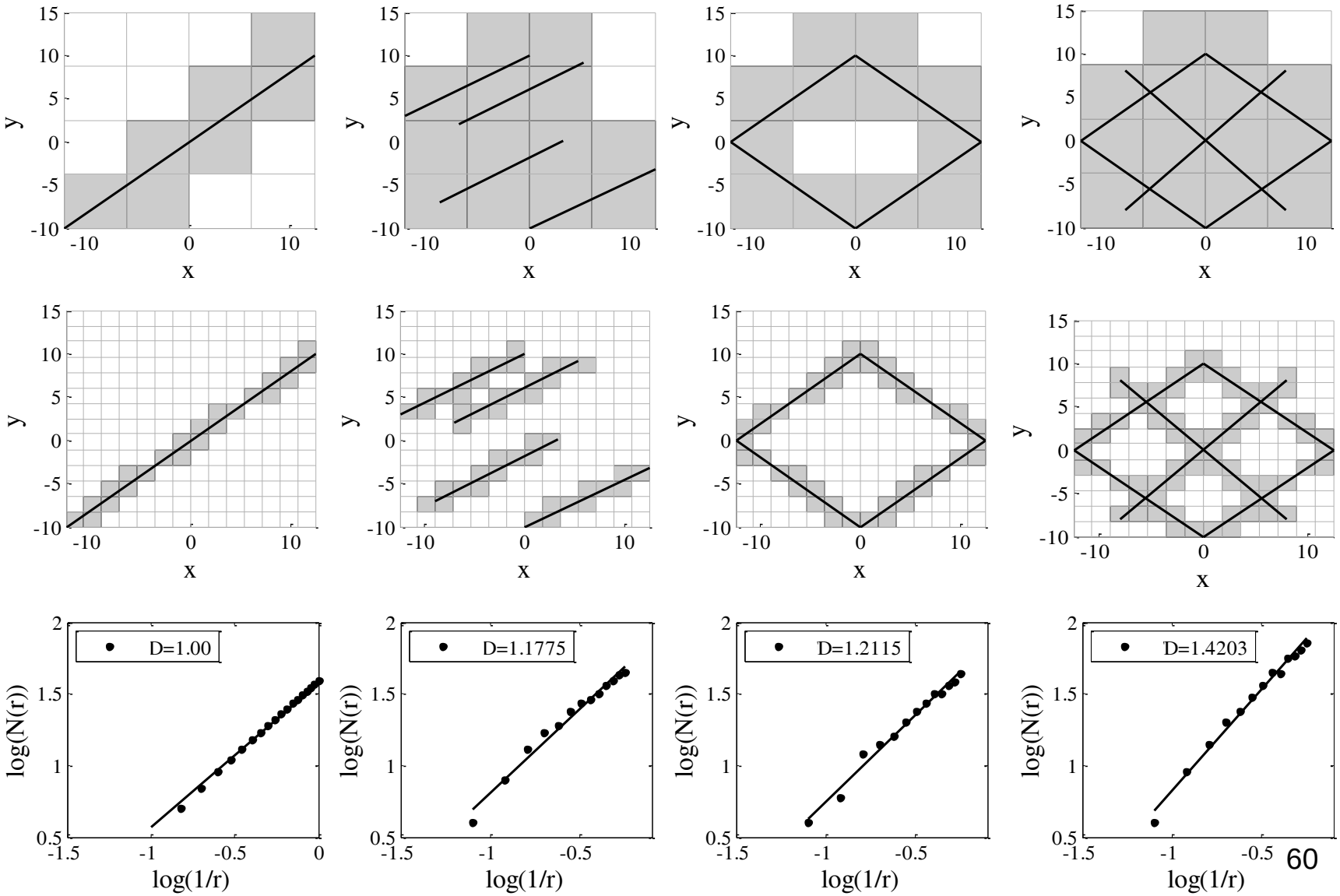
$$D = \lim_{r \to 0} \left(\frac{\log N(r)}{\log(1/r)} \right)$$



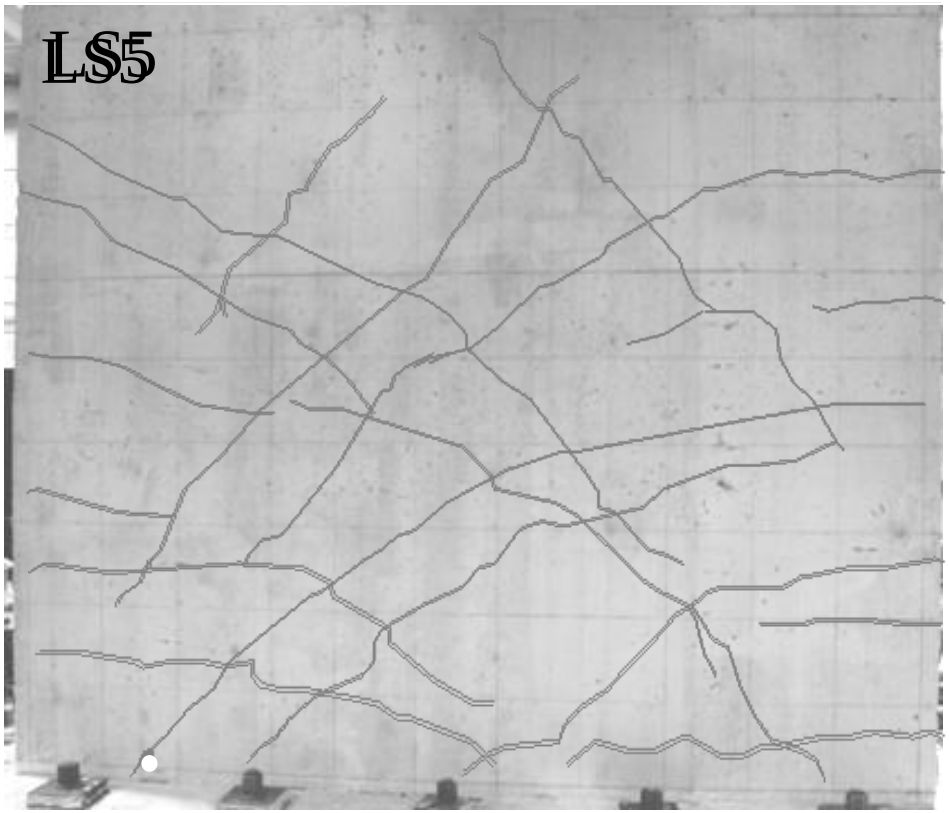
Estimation of D:

$$\log(N(r)) = D \log(1/r) + C$$

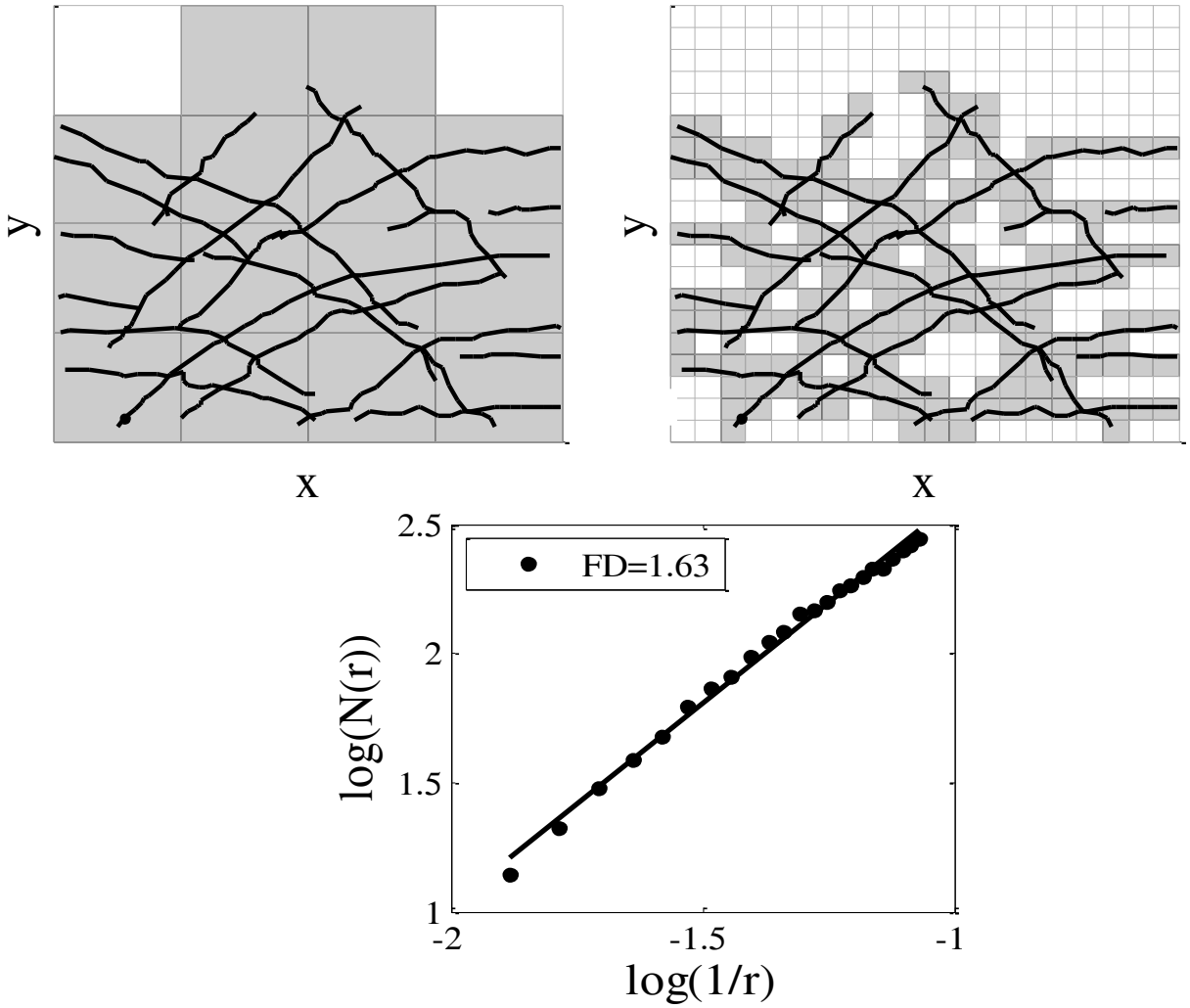
A. Farhidzadeh, et al. (2013), Damage assessment of reinforced concrete structures using fractal analysis of residual crack patterns, *Experimental Mechanics*, 53(2):1607–1619.



A. Farhidzadeh, et al. (2013), Damage assessment of reinforced concrete structures using fractal analysis of residual crack patterns, *Experimental Mechanics*, 53(2):1607–1619.



A. Farhidzadeh, et al. (2013), Damage assessment of reinforced concrete structures using fractal analysis of residual crack patterns, *Experimental Mechanics*, 53(2):1607–1619.



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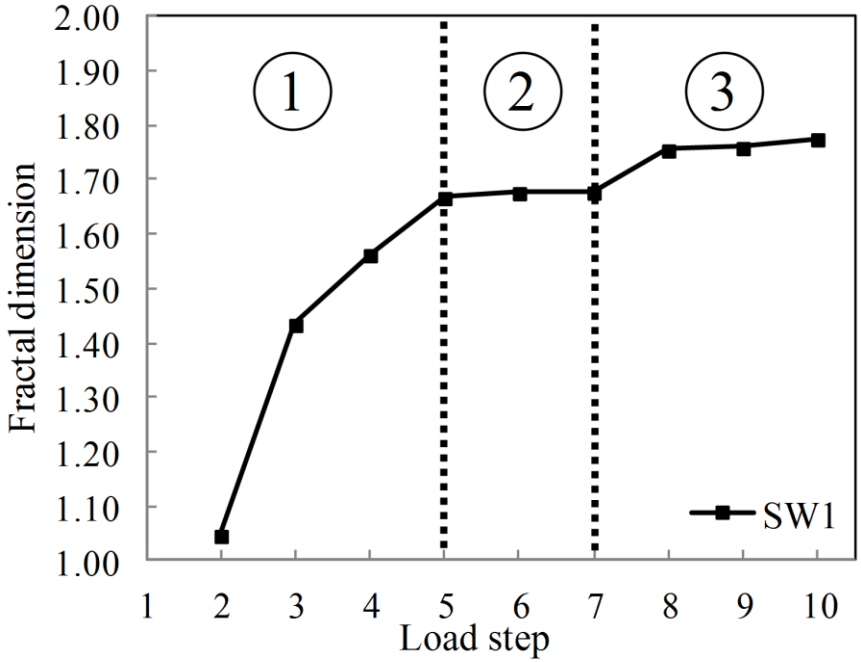
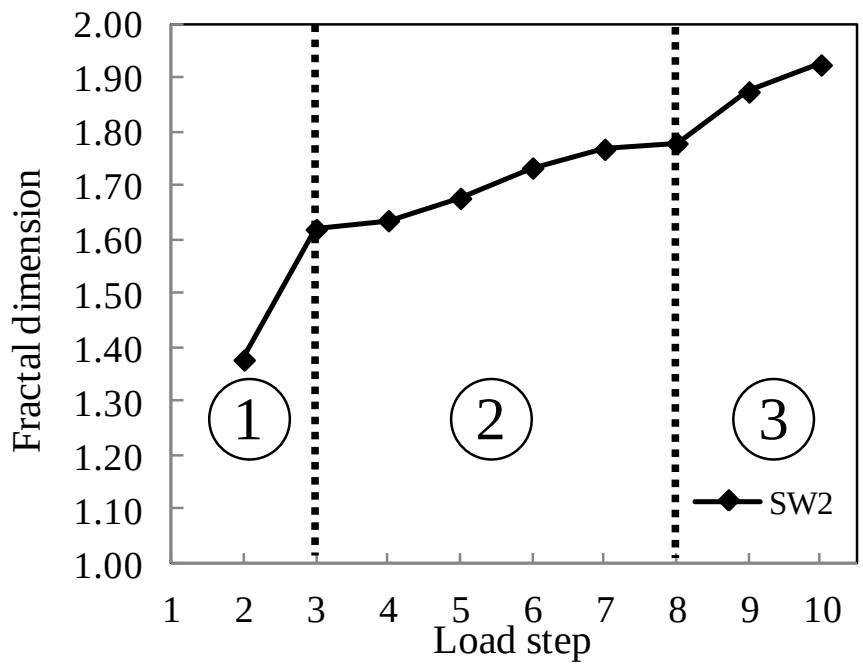


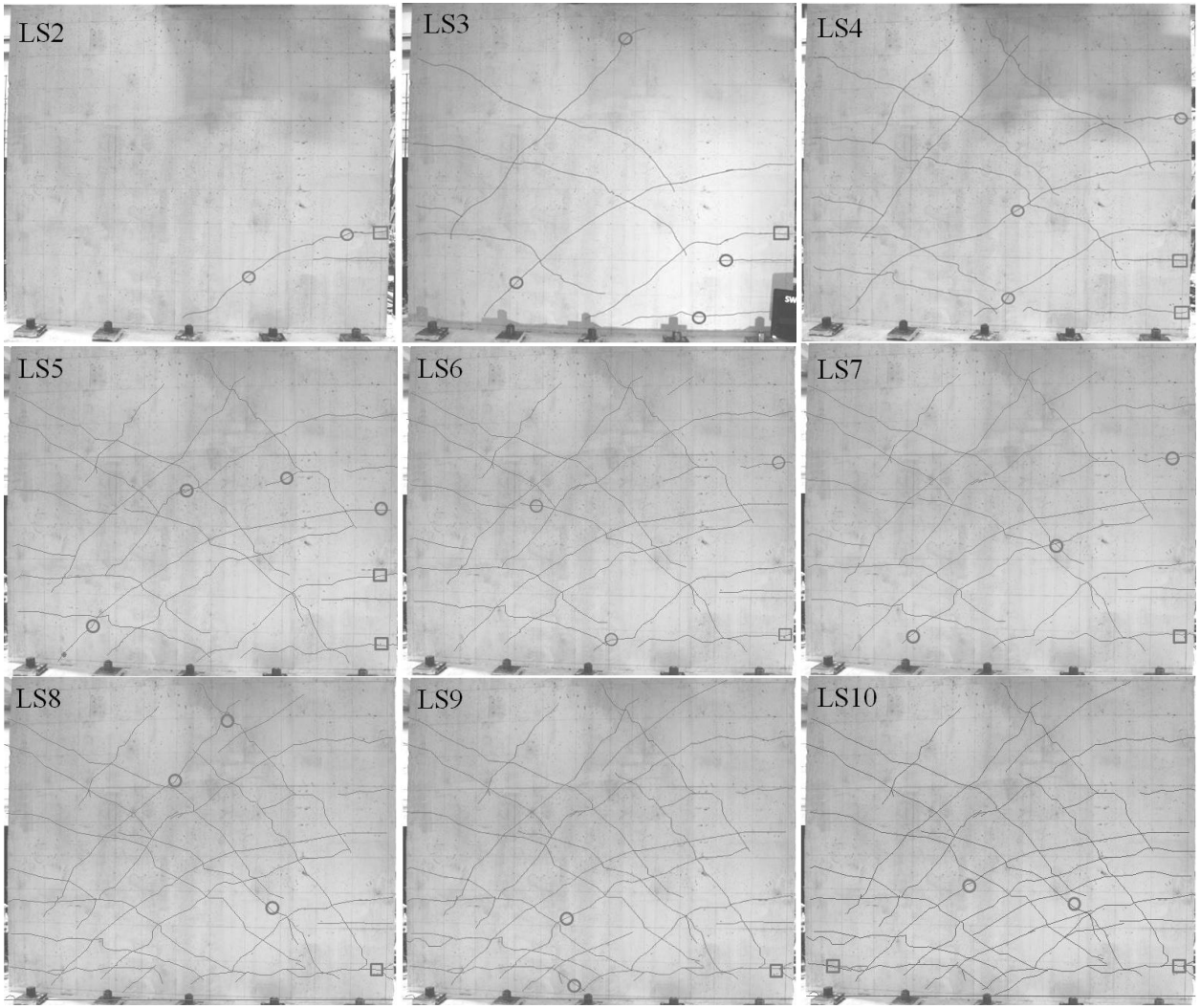


Three distinct regions can be identified:

1) An initial region of sharp increase in the fractal dimension
2) The middle region that forms a plateau of slowly evolving changes
3) The final region that shows a further increase in the fractal dimension.

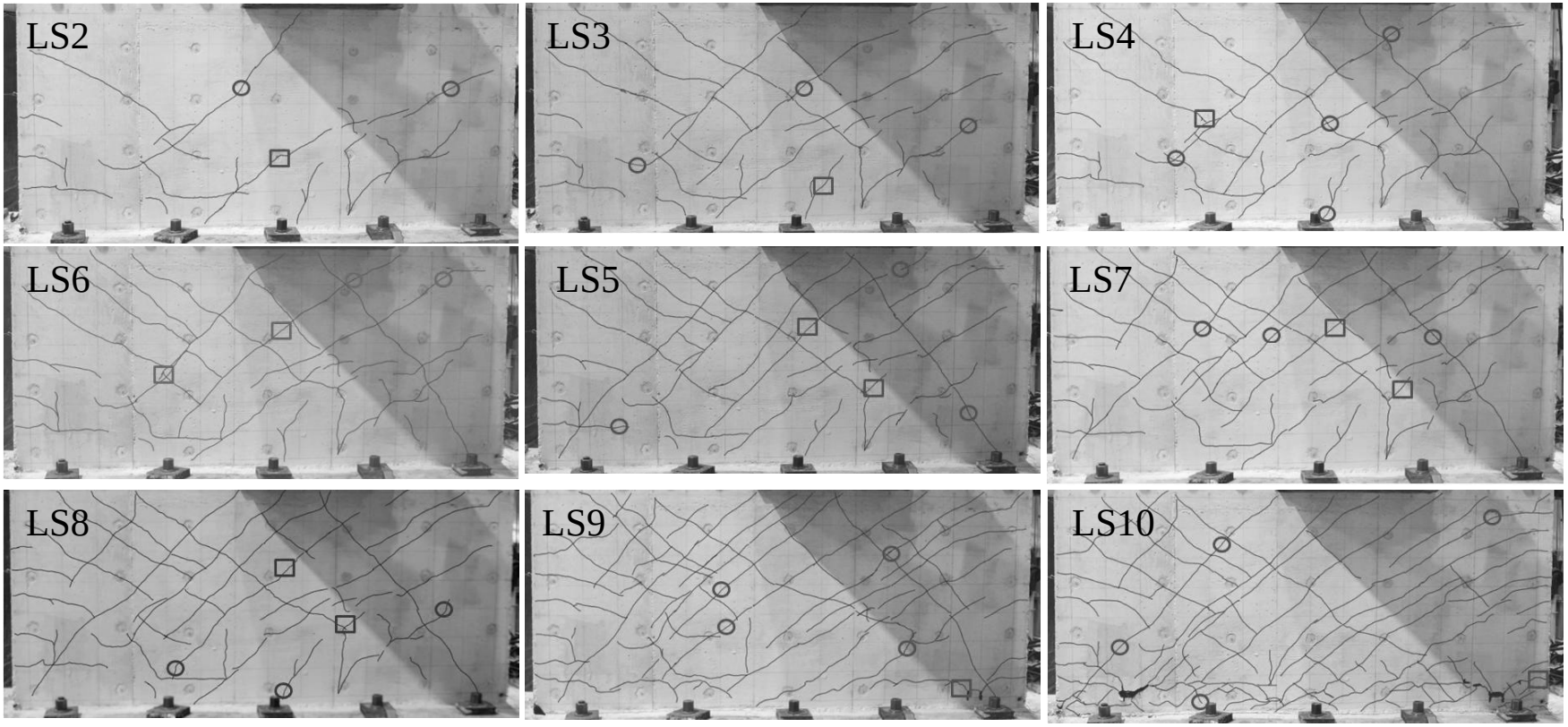
A. Farhidzadeh, et al. (2013), Damage assessment of reinforced concrete structures using fractal analysis of residual crack patterns, *Experimental Mechanics*, 53(2):1607–1619.

SW1



A. Farhidzadeh, et al. (2013), Damage assessment of reinforced concrete structures using fractal analysis of residual crack patterns, *Experimental Mechanics*, 53(2):1607–1619.

SW2



A. Farhidzadeh, et al. (2013), Damage assessment of reinforced concrete structures using fractal analysis of residual crack patterns, *Experimental Mechanics*, 53(2):1607–1619.

Damage Index:

$$DI = \frac{D_i - D_1}{2 - D_1}, \; 0 \le DI < 1$$

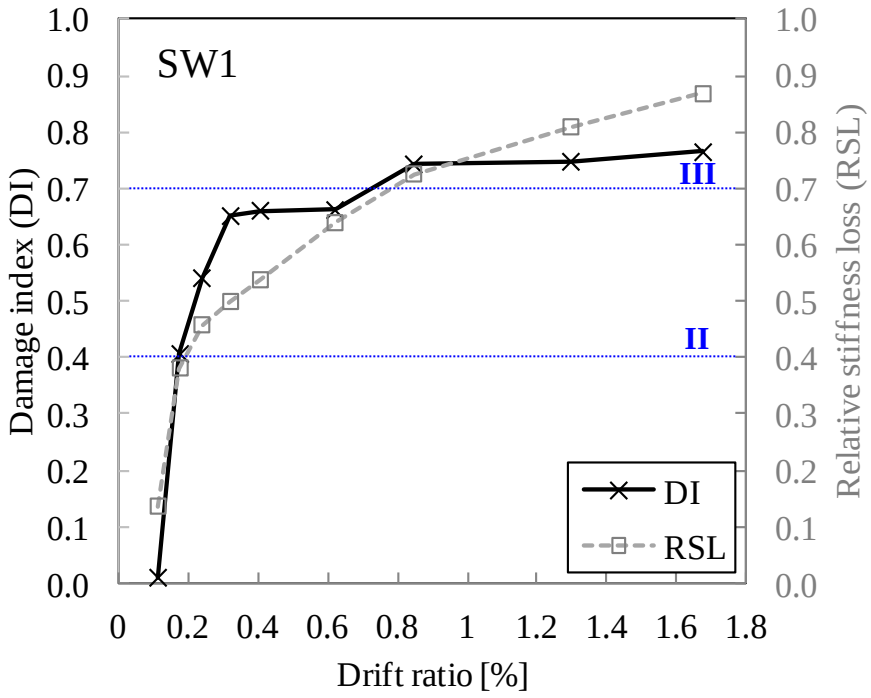
D_i : the fractal dimension of the current status of visible cracks, (e.g., in the ith inspection);
D_1 is the base line fractal dimension (fractal dimension of the first time cracks become visible)

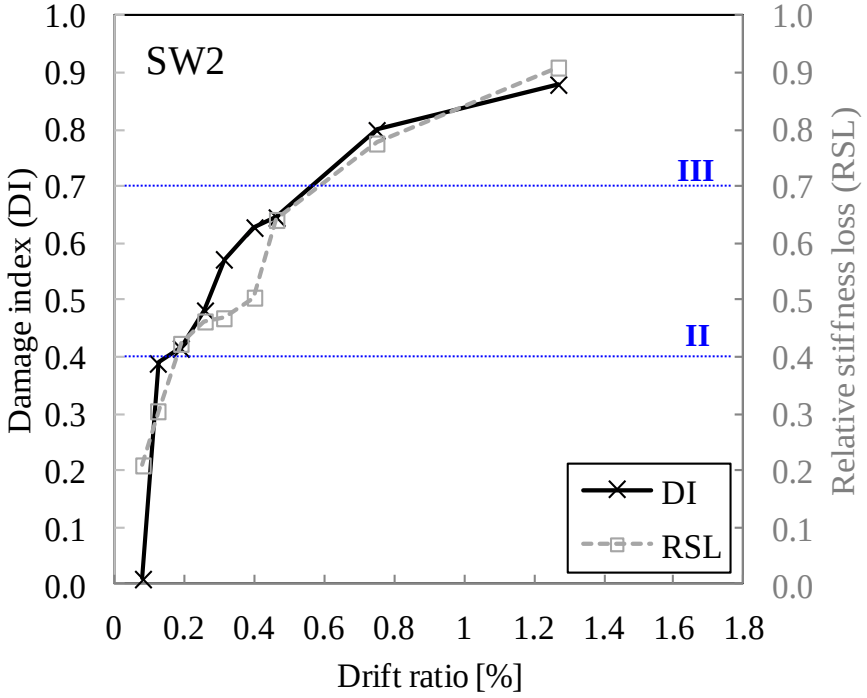
Relative Stiffness Loss (RSL) :

$$RSL = 1 - \frac{K_i}{K_1}$$

K_i is the lateral secant stiffness of the wall at the ith load step K_1 is the initial stiffness of the wall

A. Farhidzadeh, et al. (2013), Damage assessment of reinforced concrete structures using fractal analysis of residual crack patterns, *Experimental Mechanics*, 53(2):1607–1619.





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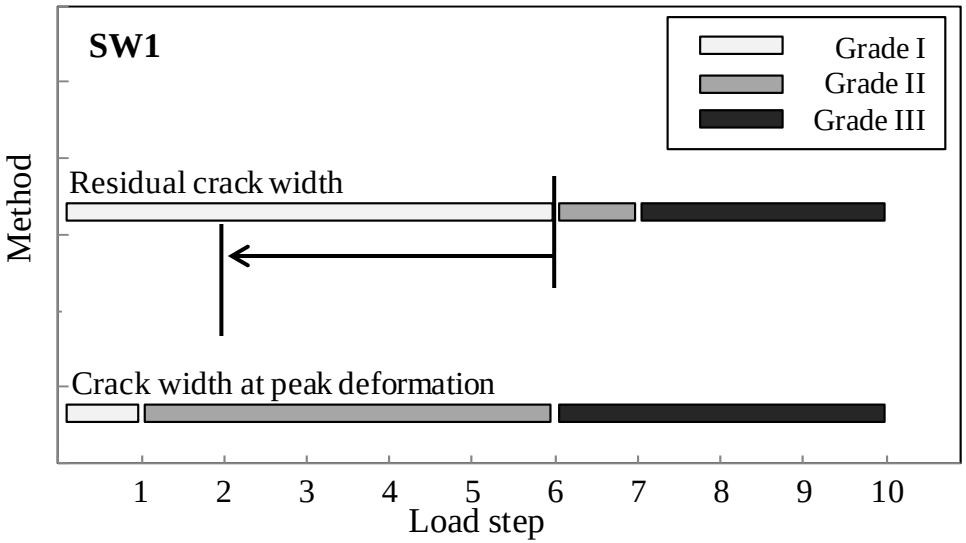
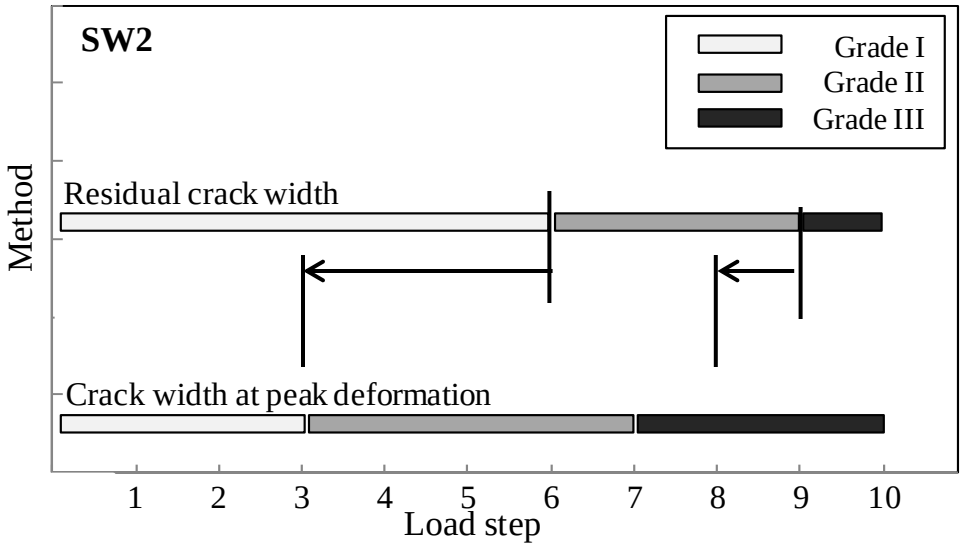


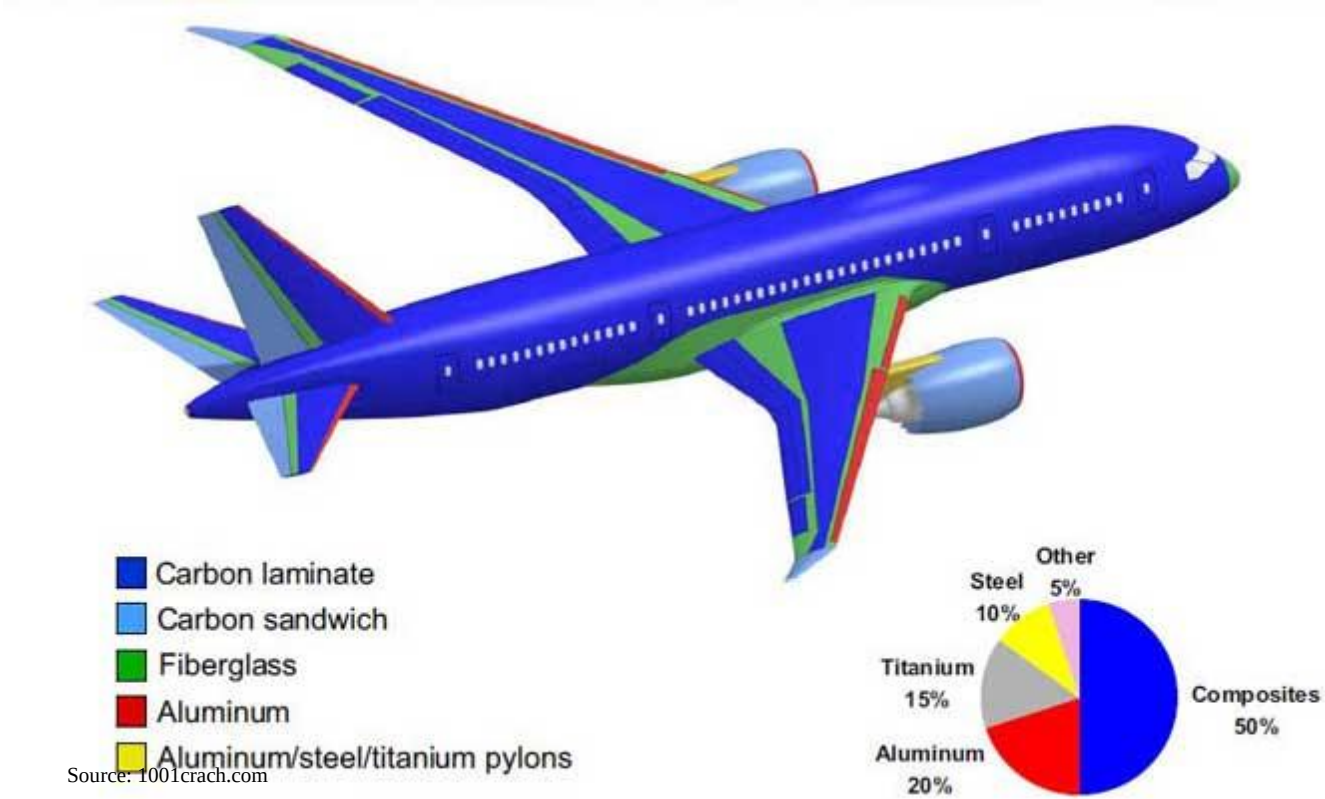


A. Farhidzadeh, et al. (2013), Damage assessment of reinforced concrete structures using fractal analysis of residual crack patterns, *Experimental Mechanics*, 53(2):1607–1619.

Overview:

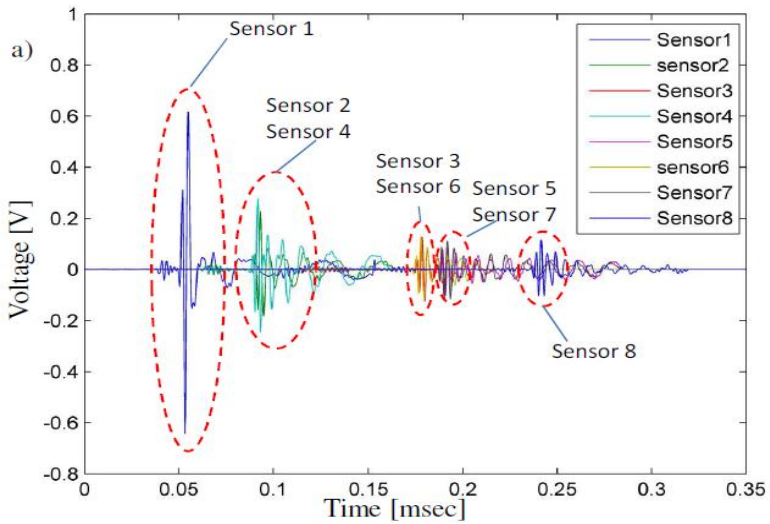
1) Motivation
2) Reference-free corrosion diagnosis in prestressed steel strands using GUW
3) Acoustic emission monitoring of concrete shear walls
4) Advanced visual inspection through fractal analysis of crack patterns
5) Complementary projects
6) Conclusions

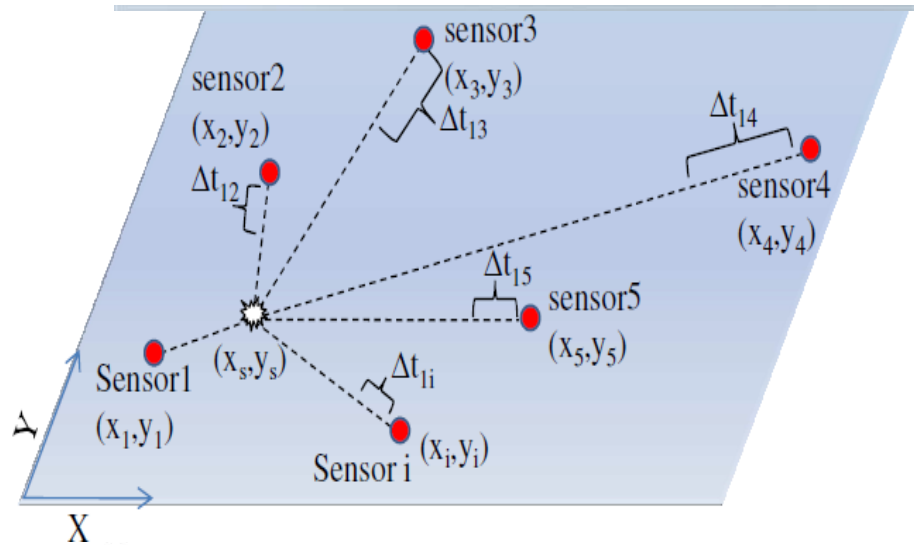
Impact and damage localization in composite panels

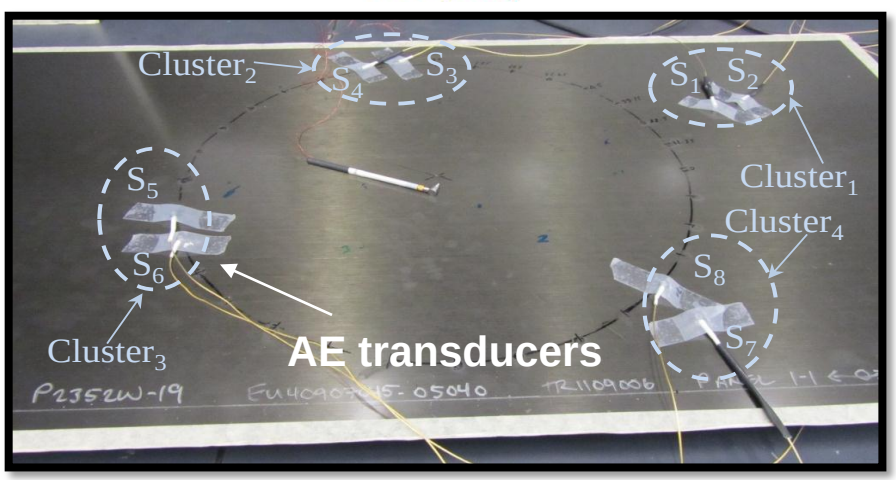


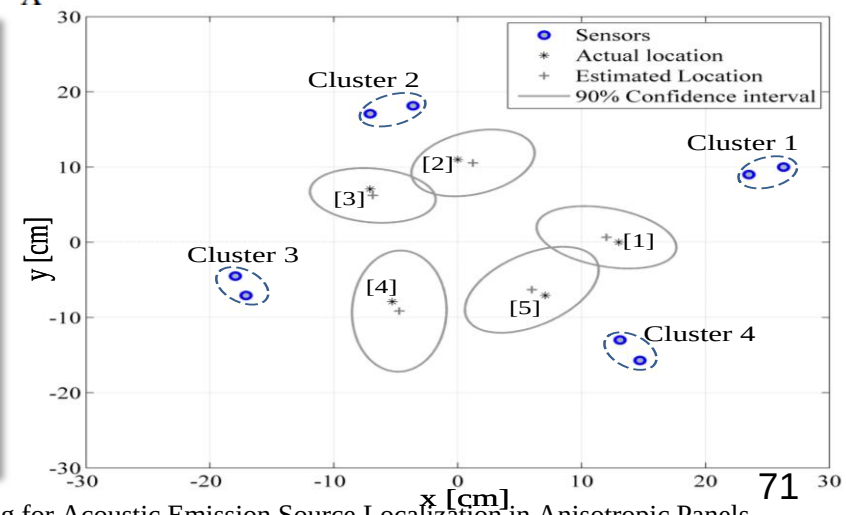
Source: 1001crach.com

Impact and damage localization in composite panels





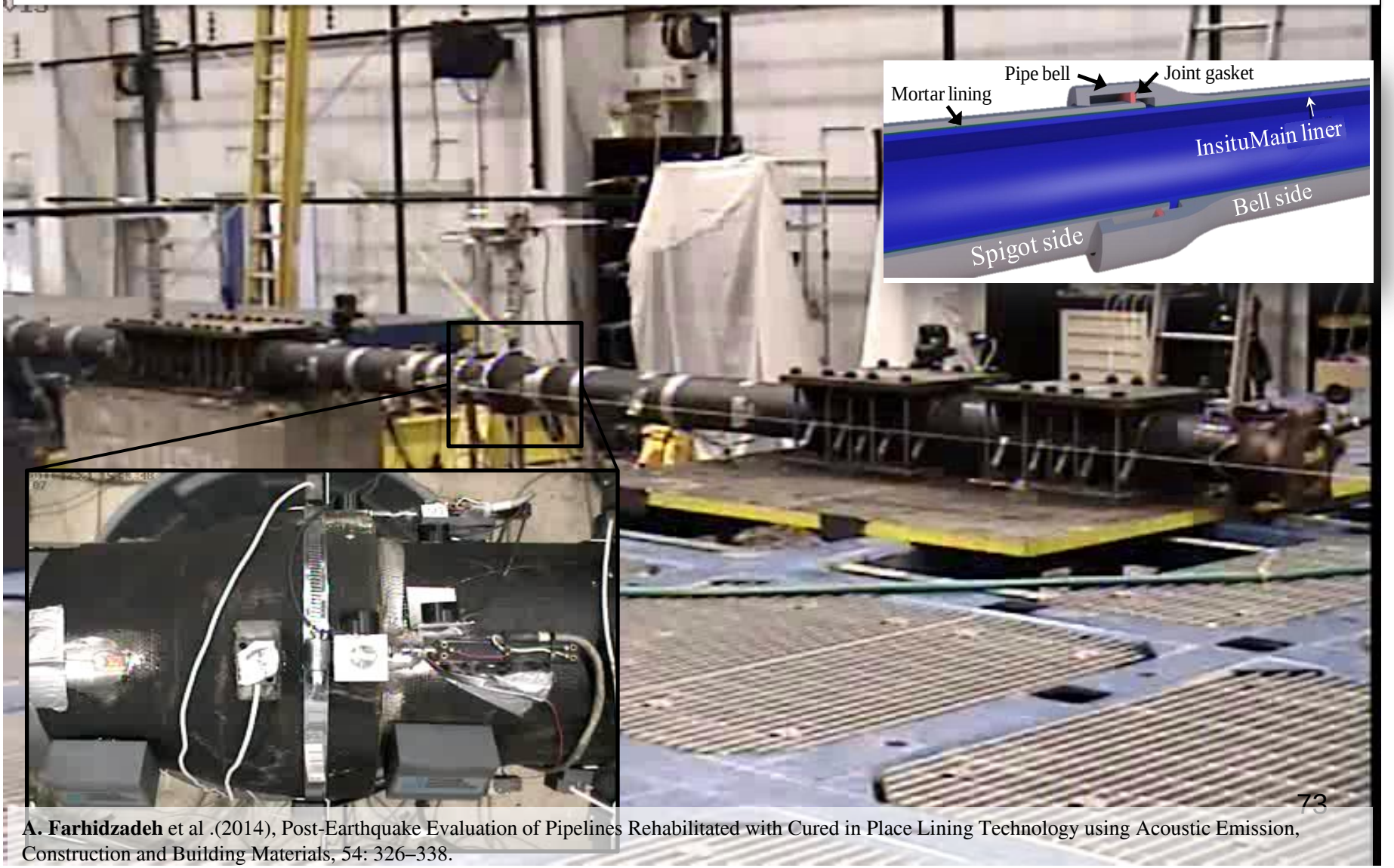




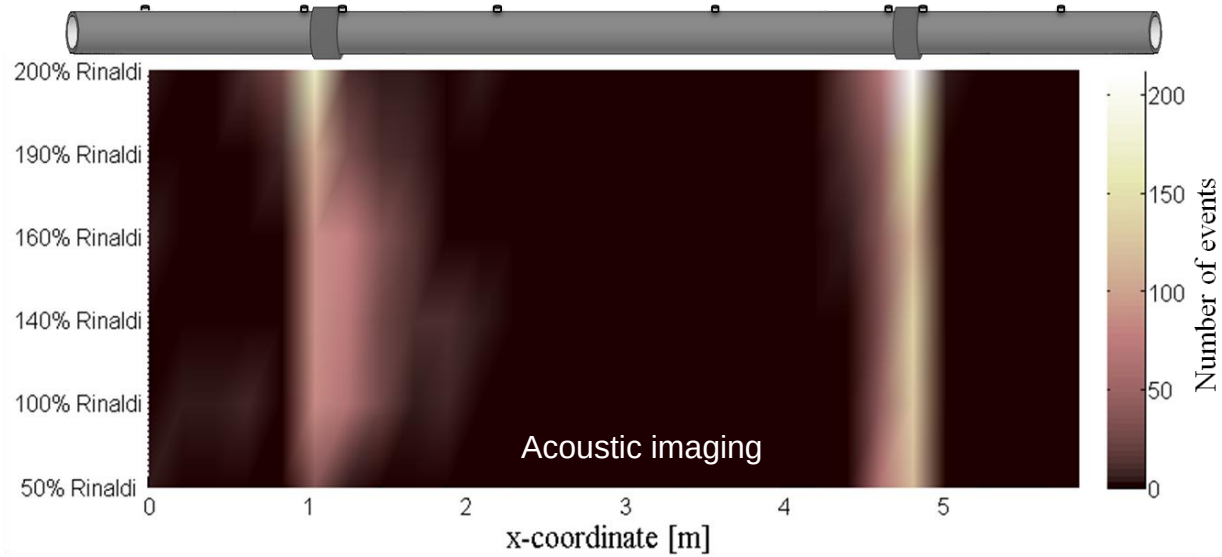
E. Dehghan-Niri, **A. Farhidzadeh**, S. Salamone, (2013), Nonlinear Kalman Filtering for Acoustic Emission Source Localization in Anisotropic Panels, Ultrasonics, 54 (2): 486–501.

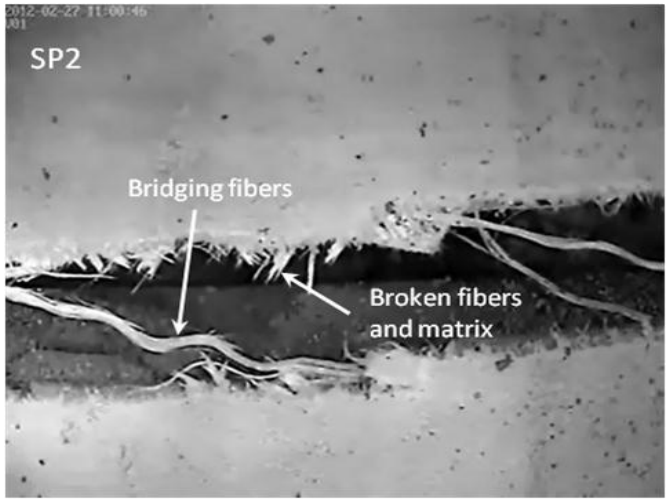
Wind turbine impact localization and damage monitoring

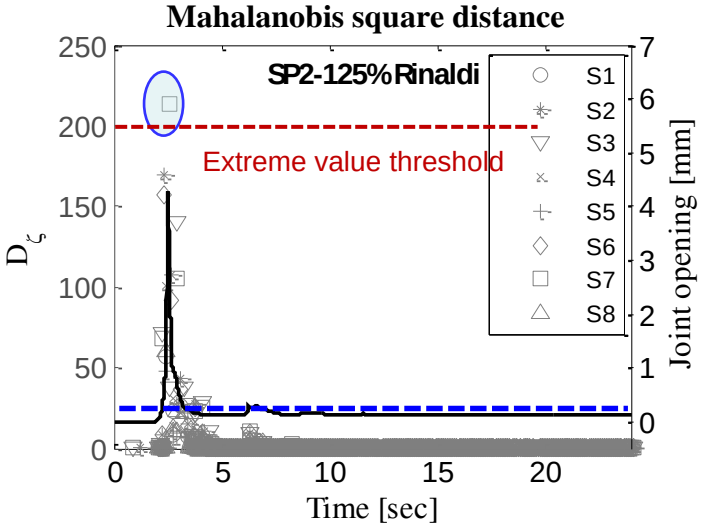
Post-earthquake evaluation of pipelines



A. Farhidzadeh et al .(2014), Post-Earthquake Evaluation of Pipelines Rehabilitated with Cured in Place Lining Technology using Acoustic Emission, Construction and Building Materials, 54: 326–338.

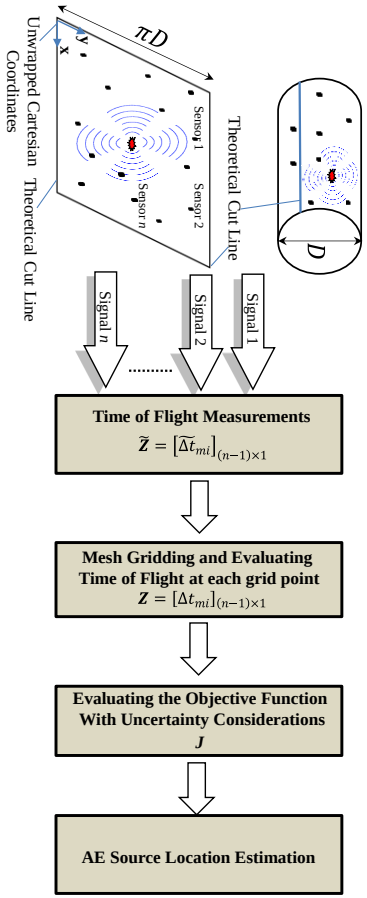


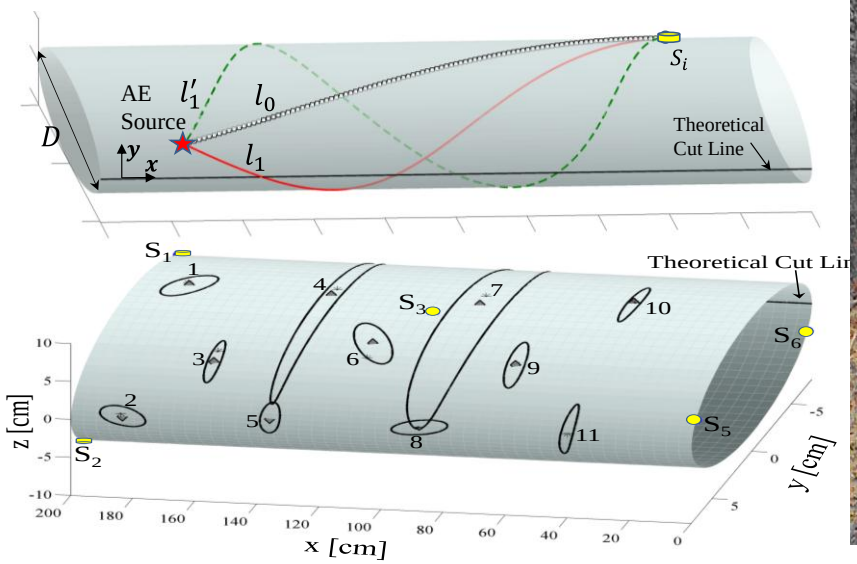


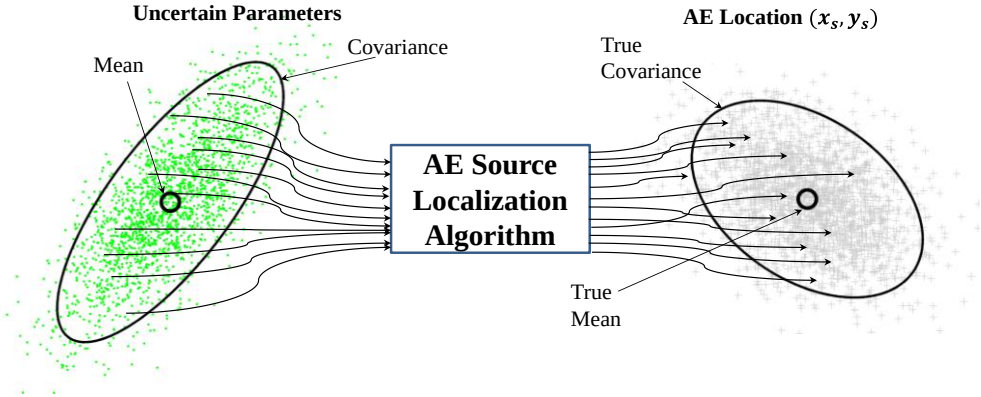


A. Farhidzadeh et al .(2014), Post-Earthquake Evaluation of Pipelines Rehabilitated with Cured in Place Lining Technology using Acoustic Emission, Construction and Building Materials, 54: 326–338.

4) Leak detection in pipelines using acoustic emission

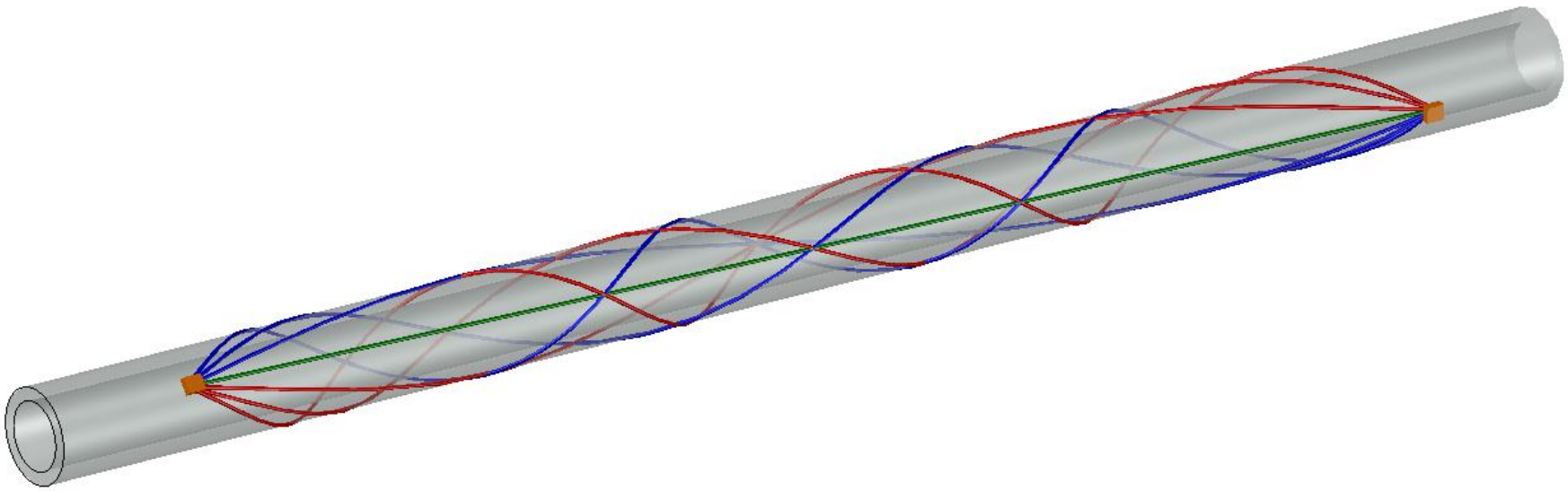






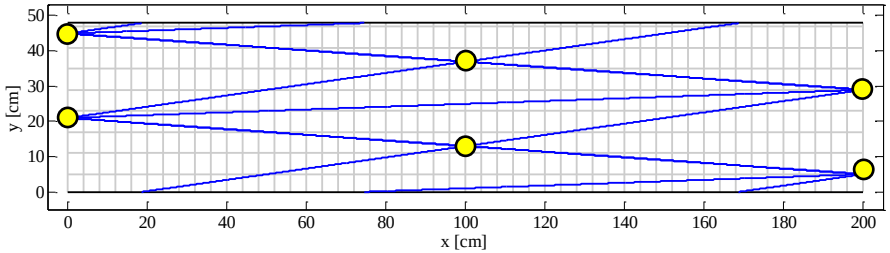
E. Dehghan-Niri, **A. Farhidzadeh**, S. Salamone, (2013), Determination of the Probability Zone for Acoustic Emission Source Location in Cylindrical Shell Structures, Mechanical Systems and Signal Processing, under review.

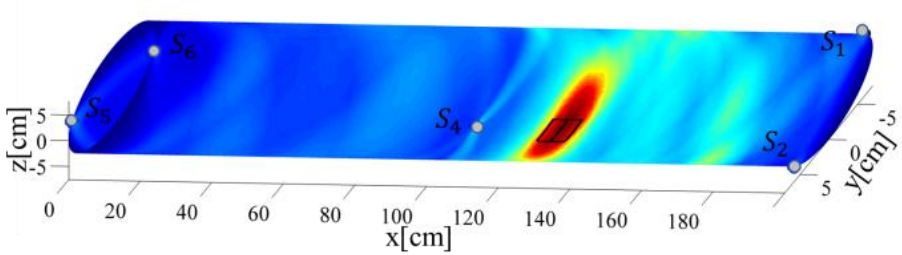
Ultrasonic inspection of pipelines for corrosion detection and localization



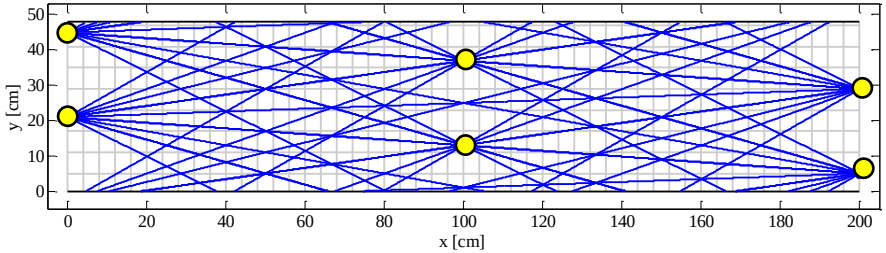
Ultrasonic inspection of pipelines for corrosion detection and localization

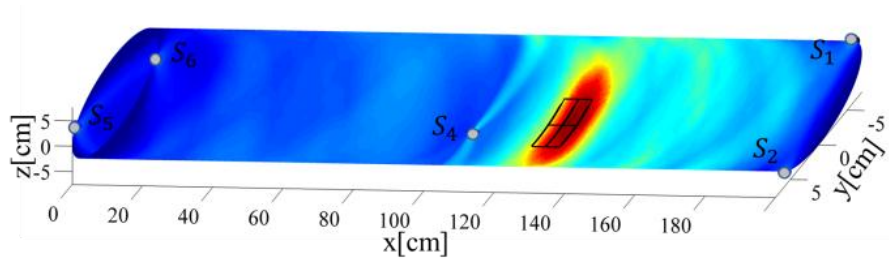
1st order



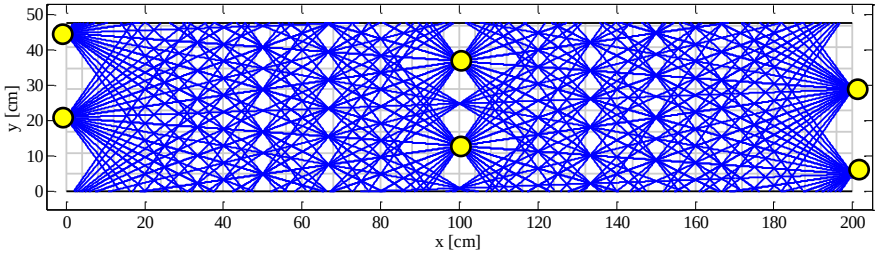


3rd order



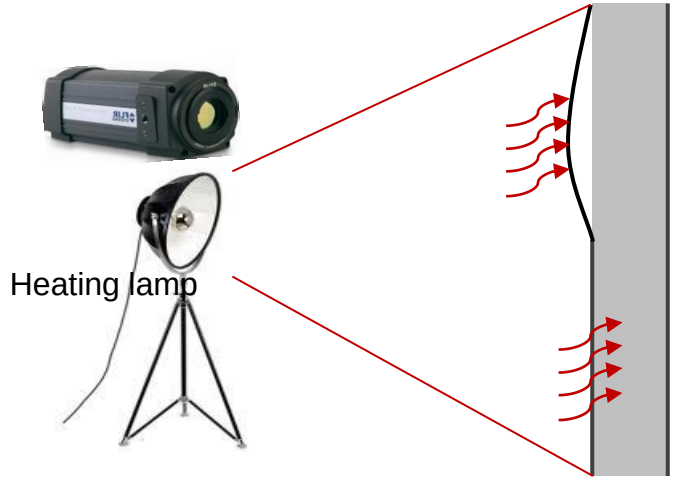


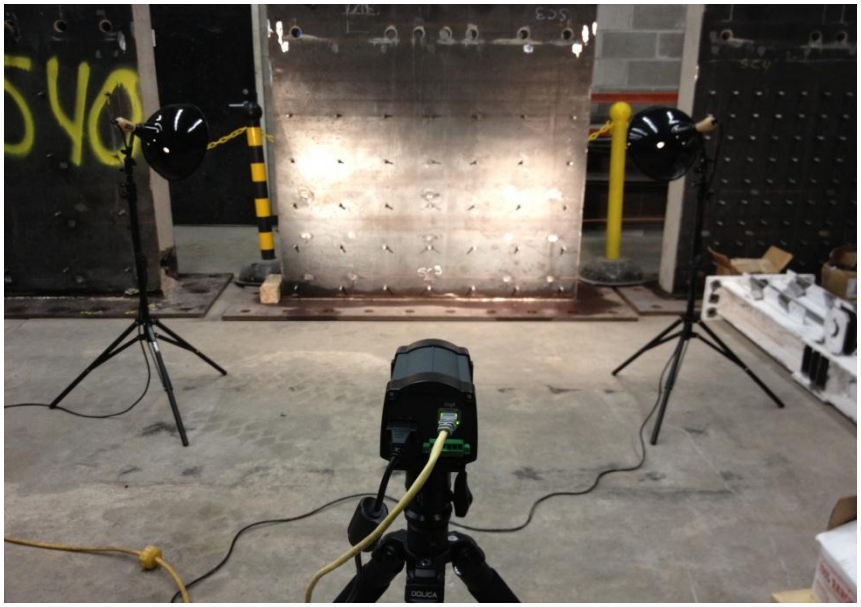
9th order

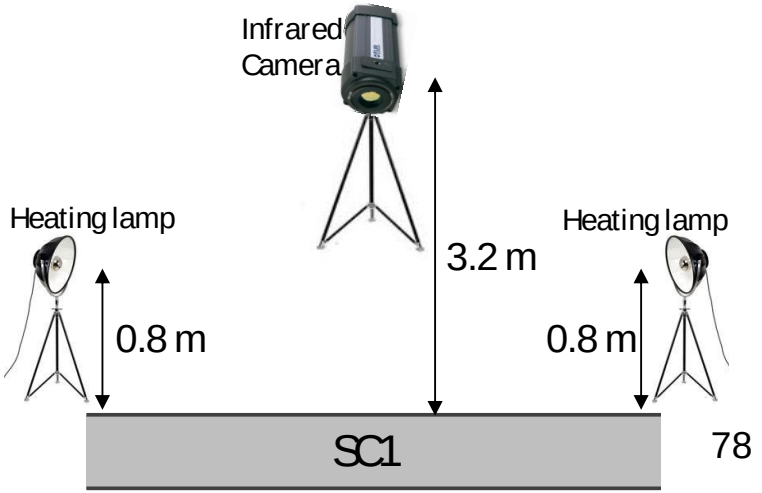


E. Dehghan-Niri, **A. Farhidzadeh***, S. Salamone, Toward permanently installed pipeline monitoring systems, Pipeline and Hazardous Materials Safety Administration, Chicago, IL, USA, 6-7 August 2014. (* presenter)

Infrared thermography for inspection of steel-concrete shear walls

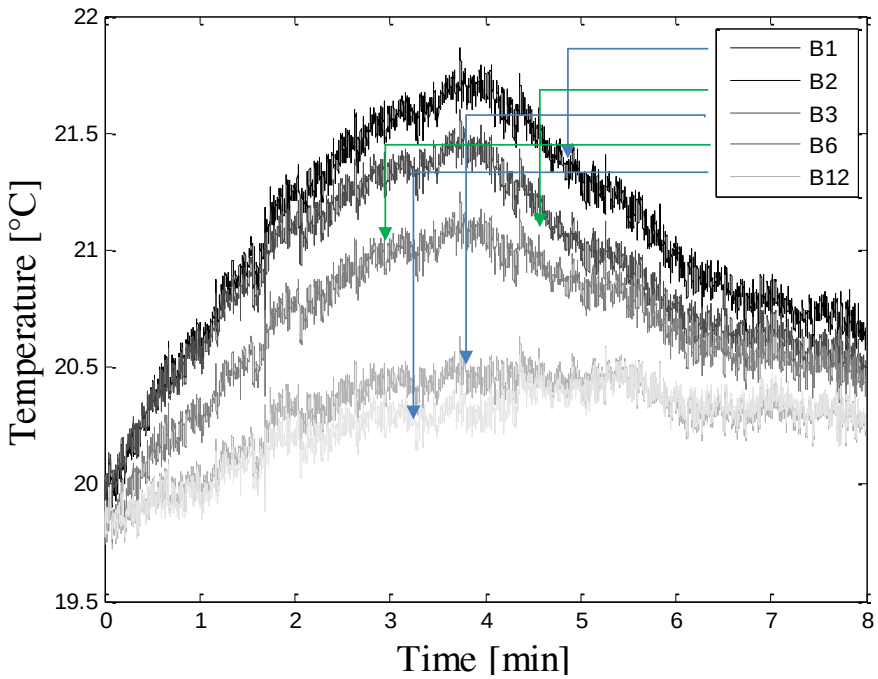


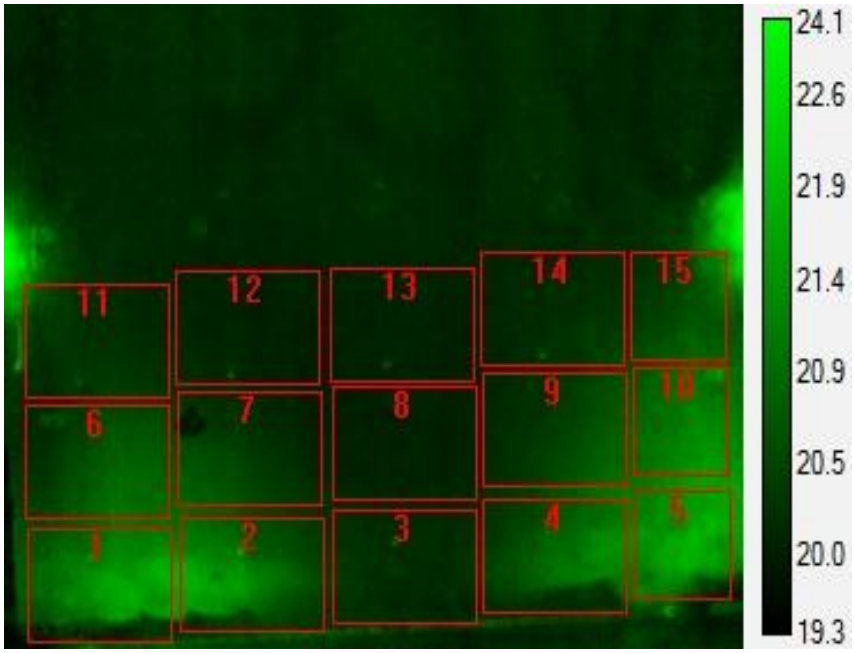




A. Farhidzadeh, S. Salamone, (2012), Structural Health Monitoring of Composite Shear Walls Using Infrared Thermography and Acoustic Emission, SSRL report to SEESL, University at Buffalo, Buffalo, NY.

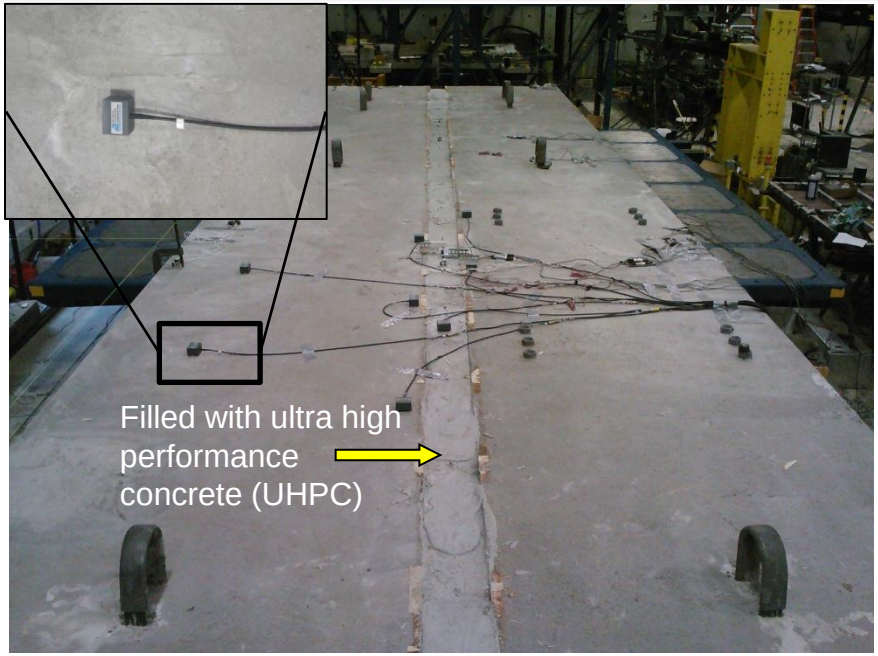
Infrared thermography for inspection of steel-concrete shear walls

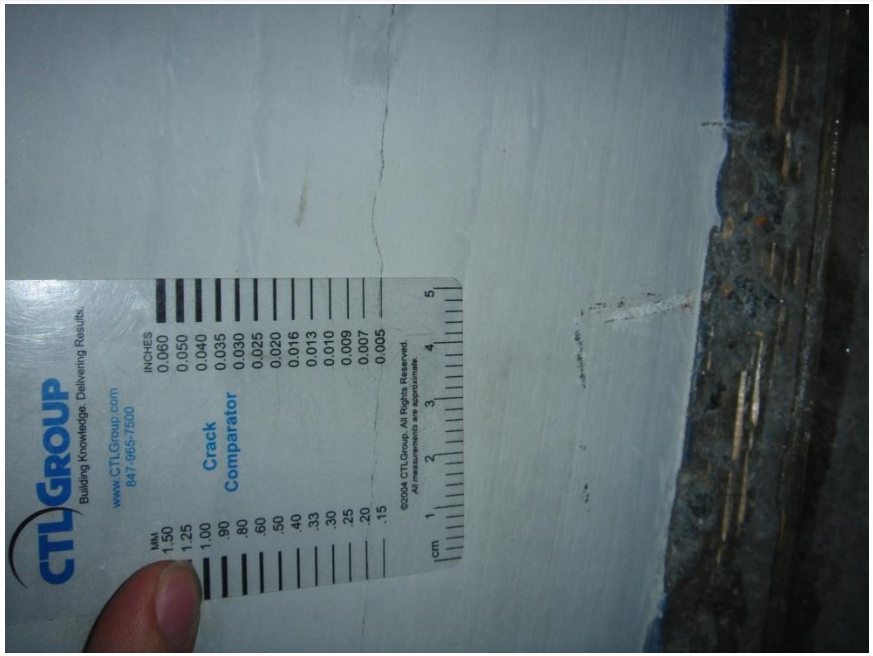


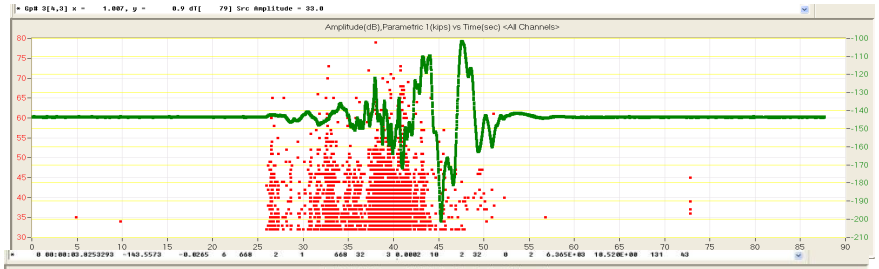


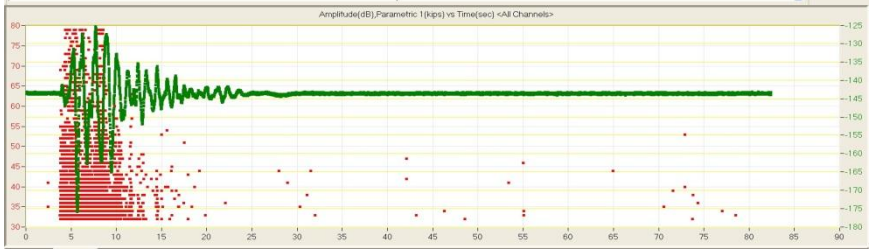
A. Farhidzadeh, S. Salamone, (2012), Structural Health Monitoring of Composite Shear Walls Using Infrared Thermography and Acoustic Emission, SSRL report to SEESL, University at Buffalo, Buffalo, NY.

Bridge Monitoring







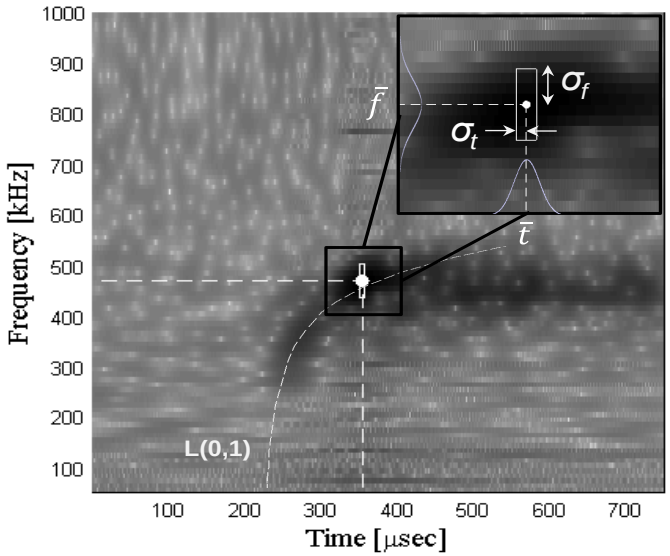


Overview:

1) Motivation
2) Reference-free corrosion diagnosis in prestressed steel strands using GUW
3) Acoustic emission monitoring of reinforced concrete shear walls
4) Complementary projects
5) Conclusions

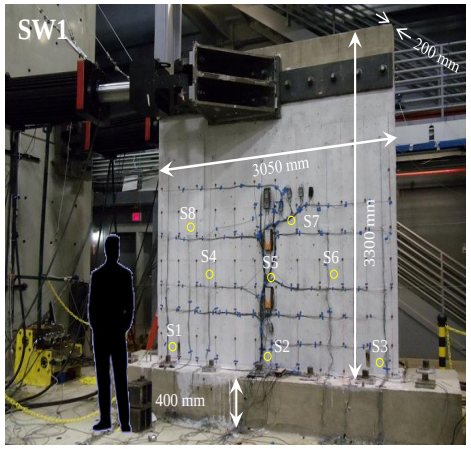
Corrosion diagnosis

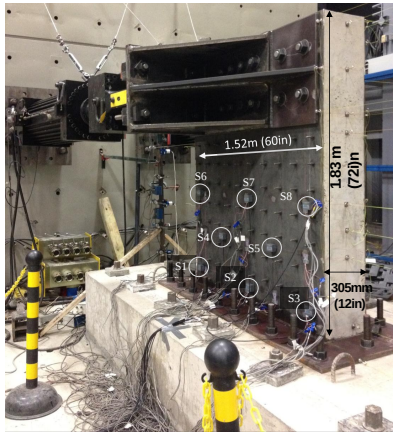
- A small-scale experiment was designed to investigate the characteristics of ultrasonic waves in loaded 7-wire steel strands under corrosion.
- Load and mass loss were measured during the experiment to monitor the extent of corrosion.
- Continuous wavelet transform and a numerically derived function were used to estimate the diameter of wires
- Uncertainty propagation to diameter measurements originated from Heisenberg principle was studied.
- The results conformed very well to the diameter measurements.

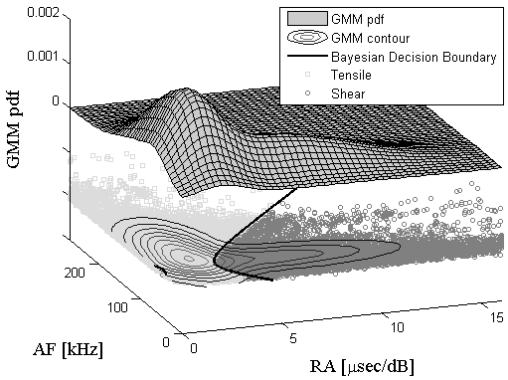


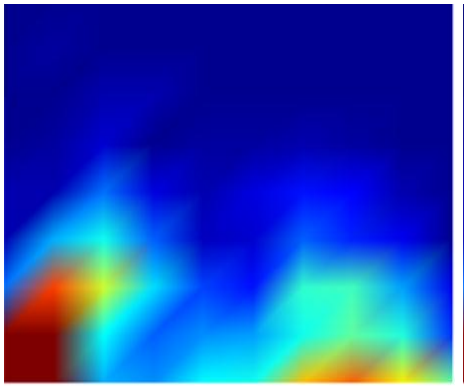
Acoustic emission monitoring of concrete shear walls

- Two full-scale concrete shear walls (one reinforced and the other composite) were monitored to investigate the behavior of acoustic emission
- A unsupervised pattern recognition algorithm based on Gaussian Mixture Modeling, Bayesian decision boundary and likelihood ratio test was proposed to classify the cracking modes.
- The population and energy of clusters were used to identify the critical state of damage (onset of yielding)
- An acoustic imaging technique was developed to identify the location of damage behind the steel plate of composite shear wall.



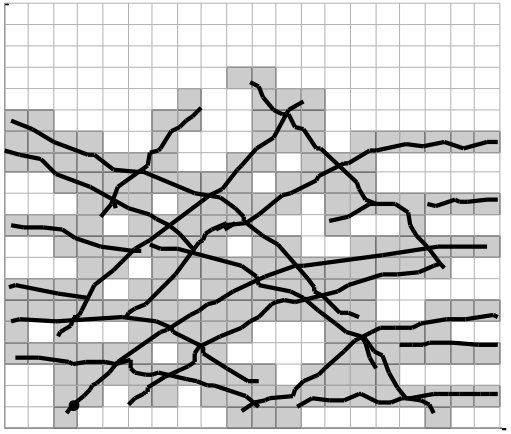


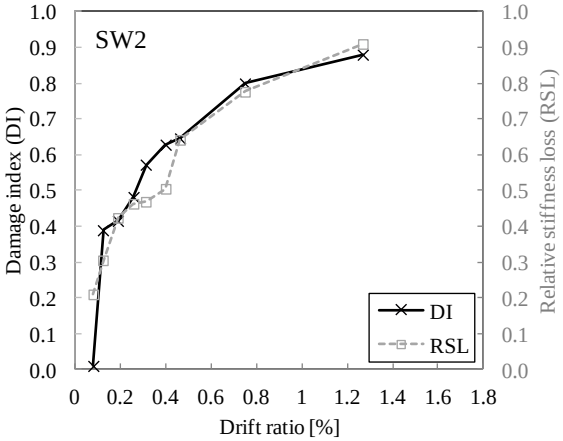


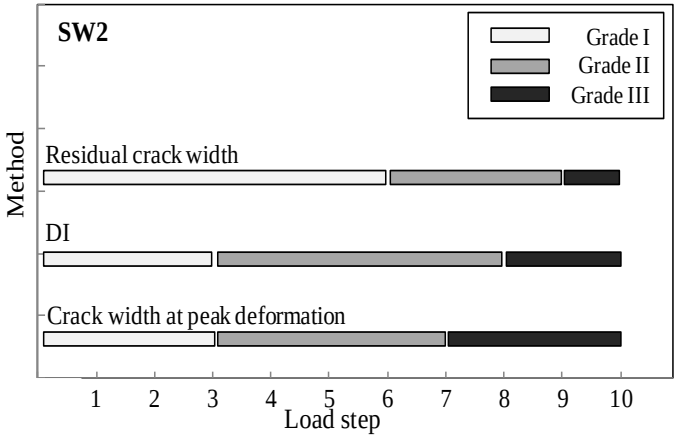


Advanced visual inspection through crack pattern quantification

- Two reinforced concrete shear walls were tested and visually inspected.
- The width of cracks resulted in erroneous decisions in case of closed cracks
- The pattern of cracks has been found as informative as their width.
- Fractal analysis was proposed to quantify the crack patterns.
- A novel vision-based damage index (DI) based on fractal dimension was defined
- It could successfully estimate the lateral stiffness loss just by using crack patterns







Closing remarks

Benefits of Smart Structures:

1- Maximizing and shortening shutdowns by preparing other NDT/SHM works in advance for targeted areas

2- Minimizing manual labor to access and prepare for tedious inspection

3- Alert facility operators on the need to repair before imminent failure

Acknowledgement

UB Faculty:

Dr. Salvatore Salamone, PhD advisor
Prof. Andrew S Whittaker, PhD committee member
Prof. Amjad Aref, PhD committee member
Prof. Andre Filiatrault

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National Science Foundation

- Performance-Based Design of Squat Reinforced Concrete Shear Walls (CMMI-0829978) PI: Prof. Andrew S Whittaker
- Earthquake Response and Rehabilitation of Critical Lifelines (CMS-421142) PI: Prof. Amjad Aref, Co-PI: Prof. Andre Filiatrault
- A Vision-Based Technique for Damage Assessment of Civil Structures (CMMI-1333506) PI: Dr. S Salamone

US Department of Transportation

- Corrosion Damage Assessment of Post-Tensioned Concrete Structures, USDOT through the University Transportation Research Center, PI: Dr. S Salamone
- Toward Permanently Installed Pipeline Monitoring Systems, USDOT through Pipeline & Hazardous Materials Safety Administration, PI: Dr. S Salamone

SUNY Research Foundation

- Collaborative Research to Advance Scientific Knowledge of the Mechanism of Corrosion in Civil Infrastructures (Grant No.: 1107907-1-63576) PI: Dr. Salvatore Salamone

Staff of SEESL laboratory at UB:

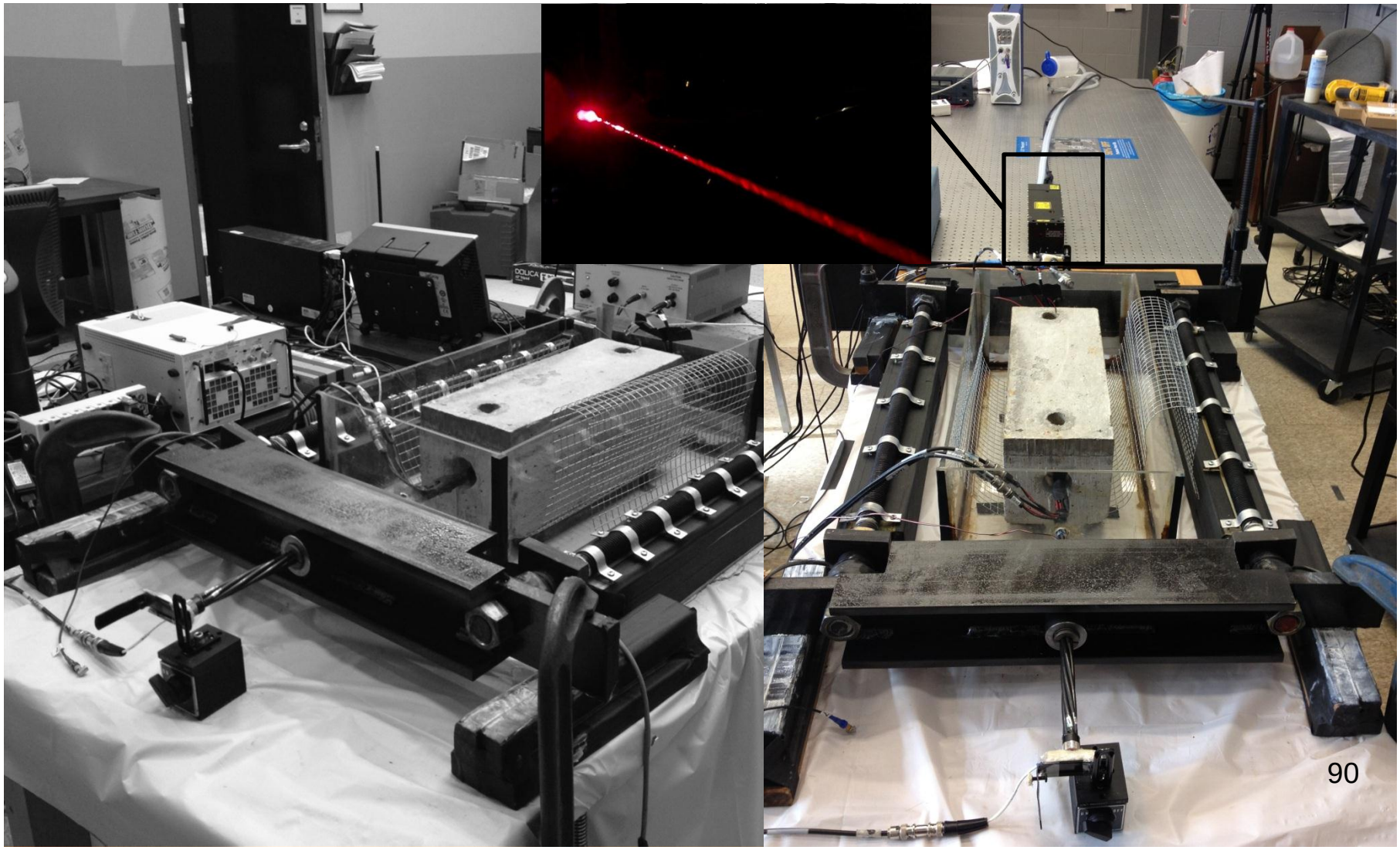
- Chris, Duane, Scott, Jeff, Louie

Thank you

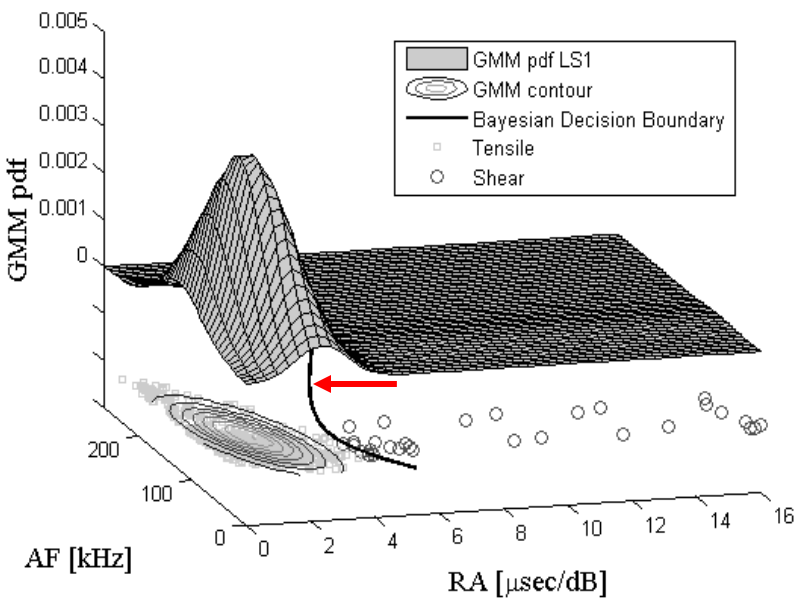
Overview:

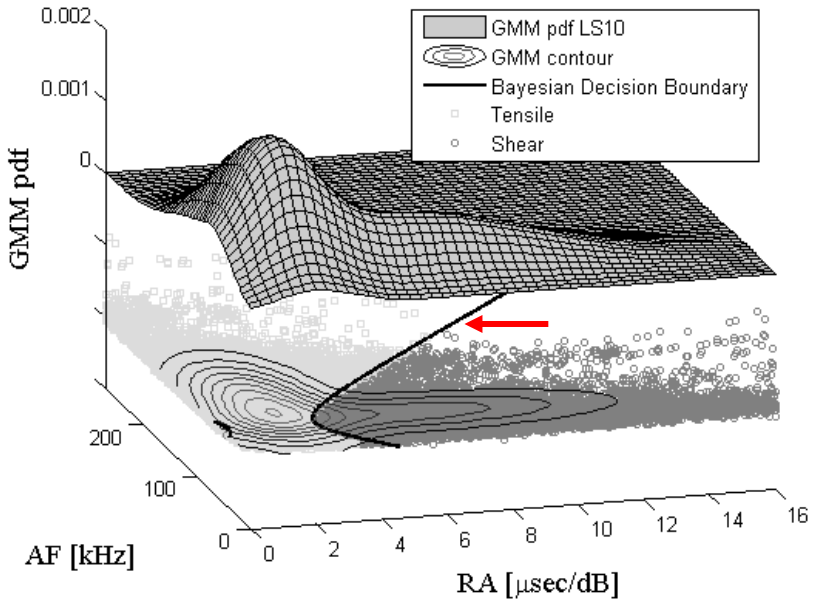
1) Motivation
2) Reference-free corrosion diagnosis in prestressed steel strands using GUW
3) Acoustic emission monitoring of reinforced concrete shear walls
4) Complementary projects
5) Conclusions
6) Outlook

1) Laser ultrasound for damage assessment of steel strands

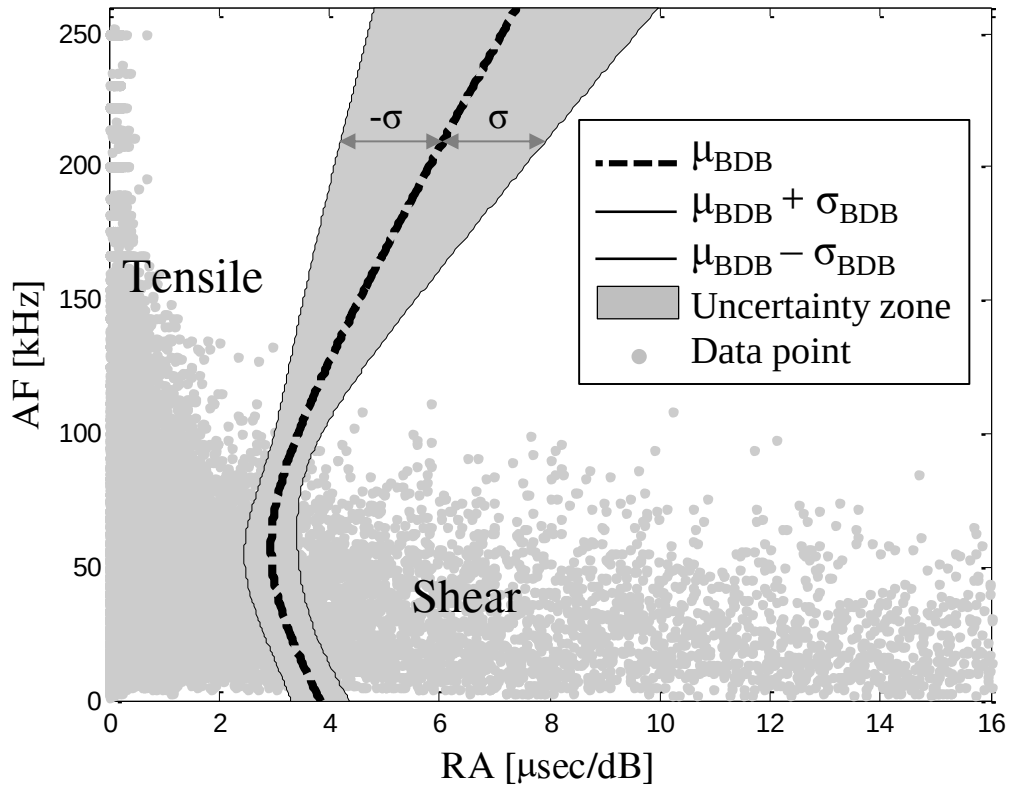


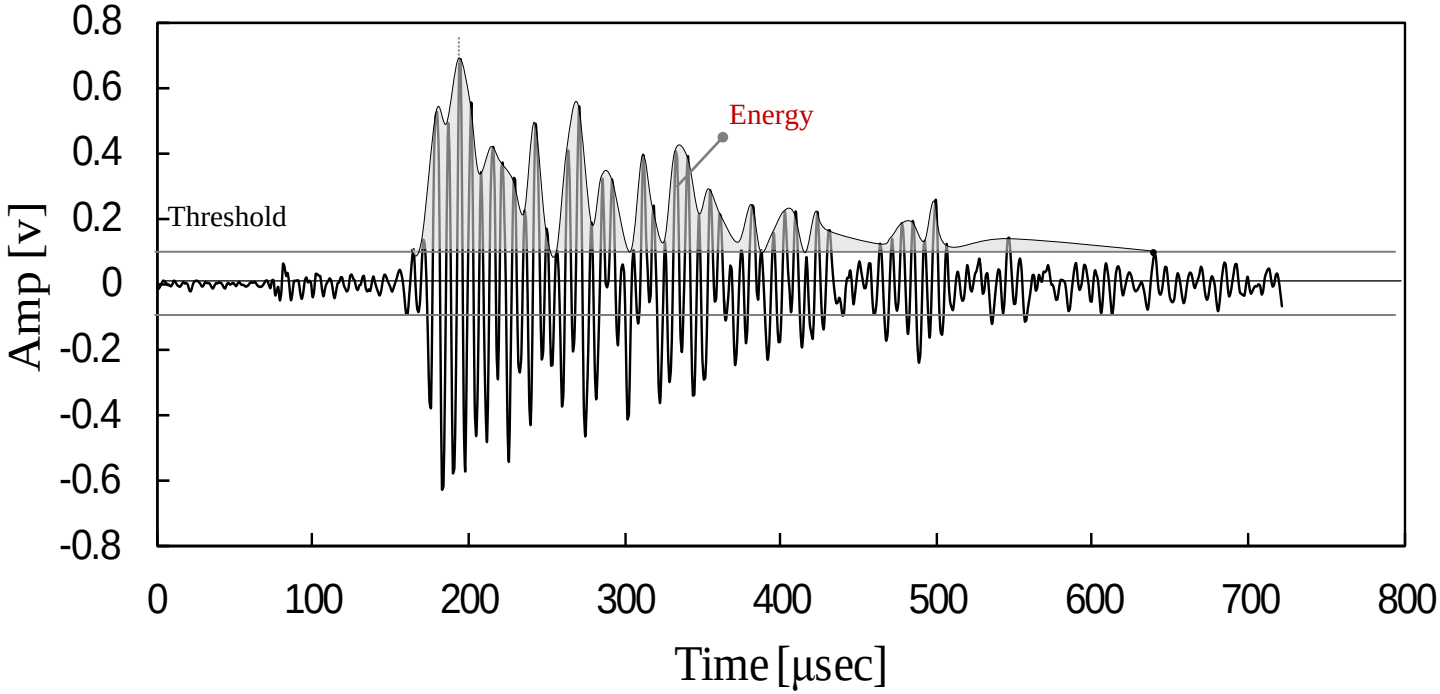
Bayesian Decision Boundary





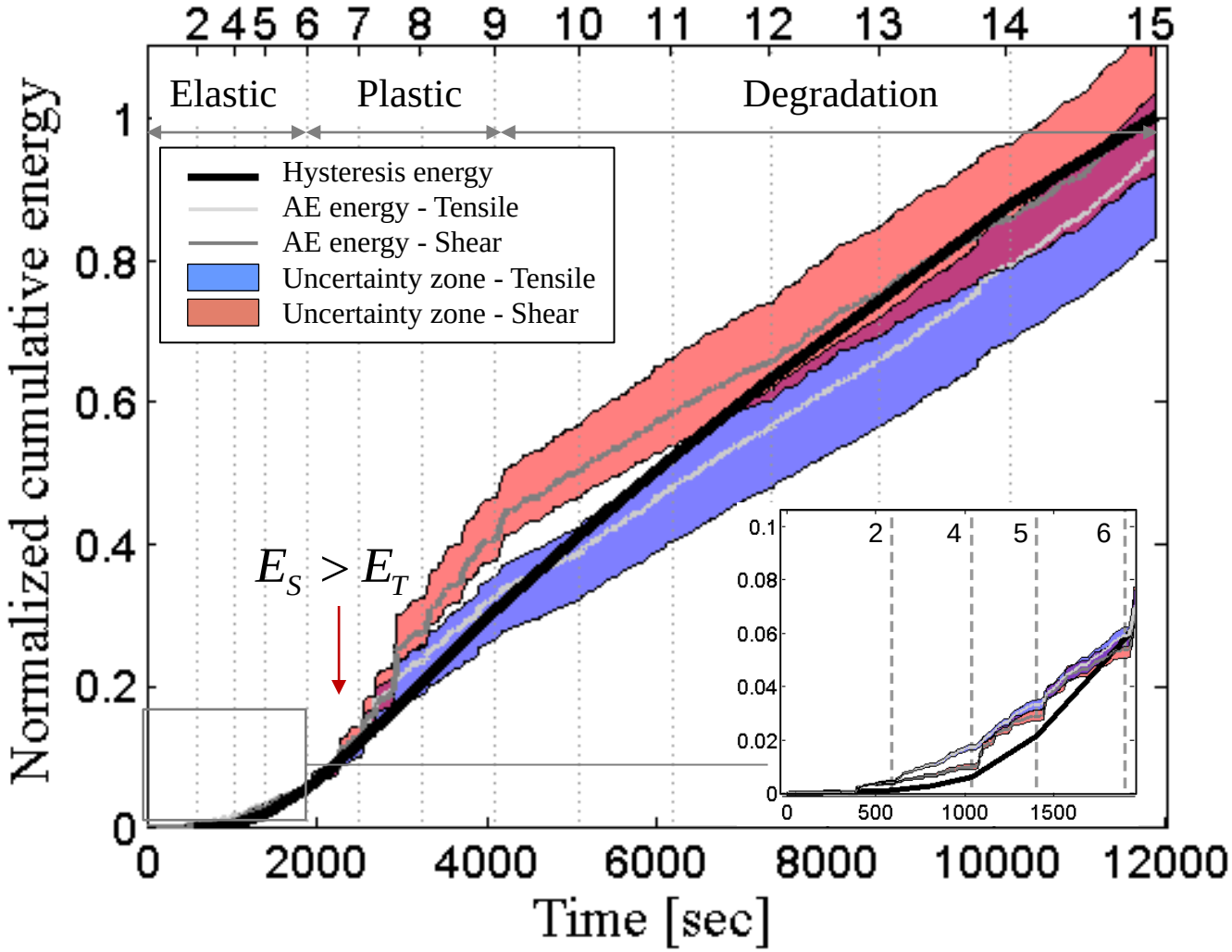
Uncertainty Zone for the Bayesian Decision Boundary





A. Farhidzadeh, S. Epackachi, S. Salamone, A. Whittaker, (2014), Bayesian Decision and Mixture Models for Multi-scale Damage Interrogation in Composite Shear Walls Using Acoustic Emission, to be submitted to an ASCE Journal

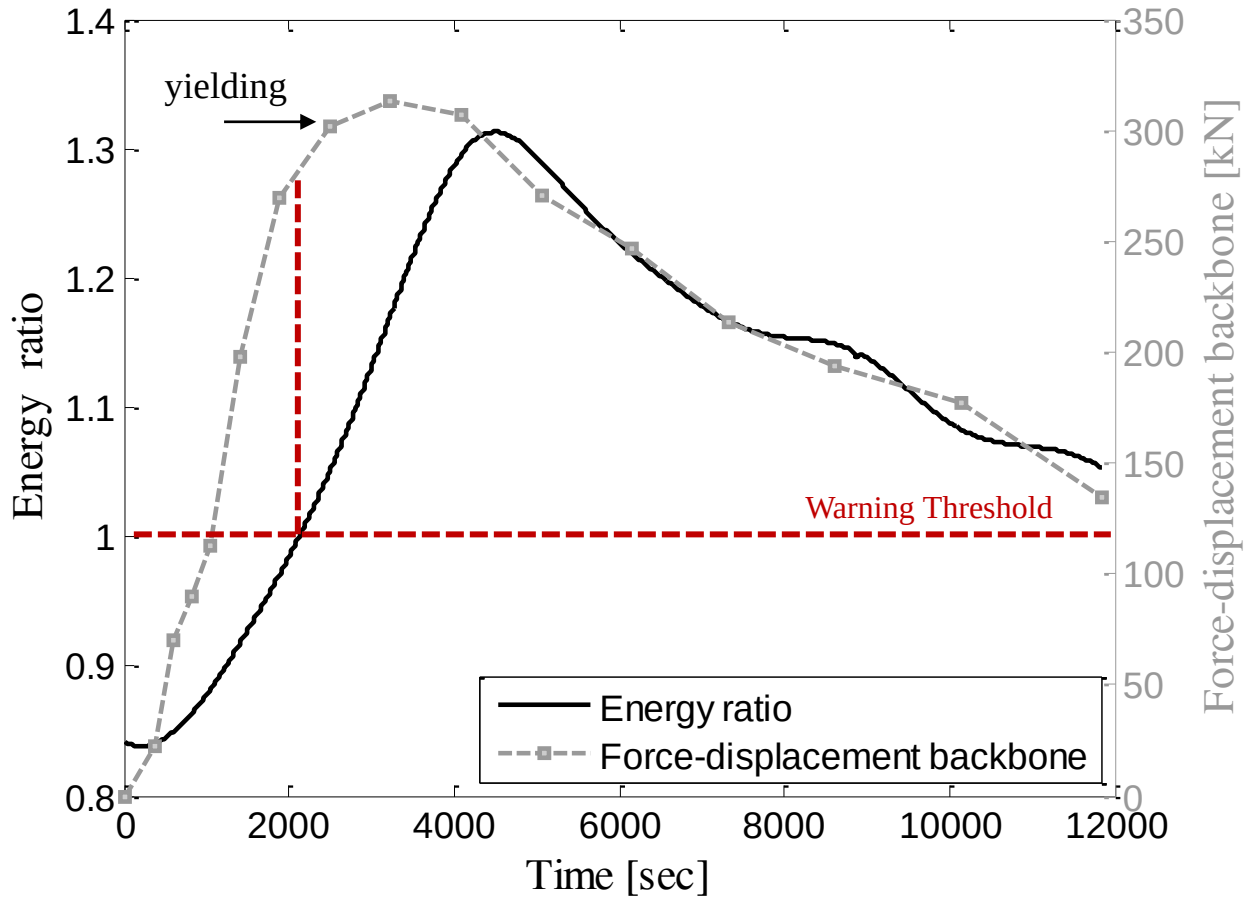
End of load step



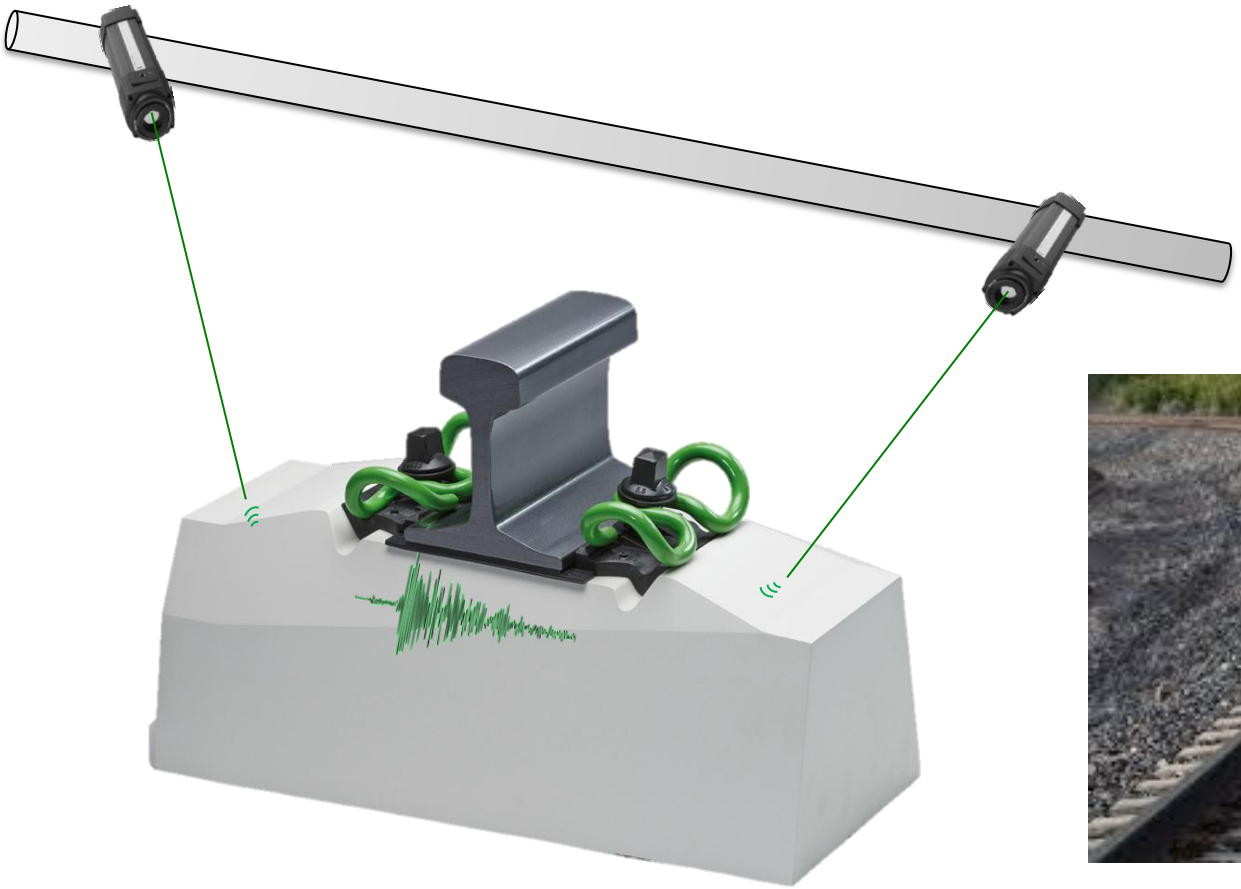
A. Farhidzadeh, S. Epackachi, S. Salamone, A. Whittaker, (2014), Bayesian Decision and Mixture Models for Multi-scale Damage Interrogation in Composite Shear Walls Using Acoustic Emission, to be submitted to an ASCE Journal

Energy ratio

$$ER = \frac{E_S}{E_T}$$



3) Damage assessment of concrete cross-ties and rails

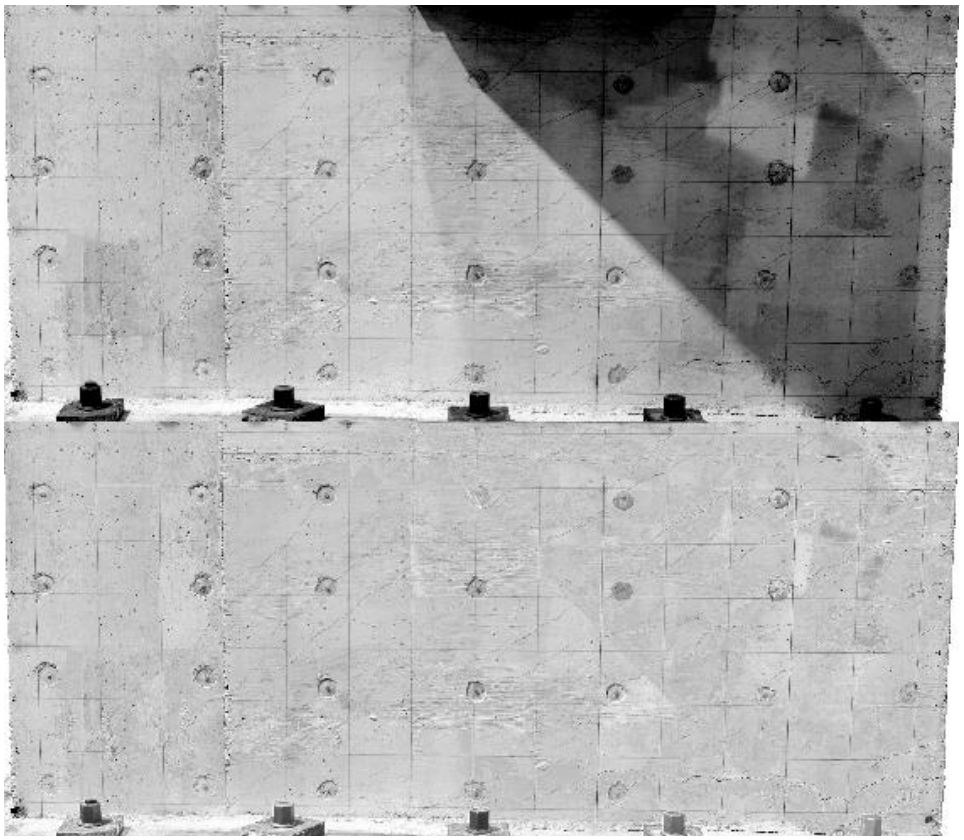


5) Automated visual inspection of concrete structures

1. Pre-processing

Shadow removal

Morphology-based Operations



5) Automated visual inspection of concrete structures

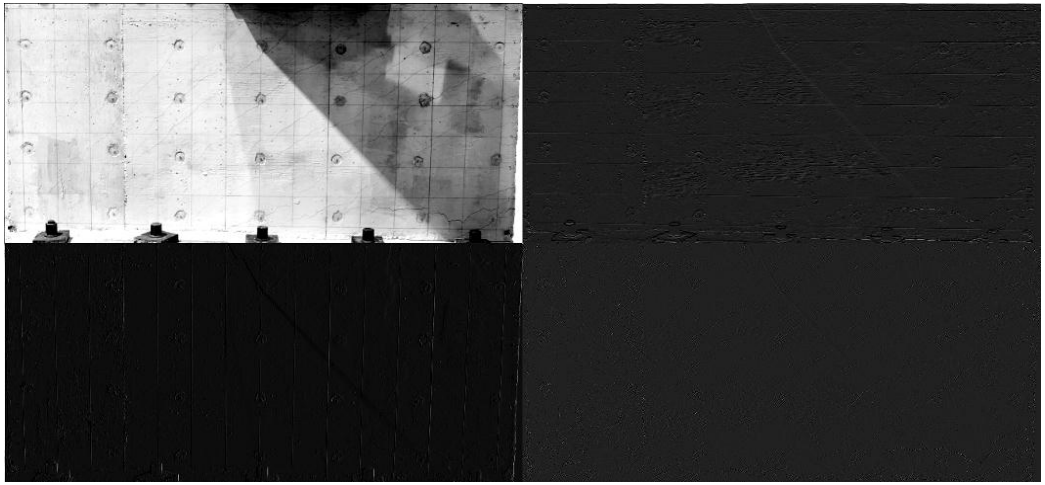
2. Edge Detection

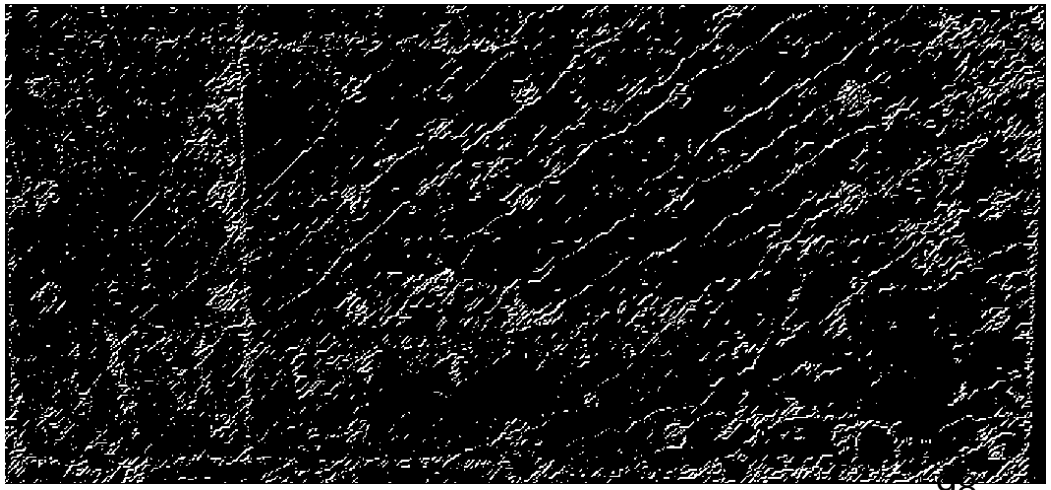
2.1. Discrete Wavelet Transform

2.2. Pruning

2.2.1. Hysteresis (strong, weak, non-edge)

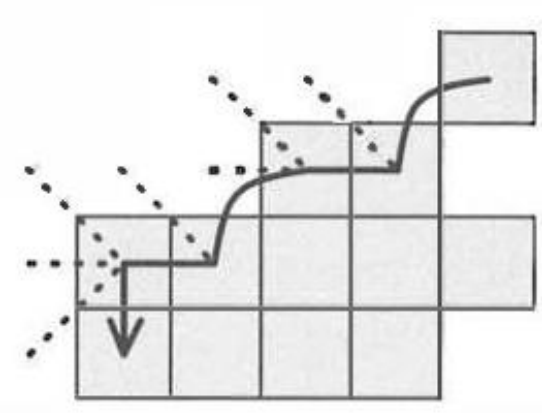
2.2.2. Non-maximal suppression (weak → strong, non-edge)

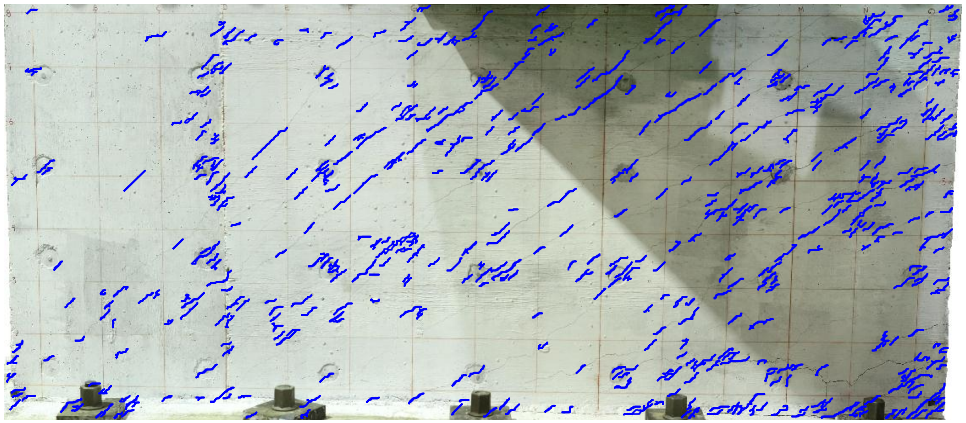




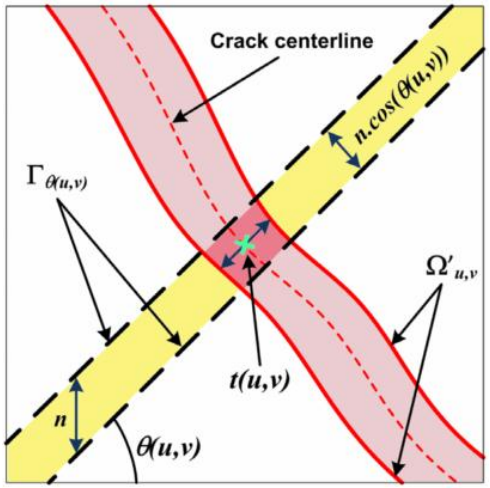
5) Automated visual inspection of concrete structures

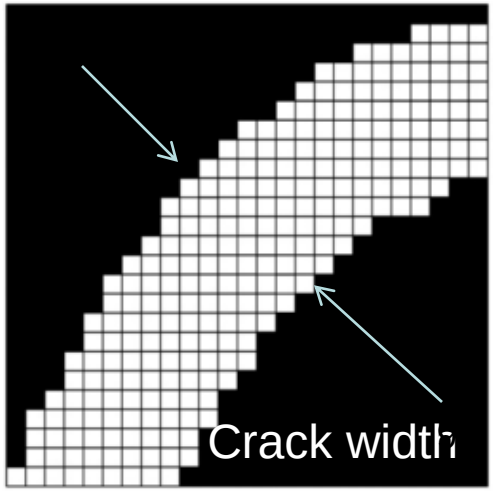
Boundary Tracking





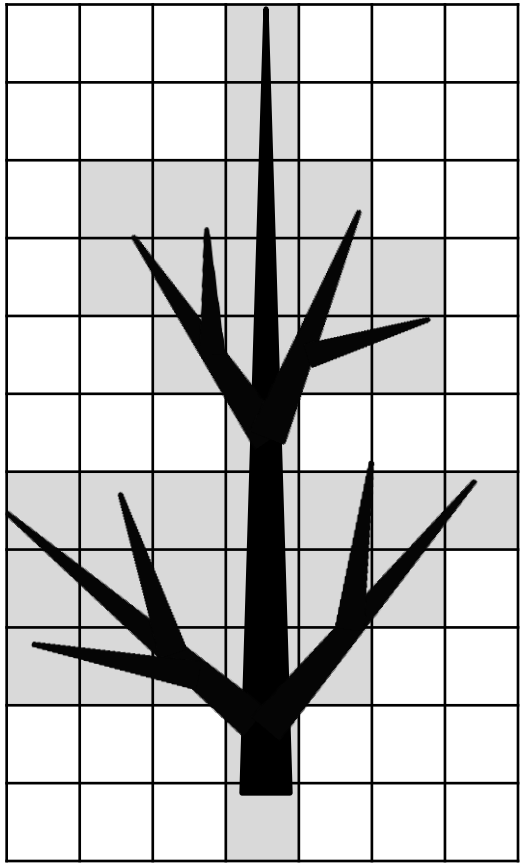
Crack width measurement





5) Automated visual inspection of concrete structures

Multi-fractal analysis to incorporate crack width
→ fusing the crack pattern and width for more accurate decision making



5) Automated visual inspection of concrete structures

Multi-fractal analysis

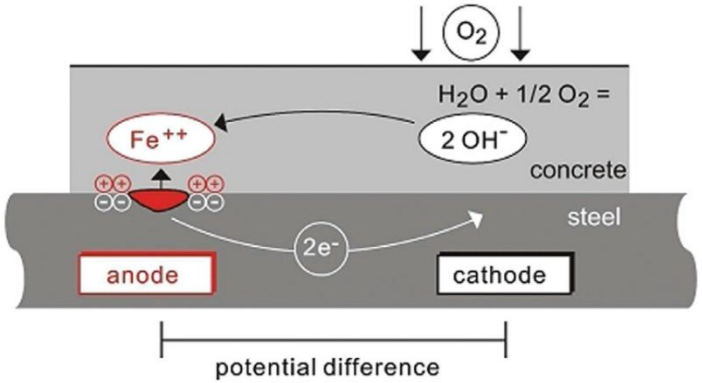
5) Automated visual inspection of concrete structures

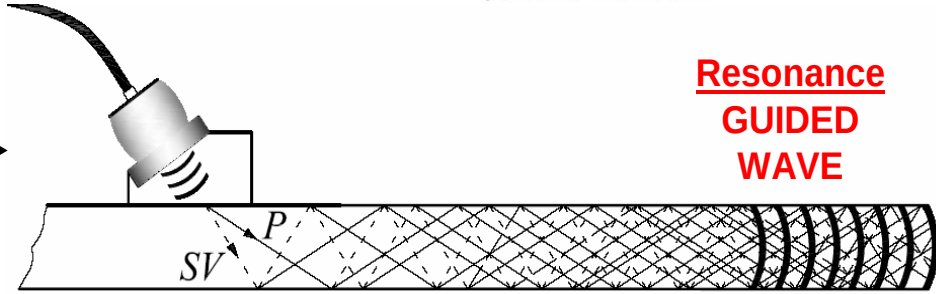
Unmanned autonomous systems

Backup slides

Detection (corrosion / cable breaks)

- Visual inspection
- Half-cell potential
- Time-domain reflectometry
- Linear Polarization Resistance (LPR)
- Magnetic flux leakage
- Microwave imaging
- Acoustic emission
- Guided Ultrasonic Waves





Resonance
GUIDED WAVE

Monitoring stress levels

- Fiber-optic strain sensors
- Modal analysis
- Magnetic permeability
- Guided Ultrasonic Waves

Estimating cross-section loss

- Modal analysis
- Guided Ultrasonic Waves
- X-ray scanning

Short-term projects (< 3 years):

- Developing non-destructive evaluation technologies for monitoring the real-time behavior and long-term health of structures such as post-tensioning strands in metal ducts.
  - Oregon Department of Transportation
  - Oregon Transportation Research and Education Consortium
  - Federal Highway Administration (FHWA)
  - National Institute of Standards and Technology (NIST)
  - Prestressed Concrete Institute (PCI)

- Leak and corrosion detection in Pipelines (water and oil) designing suitable rehabilitation strategies
  - Department of Energy
  - Pipeline and Hazardous Materials Safety Administration
  - US DOT

- Damage assessment of concrete cross-ties and rails
  - Federal Railroad Administration (FRA)

Damage assessment of Subsurface structures (e.g., Corrosion in soil nails, cracking in piles)

Long-term projects (>= 3 years):

- Application of hybrid simulation technique for monitoring of large structures
- Automated Visual Inspection of Civil Structures
  - National Science Foundation
    - Hazard Mitigation and Structural Engineering (HMSE)
    - Sensors and Sensing Systems
    - Natural hazard Engineering Research Infrastructure (NHERI)
    - Crosscutting and NSF-wide Active Funding Opportunities

- Monitoring wind turbines (wind power accounted for 12.4% of total electricity generated in Oregon)
  - Bonneville Power Administration, Portland General Electric

Department of Defense Multidisciplinary University Initiative (*MURI*)
Department of Homeland Security, Science & Technology (DHS)

U.S. Department of Commerce

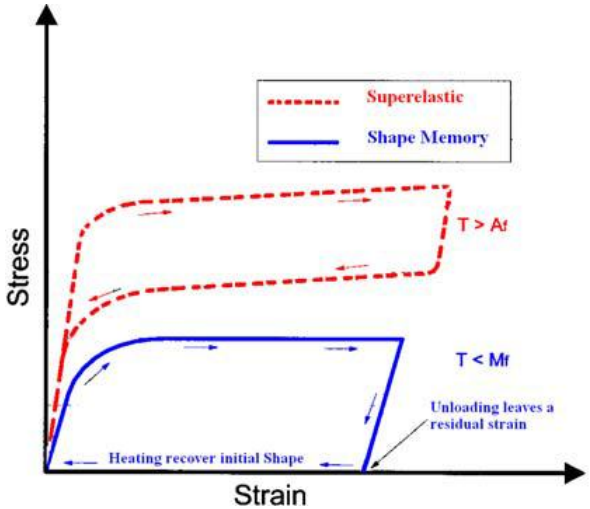
Damage Prognosis (Estimating the future loading environments for that system, predicting through simulation and past experience the remaining useful life of the system.
Integration of many technology areas including both measurement/processing/telemetry hardware and a variety of deterministic and probabilistic predictive modelling capabilities, as well as the ability to
quantify the uncertainty in these predictions. The multidisciplinary and challenging
nature of the DP problem, its current embryonic state of development, and its tremendous potential for life-safety and economic benefits qualify DP as a 'grand challenge' problem for engineers in the twenty-first century.

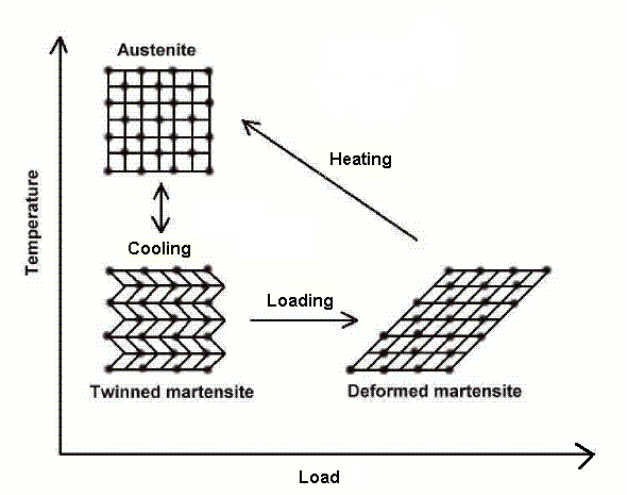
GreenSTEP model – the greenhouse gas estimation software developed by Oregon Department of Transportation

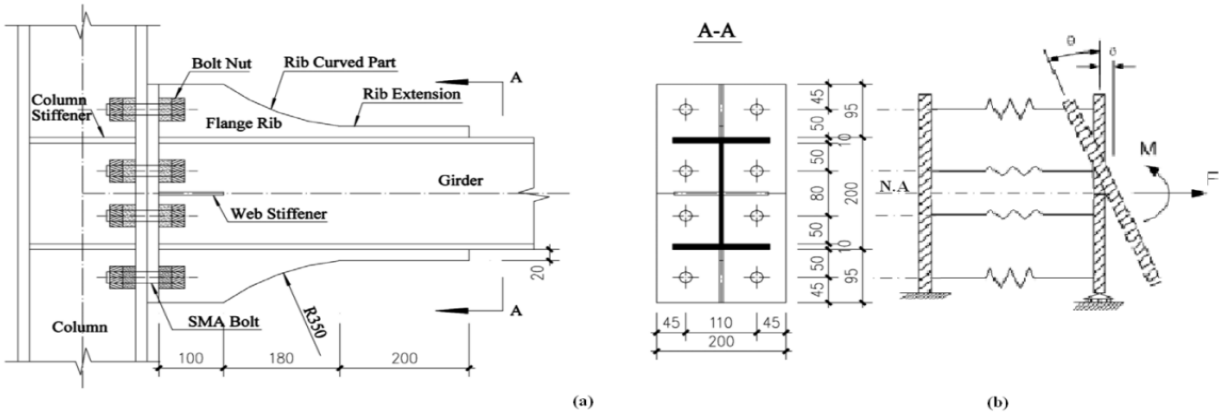
Outlook

5) Application of smart materials in structural design

Shape Memory Alloys







FR Rofooei, **A Farhidzadeh** (2011) Investigation on the seismic behavior of steel MRF with shape memory alloy equipped connections, Procedia Engineering 14, 3325-3330

Improving Visual inspection through crack pattern quantification

Visual inspection of concrete structures

Standards, codes, guidelines:

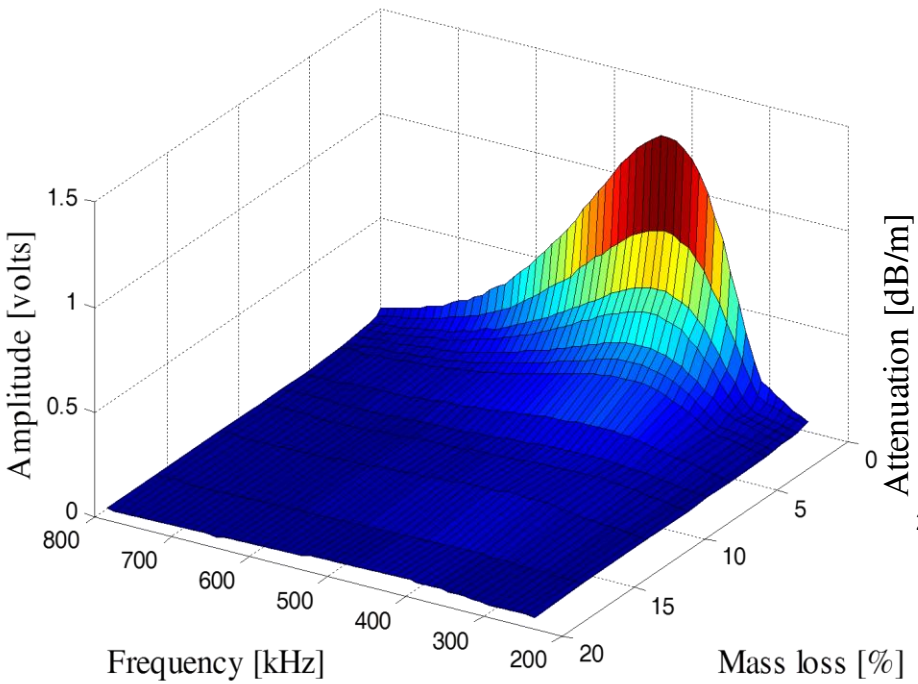
International Atomic Energy Agency guidebook (IAEA)
Federal Highway Administration code
National Bridge Inspection Standards
FEMA 306: Evaluation of Earthquake Damaged Concrete and Masonry Wall Buildings
…

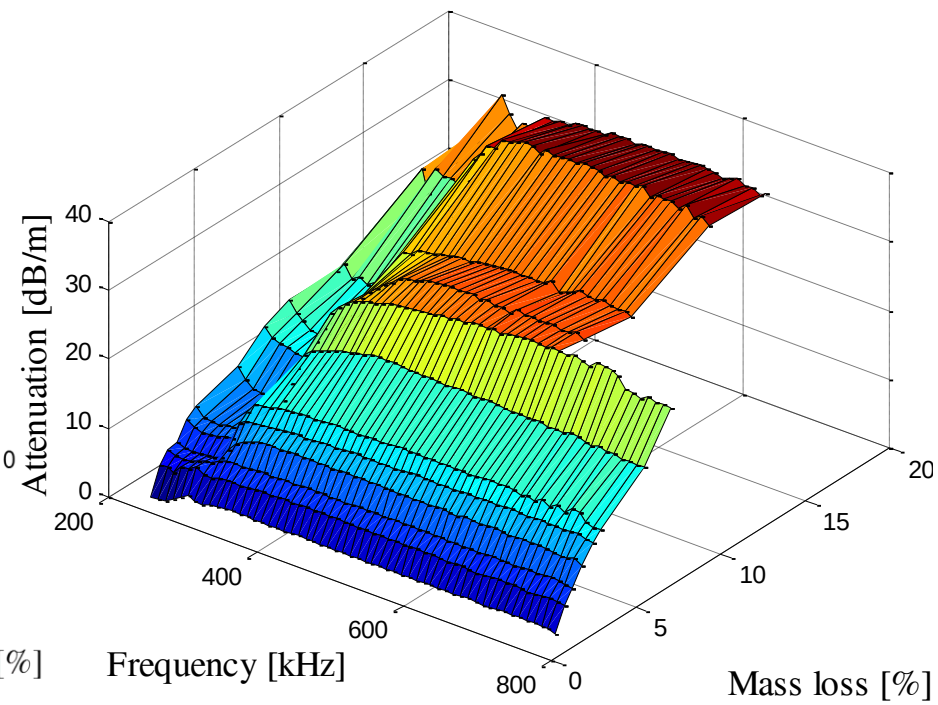
They usually categorize damage condition in terms of visible distress attributes such as

cracks, (width and pattern)
surface pitting,
spalling,
delamination,
wear or abrasion,
concrete color change, …

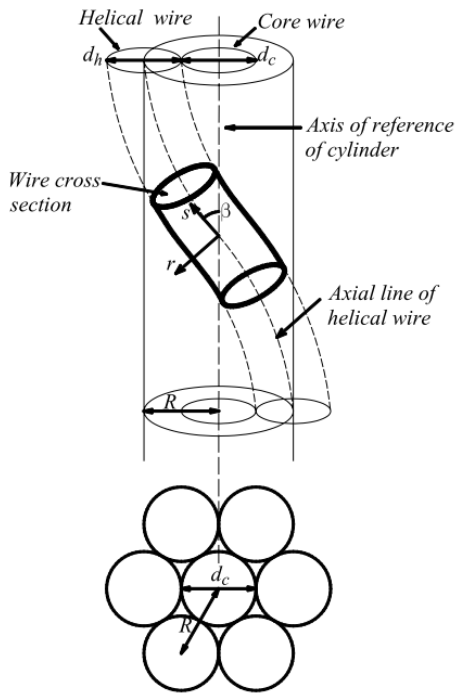
Cracks & Pattern

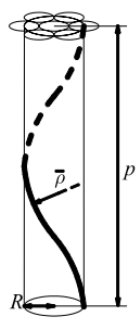
Corrosion diagnosis in prestressing steel strands using ultrasonic waves





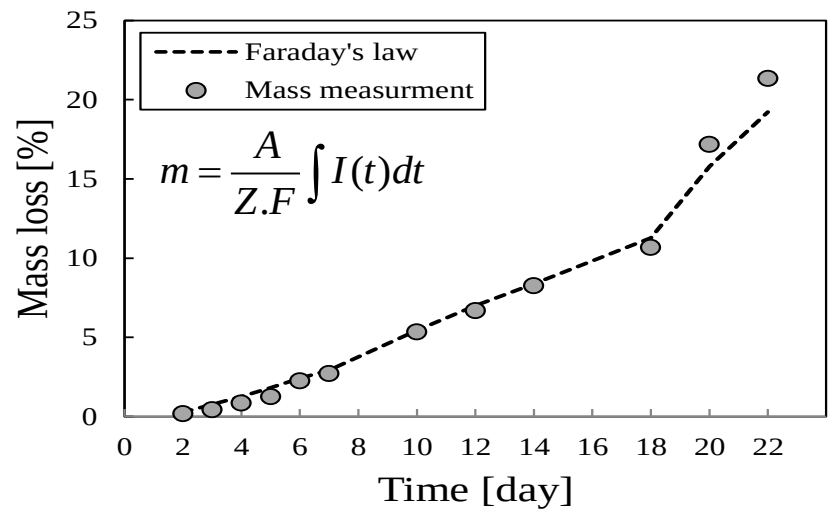
Corrosion diagnosis in prestressing steel strands using ultrasonic waves

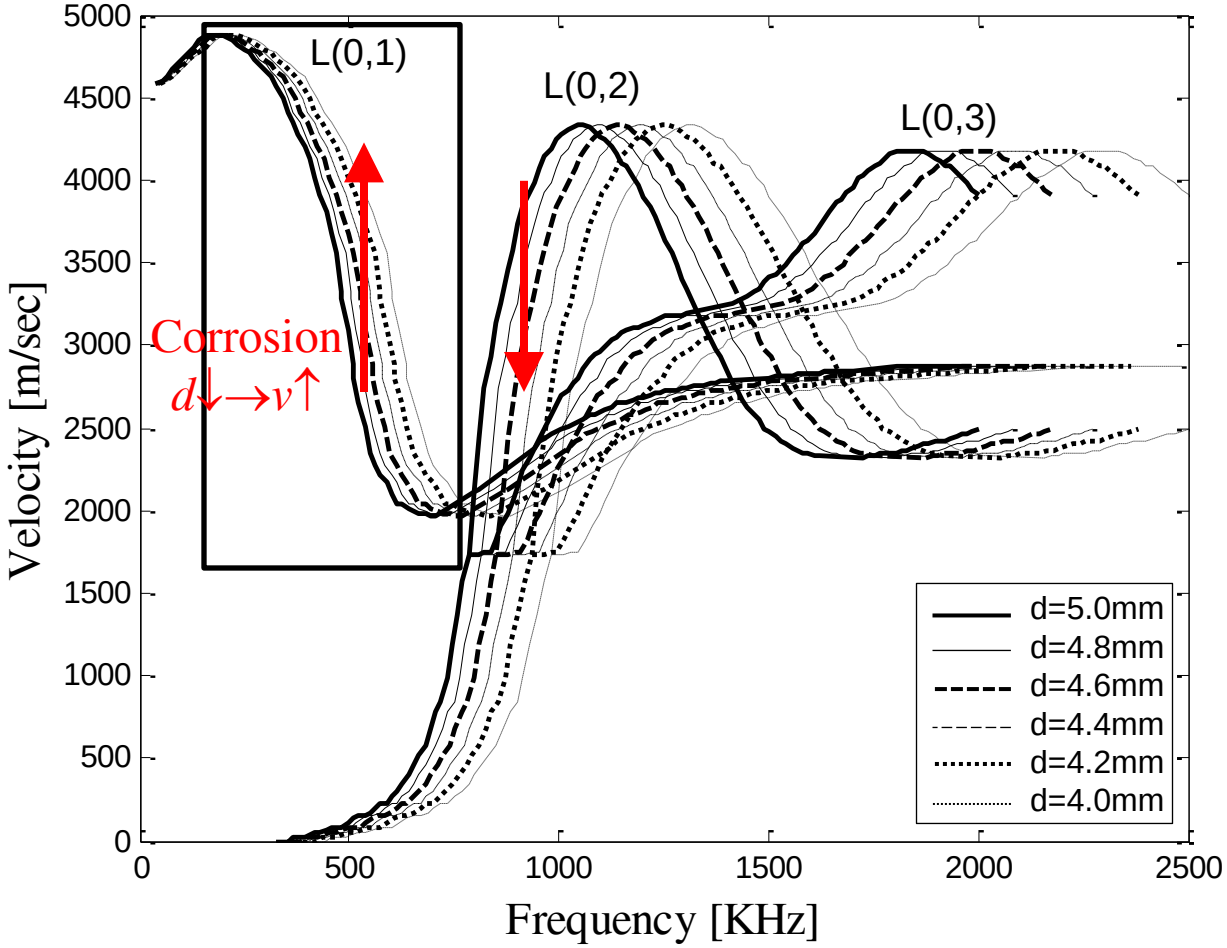




β=Lay angle of helical wire
$\bar{p}$=Radius of curvature of the axis of helical wire
s=Arc Length of helical wire
R=Radius of strand (radius of reference cylinder)
p=Pitch of helical wire
A=cross sectional area of wire
d=Wire diameter

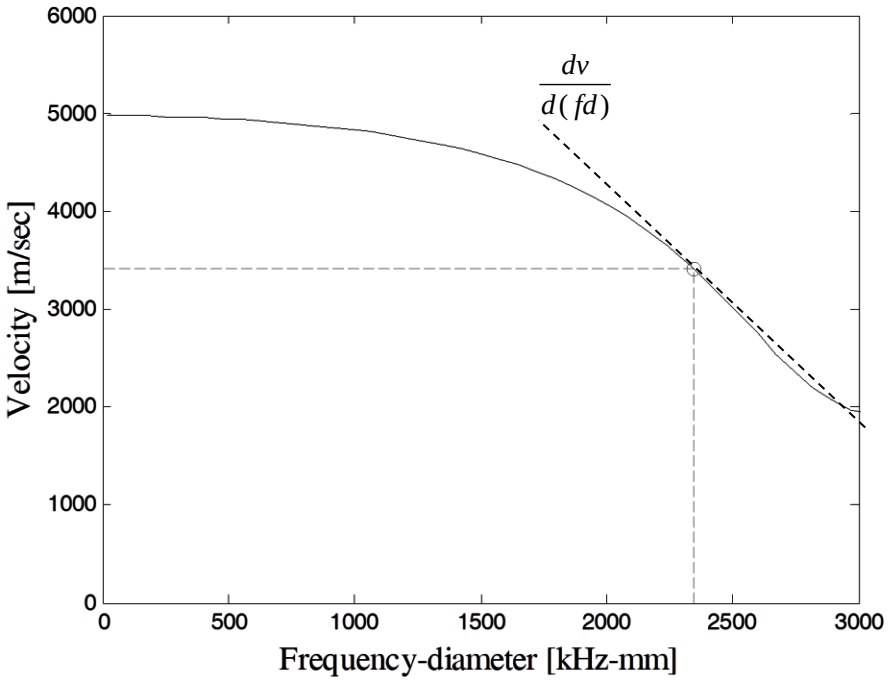
Subscripts c (core wire) and h (helical wire)

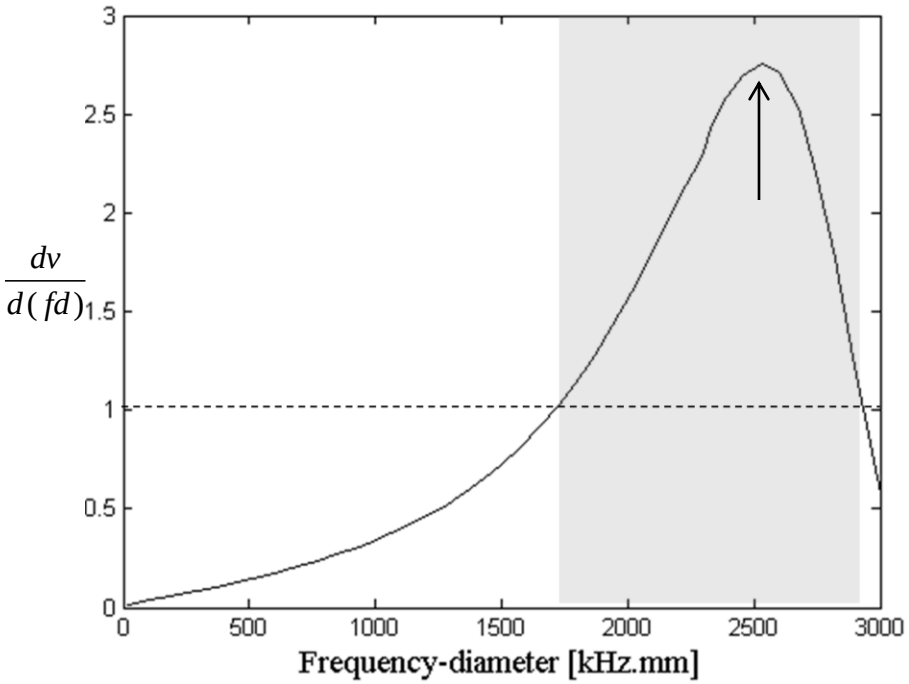



L(0,1)
L(0,2)
L(0,3)
Corrosion
d↓→v↑
Velocity [m/sec]
Frequency [KHz]
0
500
1000
1500
2000
2500
3000
3500
4000
4500
5000
d=5.0mm
d=4.8mm
d=4.6mm
d=4.4mm
d=4.2mm
d=4.0mm

Numerical Modeling

Optimum frequency



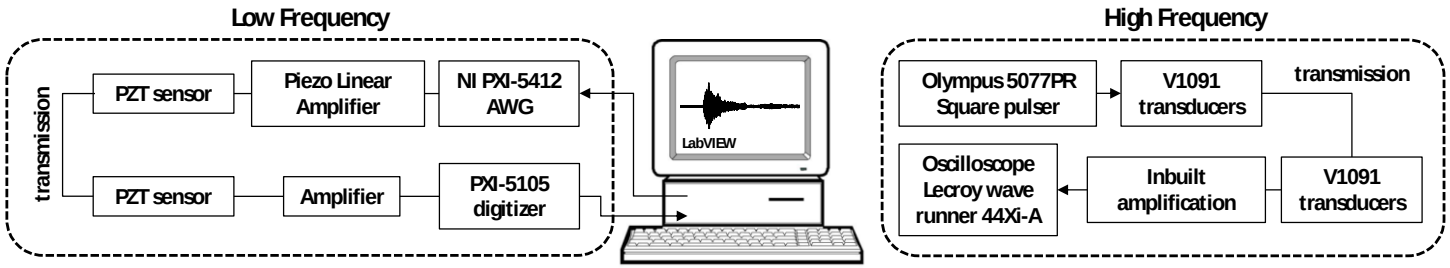


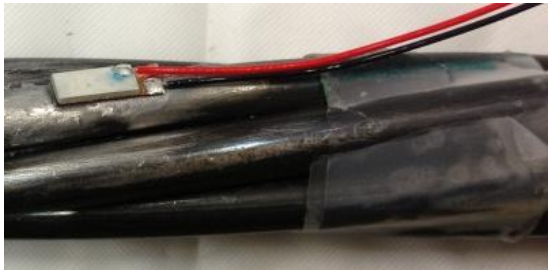
$$fd = \arg\max\left(\frac{dv}{d(fd)}\right) \rightarrow \frac{d^2v}{d(fd)^2} = 0$$

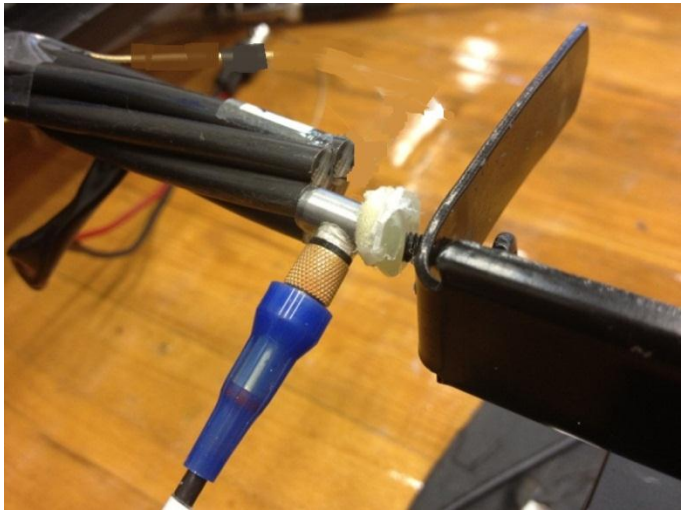
fd=2500 kHz-mm (e.g., f=500kHz × d=5mm)

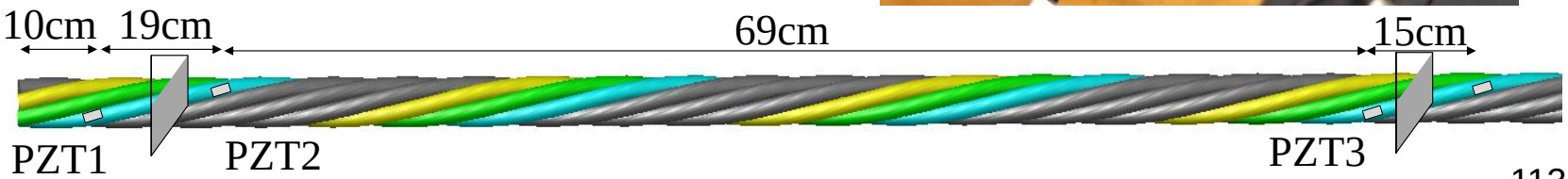
Farhidzadeh A., Salamone, S. (2014), Reference-free Corrosion Damage Diagnosis in Steel Strands Using Guided Ultrasonic Waves, Ultrasonics, revised and resubmitted

Sensor layout Specimen 2

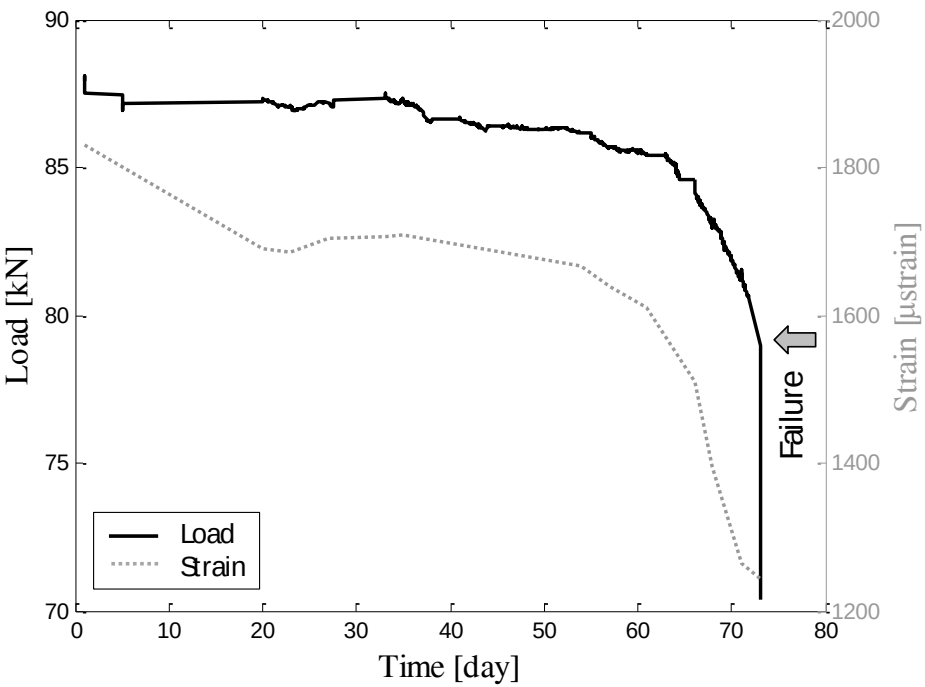


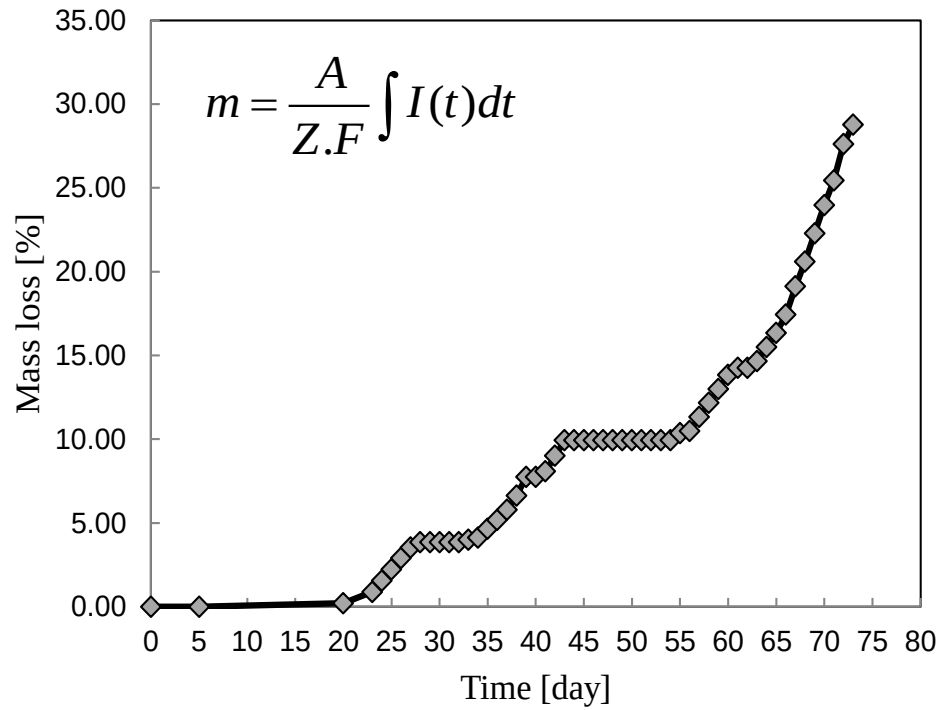






Load and mass loss monitoring





Uncertainty quantification

Heisenberg principle:

$$\sigma_t \sigma_f \geq \frac{1}{2}$$

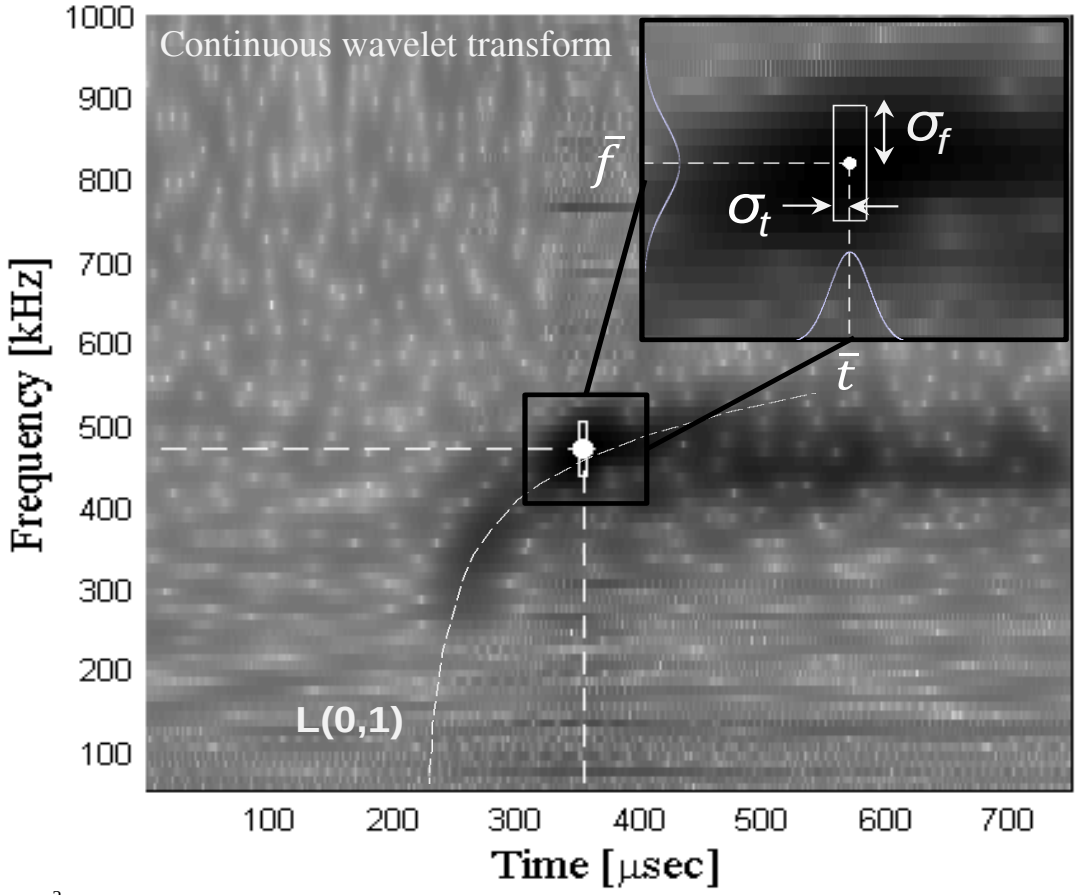
If mother wavelet is complex Morlet

$$\Rightarrow \sigma_t \sigma_f = \frac{1}{2}$$

$$\sigma_t = \frac{s\sqrt{f_b}}{2 f_s}$$

$$\sigma_f = \frac{f_s}{s\sqrt{f_b}}$$

$$s = \frac{f_s f_c}{\bar{f}}$$



complex Morlet: $\psi(t) = \frac{1}{\sqrt{\pi f_b}} \exp(2i\pi f_c t) \exp(\frac{t^2}{f_b})$

Farhidzadeh A., Salamone, S. (2014), Reference-free Corrosion Damage Diagnosis in Steel Strands Using Guided Ultrasonic Waves, Ultrasonics, revised and resubmitted

Uncertainty quantification

1) Monte Carlo:
- sample from velocity pdf
- Calculated *fd* deterministically
- Sample from frequency pdf

2) Unscented Transform

$$\chi_0 = \bar{v} \quad ; W_0 = \frac{\kappa}{1+\kappa}$$

$$\chi_1 = \bar{v} + \sqrt{(1+\kappa)\sigma_v^2} \quad ; W_1 = \frac{1}{2(1+\kappa)}$$

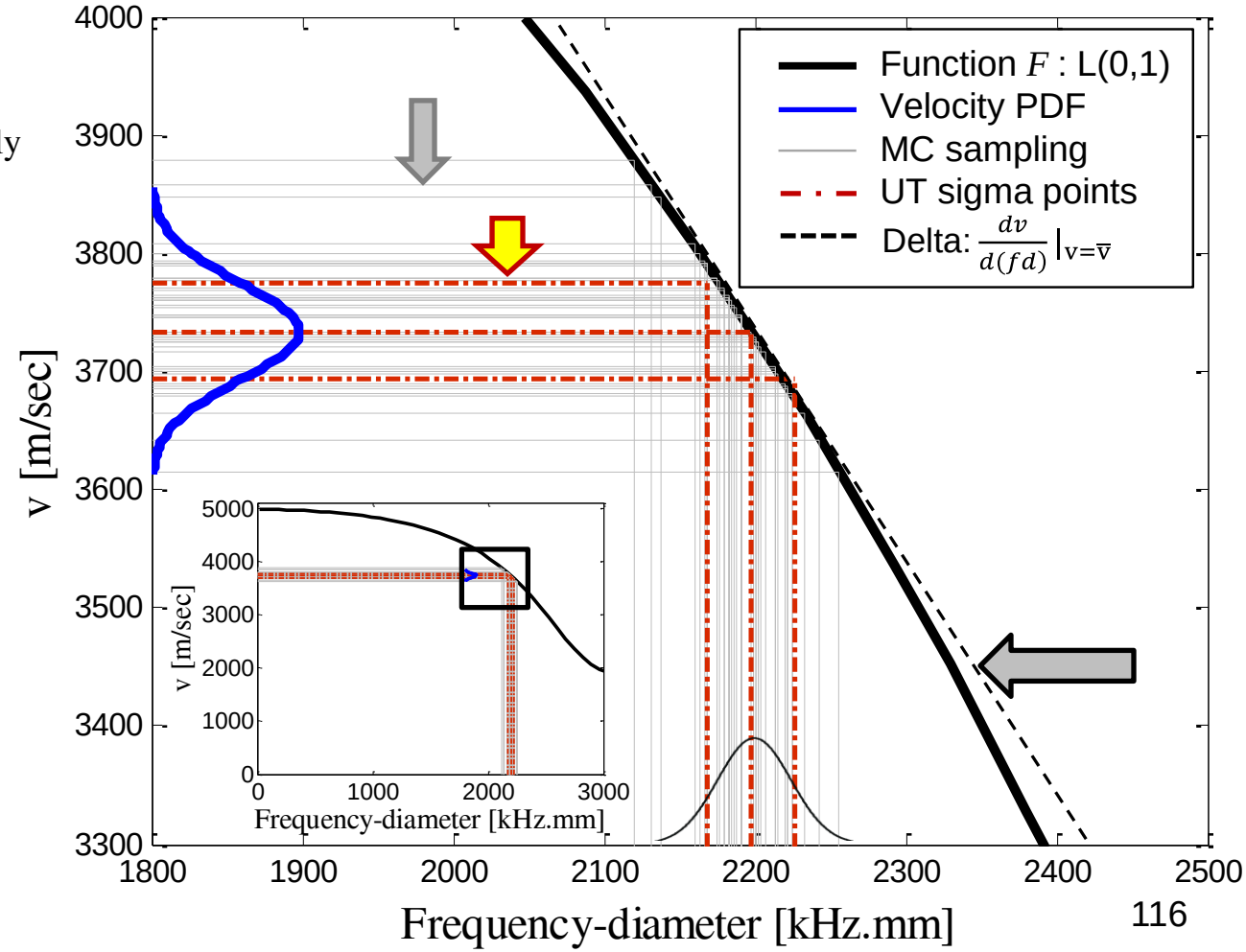
$$\chi_2 = \bar{v} - \sqrt{(1+\kappa)\sigma_v^2} \quad ; W_1 = \frac{1}{2(1+\kappa)}$$

$$\overline{fd} = \sum_{i=0}^{2} W_i F^{-1}(\chi_i)$$

$$\sigma_{fd}^2 = \sum_{i=0}^{2} W_i ((fd)_i - \overline{fd})^2$$

3) Delta method

$$\sigma_{fd}^2 \approx (F^{-1}{}'(\bar{v}))^2 \sigma_v^2$$

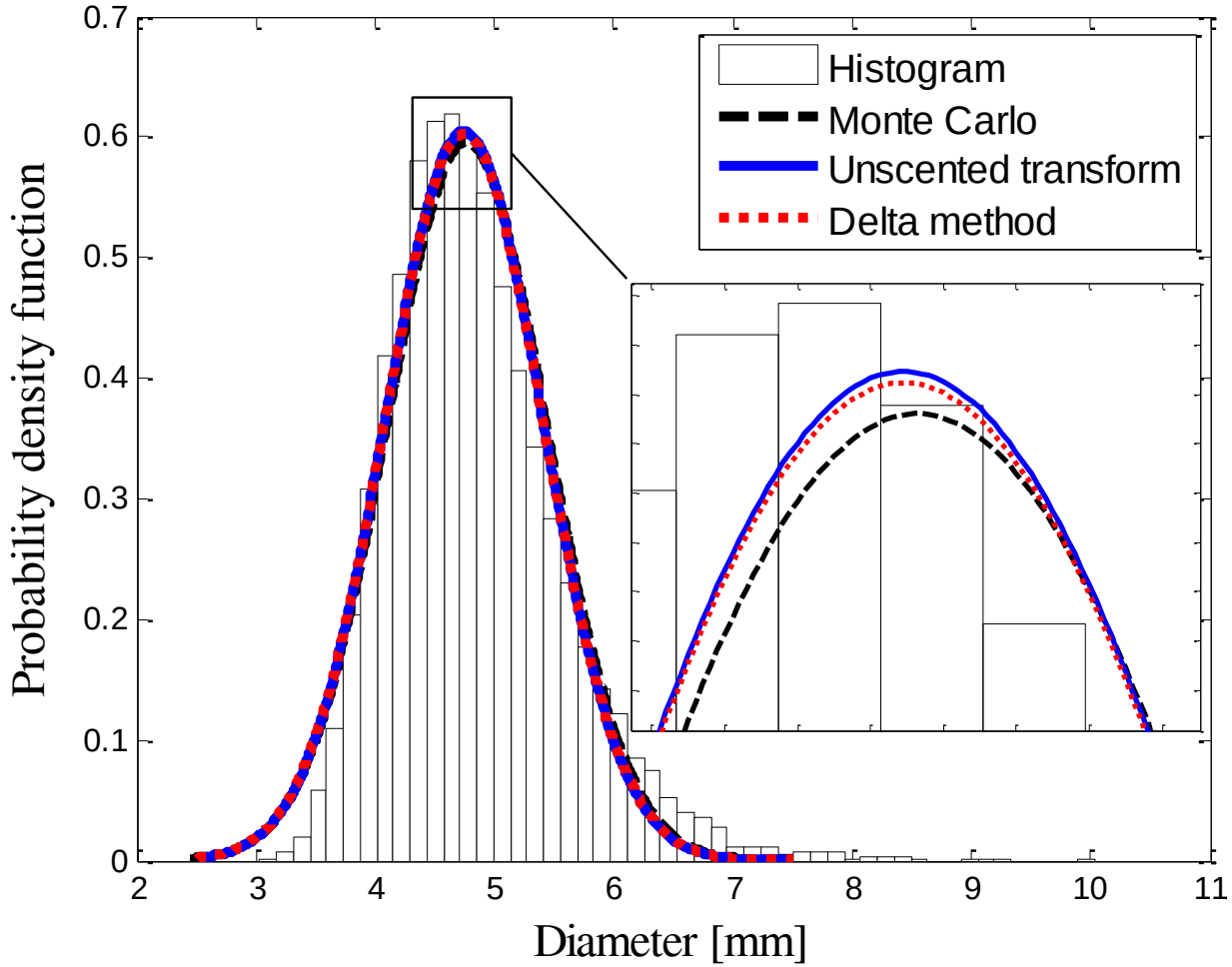


Farhidzadeh A., Salamone, S. (2014), Reference-free Corrosion Damage Diagnosis in Steel Strands Using Guided Ultrasonic Waves, Ultrasonics, revised and resubmitted

Uncertainty quantification

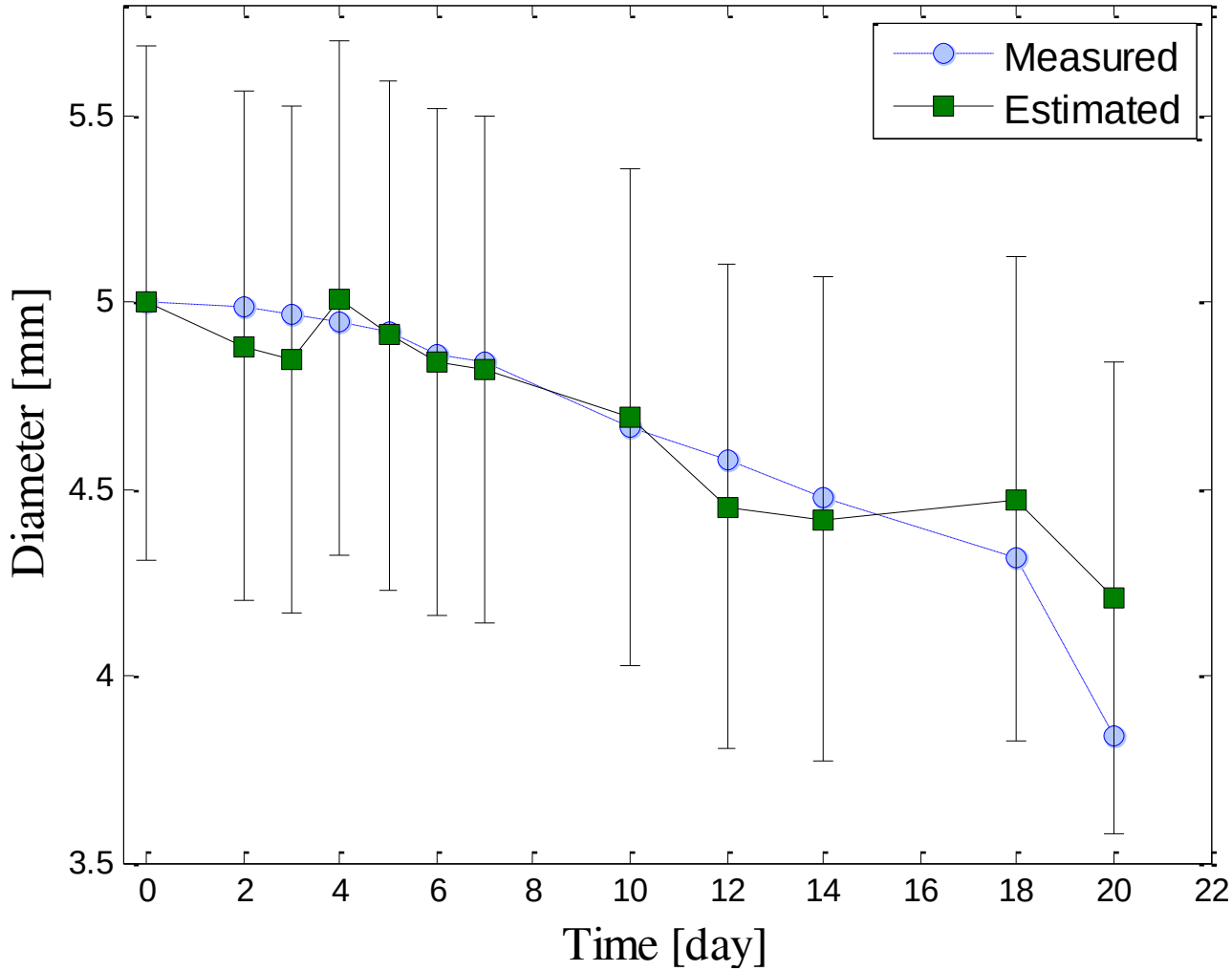
$$\bar{d} = \overline{fd} / \bar{f}$$

$$\sigma_d^2 = \frac{\sigma_{fd}^2 - \bar{d}^2 \sigma_f^2}{\bar{f}^2 + \sigma_f^2}$$



Farhidzadeh A., Salamone, S. (2014), Reference-free Corrosion Damage Diagnosis in Steel Strands Using Guided Ultrasonic Waves, Ultrasonics, revised and resubmitted

Uncertainty quantification



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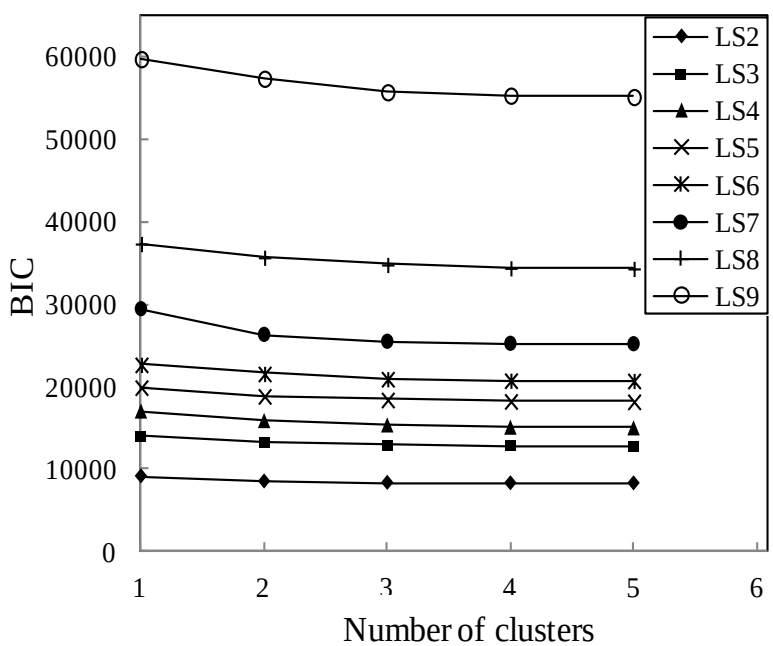
Geometrical Characteristics		Mechanical Characteristics	
Core wire diameter d_c [mm]	5.2	Young's modulus E [GPa]	196
Helical wire diameter d_h [mm]	5.0	Poisson's ratio [v]	0.29
Strand diameter D [mm]	15.2	Yielding load [KN]	203
Pitch of helical wire p [mm]	230	Ultimate tensile strength [MPa]	1860
Lay angle β [deg]	7.9	Linear weight [kg/m]	1.10

Optimum number of hidden clusters

Bayesian Information Criterion (BIC)

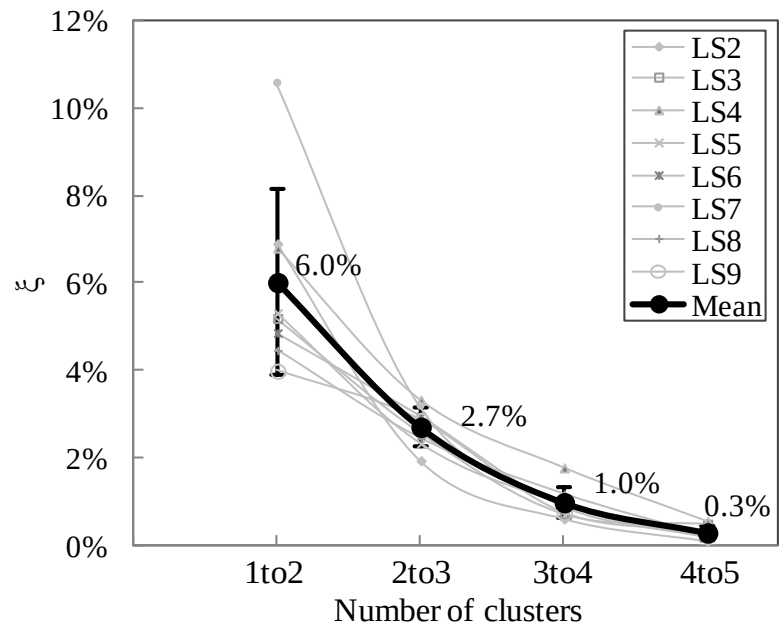
$$BIC = -2\ln(L) + k \times \ln(T)$$



Bayesian Information Criterion for each load step

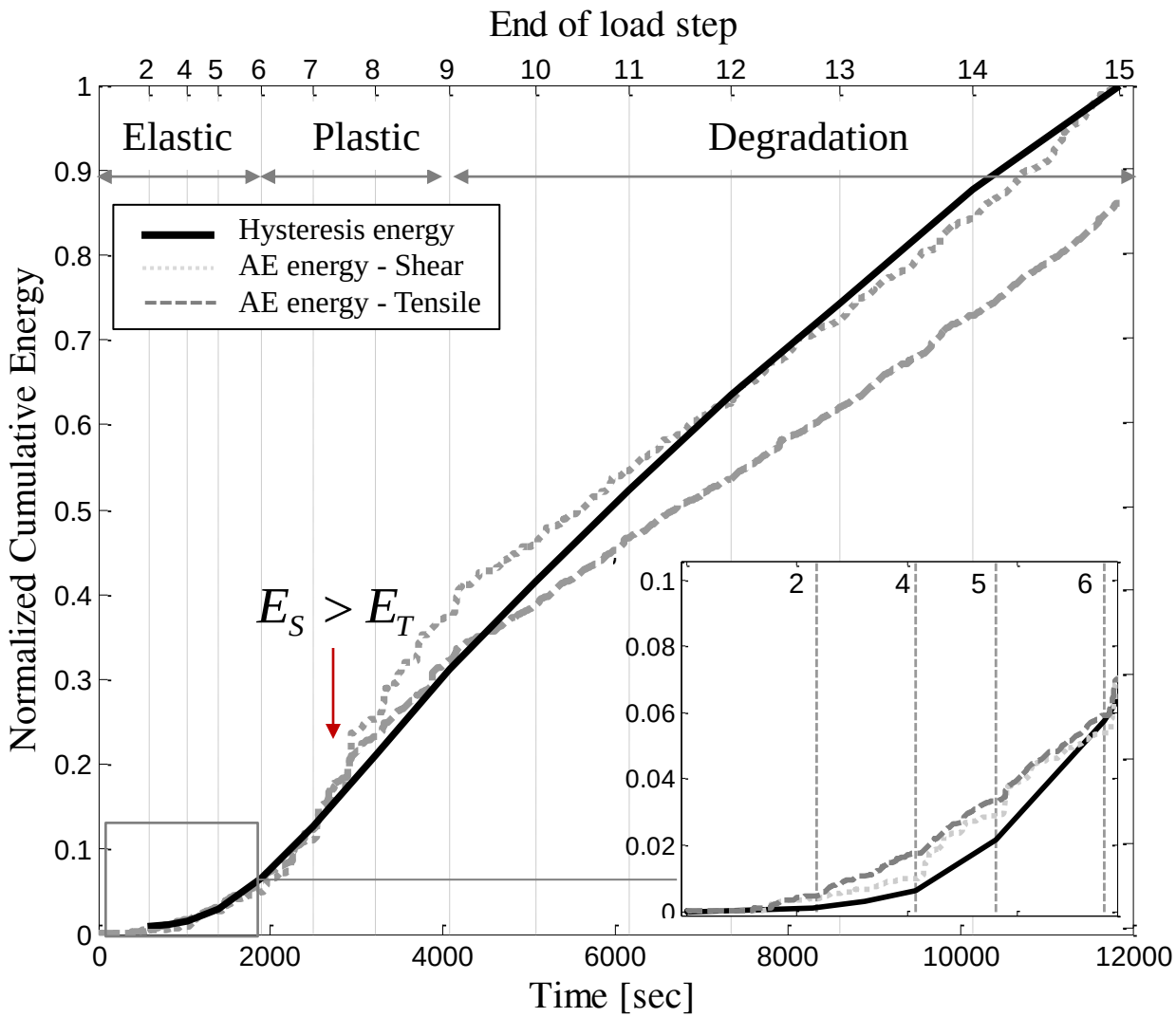
BIC change ratio

$$\xi_{M+1} = \frac{BIC_M - BIC_{M+1}}{BIC_M}$$



Percentage of reduction in BIC by adding one cluster to the previous number of clusters. The bars represent the standard deviation.

A. Farhidzadeh, S. Salamone, P. Singla, (2012), "A Probabilistic Approach …", *J Intelligent Material Systems and Structures*, 24 (14), 1722-1735.



A. Farhidzadeh, S. Epackachi, S. Salamone, A. Whittaker, (2014), Bayesian Decision and Mixture Models for Multi-scale Damage Interrogation in Composite Shear Walls Using Acoustic Emission, to be submitted to an ASCE Journal