Structural Health Monitoring in the Digital Era

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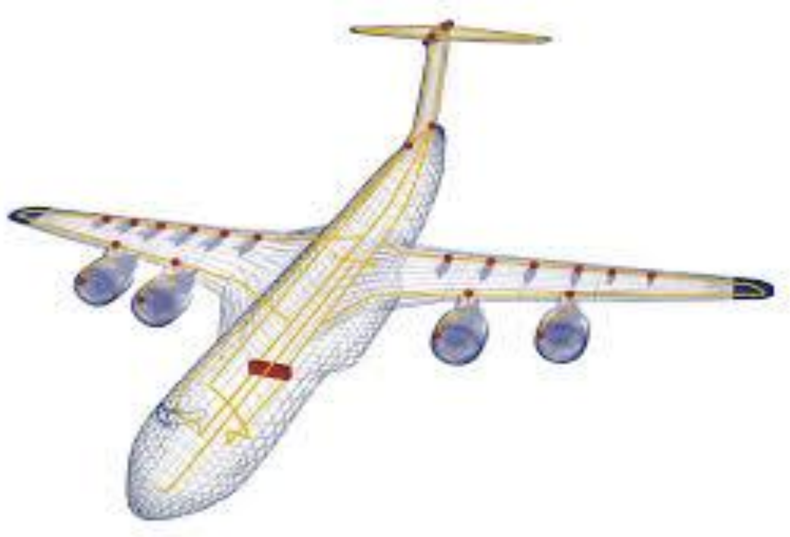
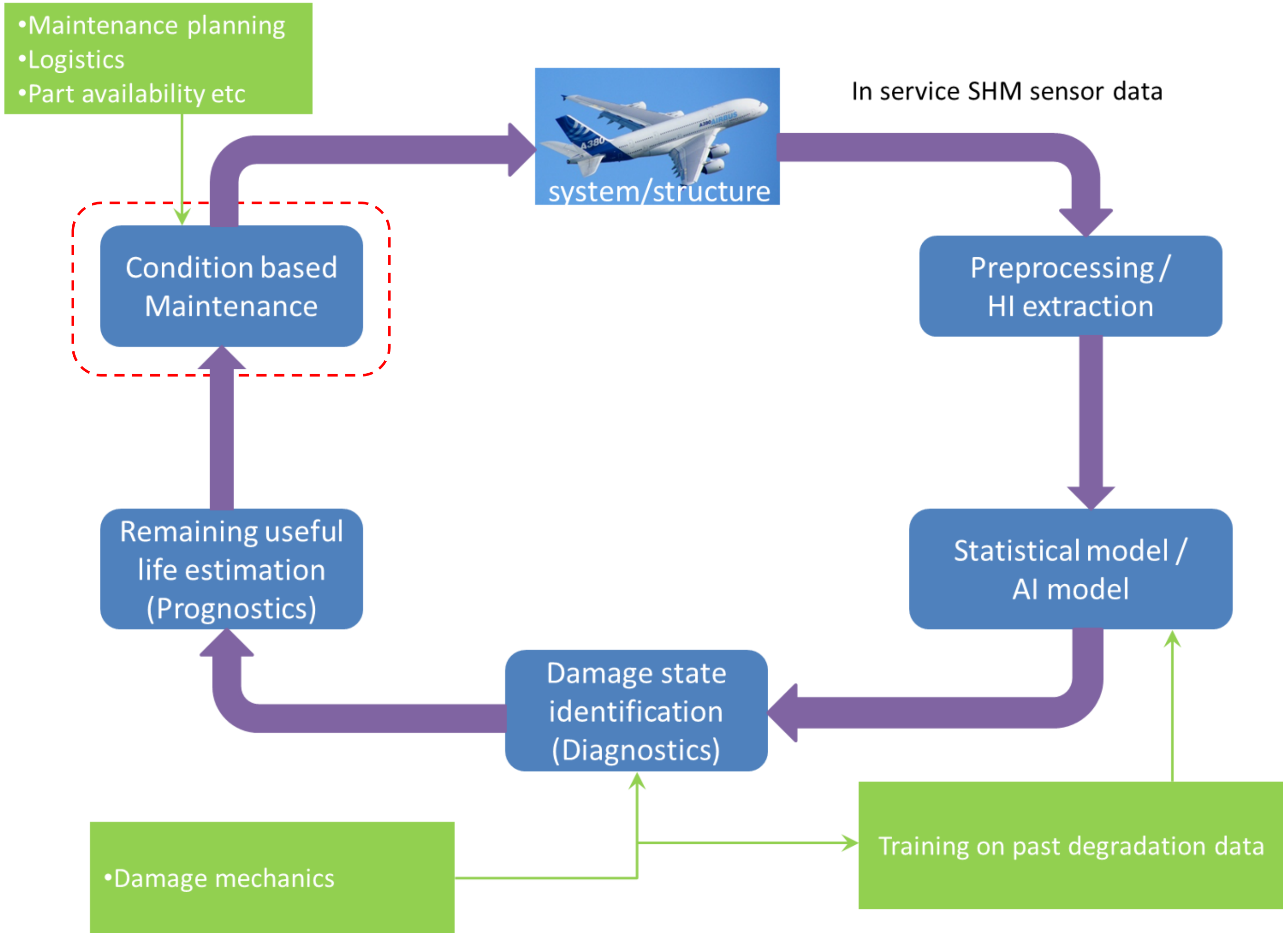


Outline

- Definitions
- Levels of SHM
- Axioms of SHM
- SHM system design guidelines
- Sensing technologies for SHM
- Case Study I: Digital twin based SHM
- Case Study II- Remaining Useful Life Prognostics

The vision – towards Condition Based Maintenance

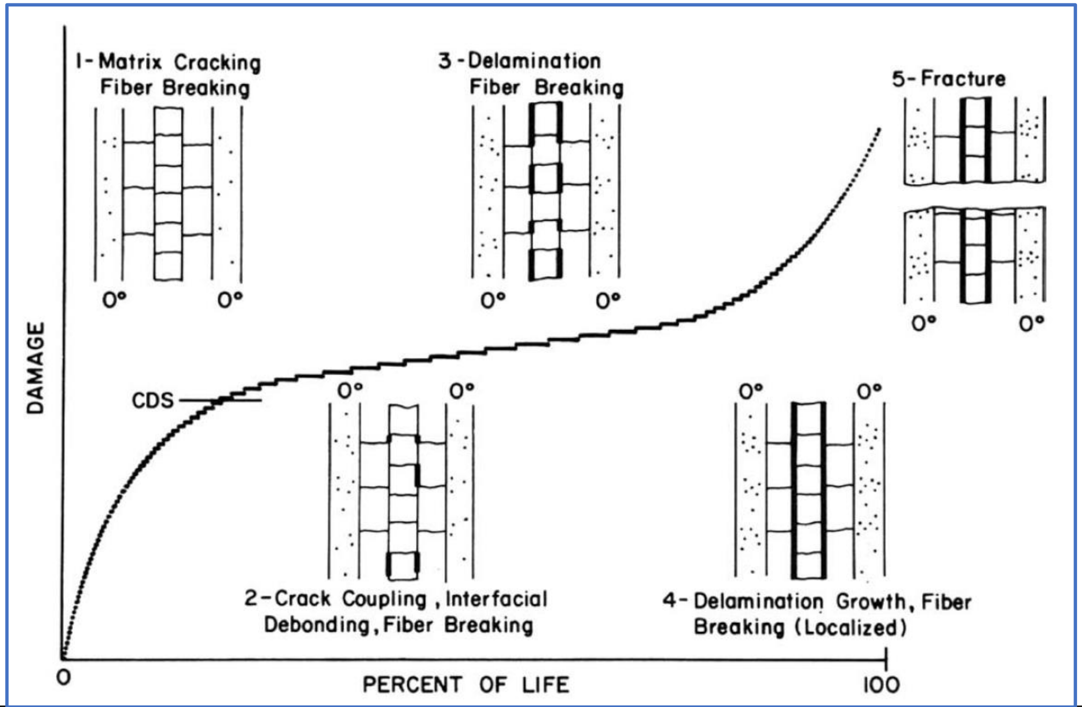
The prognostication of the remaining useful life in composite structures based on SHM data



Definitions

Damage: changes to the material and/or geometric properties of structures or systems, including changes to the boundary conditions, which adversely affect the current or future performance of the material

Structural Health Monitoring: the process of implementing a damage identification strategy for aerospace, civil and mechanical engineering infrastructure



Damage accumulation in a composite's lifetime (Reifsnider early 1980s)

Levels of SHM

Non-destructive testing

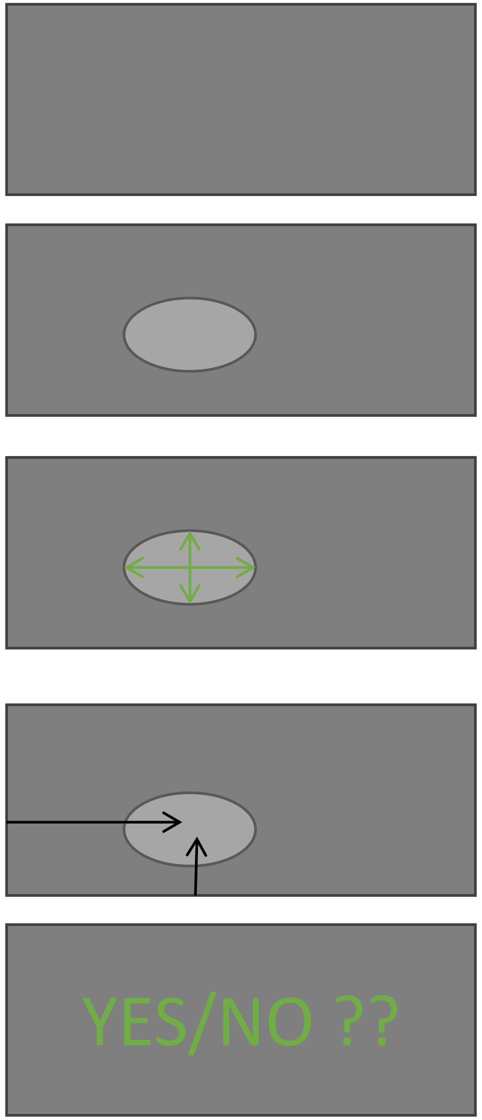
Level 5
Self-healing
- Introduce damage restoration mechanisms

Level 4
Remaining Lifetime
- Prognosis of the remaining service life of the structure

Level 3
Sizing of Damage
- Quantification of the severity of the damage

Level 2
Locating Damage
- Determination of the geometric location of the damage

Level 1
Anomaly detection
- Determination that damage is present in the structure



Fundamental axioms of SHM*

Axiom I: All materials have inherent flaws or defects. Service loading induces new faults or propagates existing ones

Axiom II: The assessment of damage requires a comparison between two system states.

Axiom III: Identifying the existence and location of damage (i.e. Levels I & II) can be done in an unsupervised learning mode, but identifying the type of damage present and the damage severity (i.e. Levels III & IV) can generally only be done in a supervised learning mode.

Axiom IVa: Sensors cannot measure damage. Feature extraction through signal processing and statistical classification is necessary to convert sensor data into damage information.

Axiom IVb: Without intelligent feature extraction, the more sensitive a measurement is to damage, the more sensitive it is to changing operational and environmental conditions.

Axiom V: The length- and time- scales associated with damage initiation and evolution dictate the required properties of the SHM sensing system.

Axiom VI: There is a trade-off between the sensitivity to damage of an algorithm and its noise rejection capability.

Axiom VII: The size of damage that can be detected from changes in system dynamics is inversely proportional to the frequency range of excitation.

**Worden et al., Proceedings of The Royal Society A, 2007*

SHM system design guidelines

(i) Sensor types, number and locations

(ii) Bandwidth, sensitivity and dynamic range

(iii) Data acquisition/telemetry/storage system

(iv) Power requirements

(v) Sampling intervals (continuous monitoring versus monitoring only after extreme events or at periodic intervals)

(vi) Processor/memory requirements

(vii) Excitation source (active sensing)

SHM system design parameters

(i) The length-scales on which damage is to be detected (global vs local approaches)

(ii) The time-scale on which damage evolves (milliseconds vs hrs of flight)

(iii) How will varying and/or adverse operational and environmental

conditions affect the sensing system

(iv) Cost

Sensing technologies for SHM

1. Piezoelectric (PZT)

2. Fibre optic sensors (Fibre Bragg Gratings, distributed sensing)

3. Accelerometers

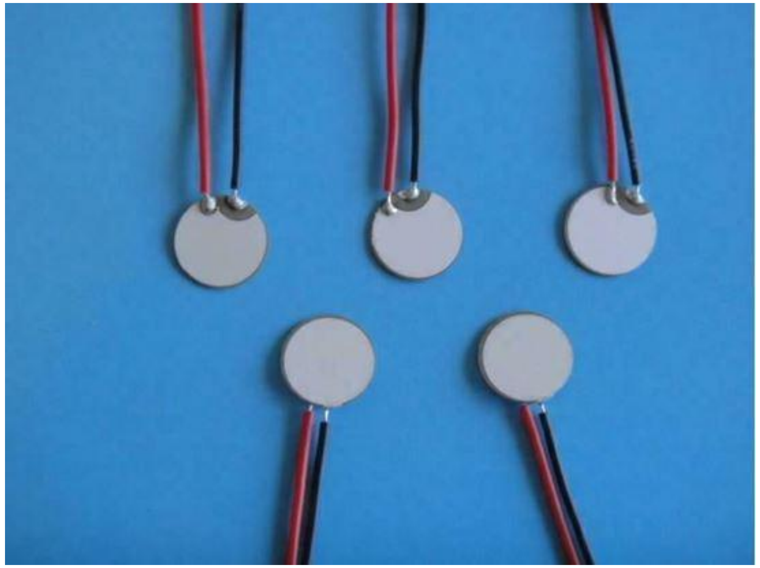
4. Acoustic Emission

5. Classical strain gauges

6. Temperature sensors

7. Hybrid schemes and others

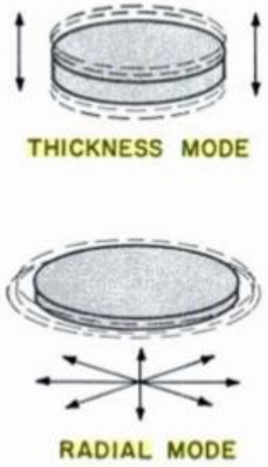
1. PZTs (Piezoceramic elements)

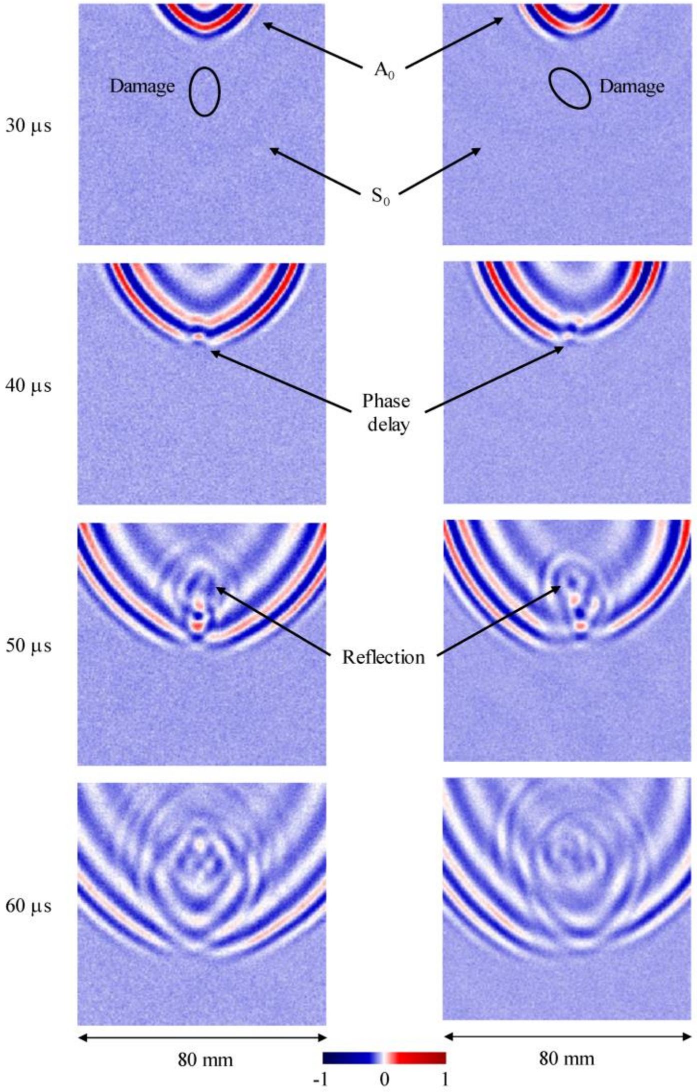


Modes of Vibration

2 TYPES:

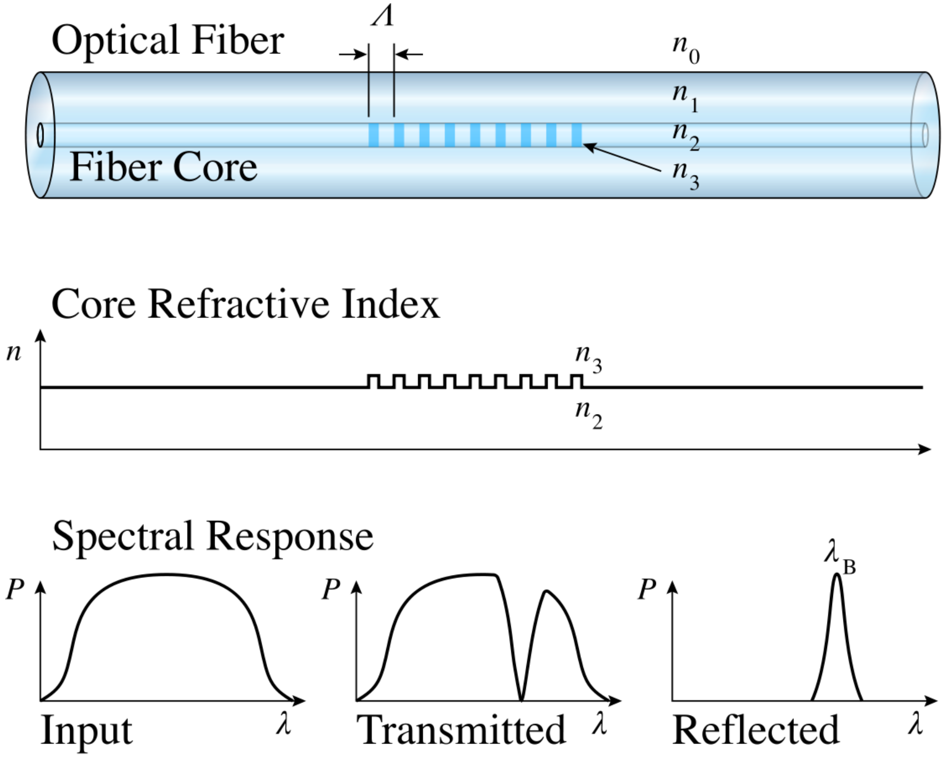
1. thickness mode
   - most common
   - Used in medical crystals
2. radial mode

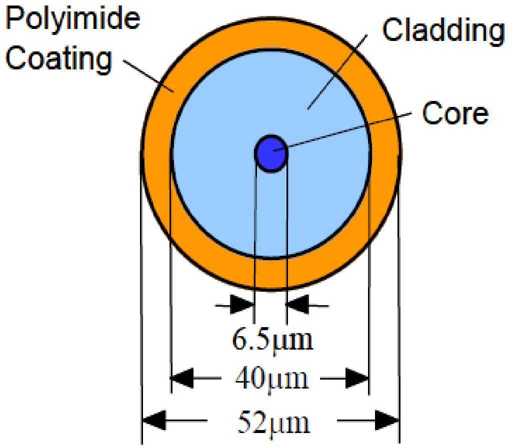




Toyama et al. Appl. Sci. **2019**

2. Optical fiber sensors (Fiber Bragg sensors)





Fiber grating is made by periodically changing the refraction index in the glass core of the fiber. The refraction changes are made by exposing the fiber to UV-light with a fixed pattern.

$$\Delta\lambda_B = 2n\Lambda\left(\left\{1-\left(\frac{n^2}{2}\right)\left[P_{12}-\nu\left(P_{11}+P_{12}\right)\right]\right\}\varepsilon+\left[\alpha+\frac{\left(\frac{dn}{dT}\right)}{n}\right]\Delta T\right)$$

2. Optical fiber sensors (Distributed sensing)

Distributed sensing is a technology (based on Brillouin scattering) that enables very dense, real-time measurements along the entire length of a fibre optic cable. Unlike traditional sensors that rely on discrete sensors measuring at pre-determined points, distributed sensing does not rely upon manufactured sensors but utilizes the optical fibre. The optical fibre is the sensing element without any additional transducers in the optical path.

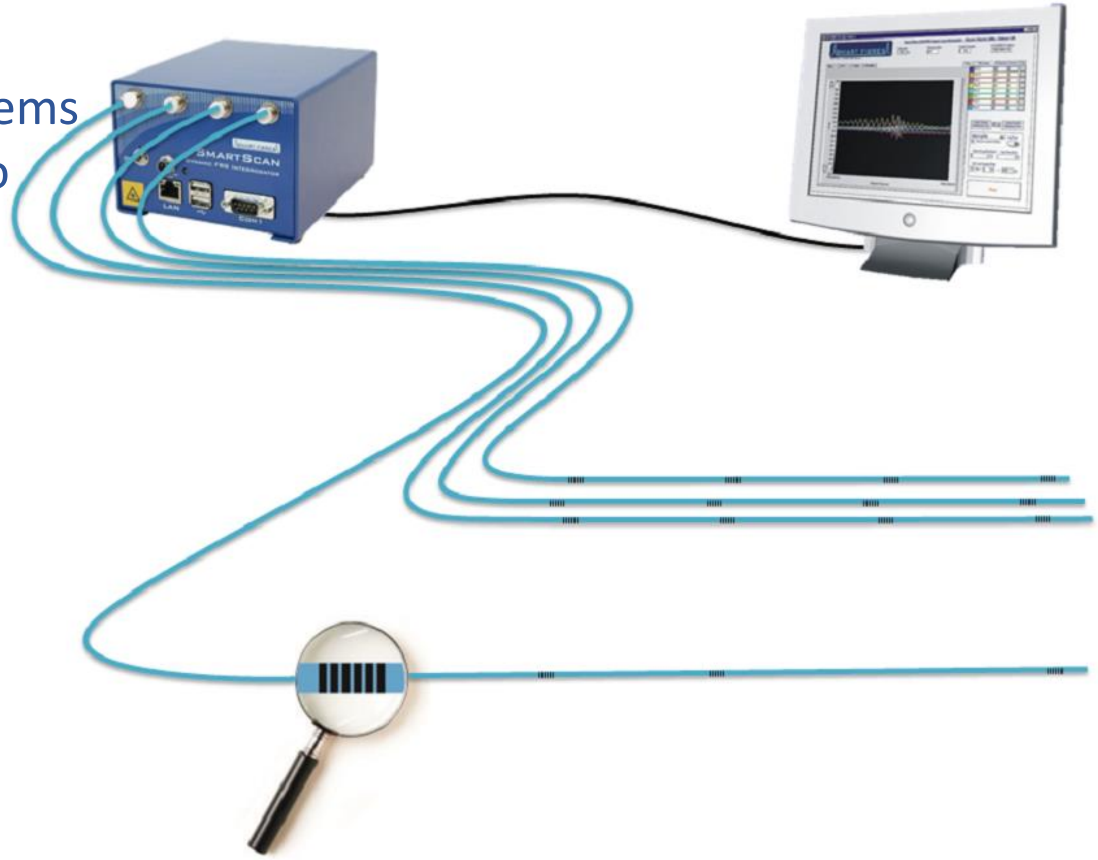
As the fibre is the sensor, it is also a cost-effective method that can be easily deployed even in the harshest and most unusual environments.

2. Optical fiber sensors

Interrogation unit (laser source) required

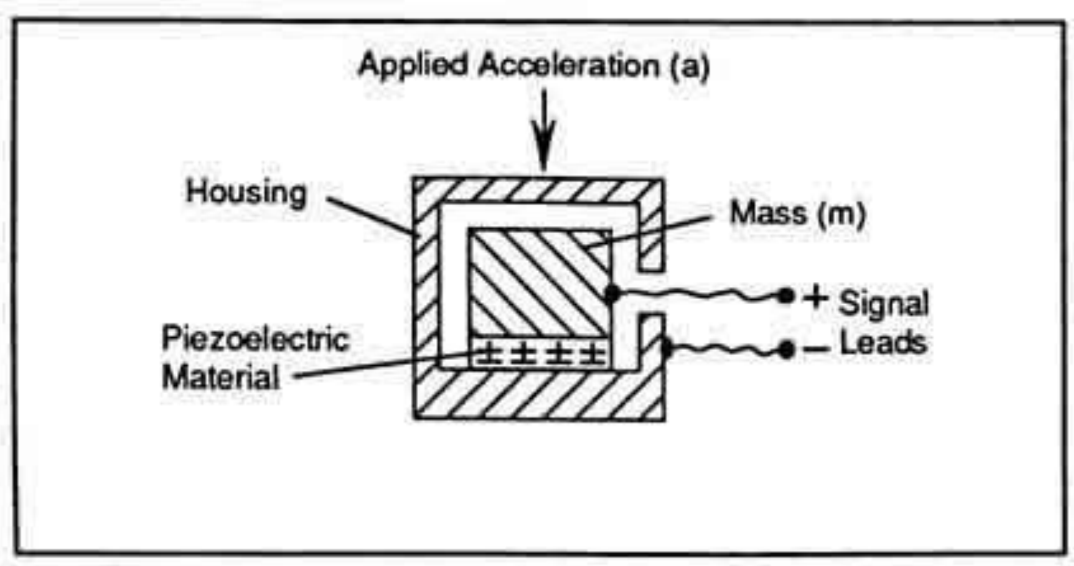
Advantages:

- Small size and easy integration into a wide variety of systems
- Electrically immune, no conduction of electric current, no spark peril
- Capacity for static and/or dynamic measurements
- Immune to electromagnetic interference and radio frequency interference
- Light in weight
- Ideal for harsh environments
- High sensitivity
- Multiplexing capability thus forms sensing networks
- Remote sensing capability



3. Accelerometers

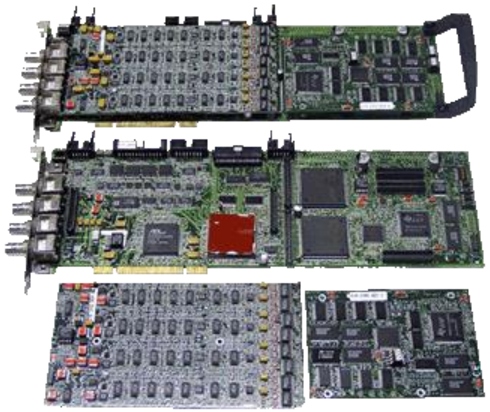
Working principle



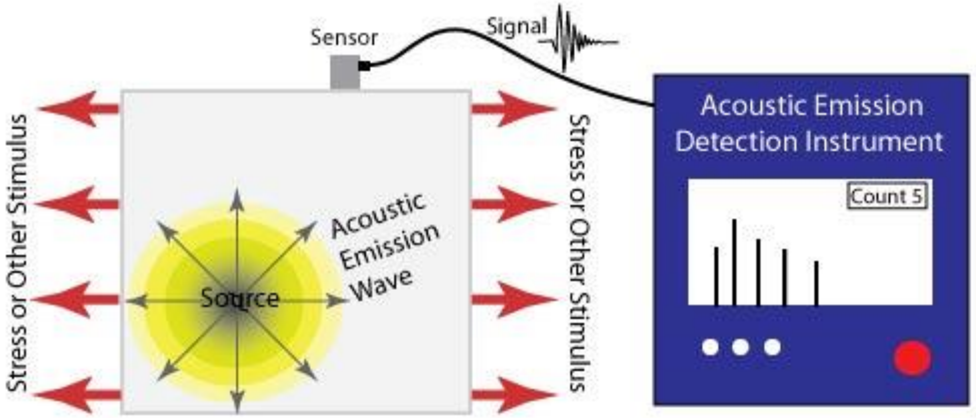
Very popular for structural dynamic measurements (vibrations)

4. Acoustic emission

A/D boards



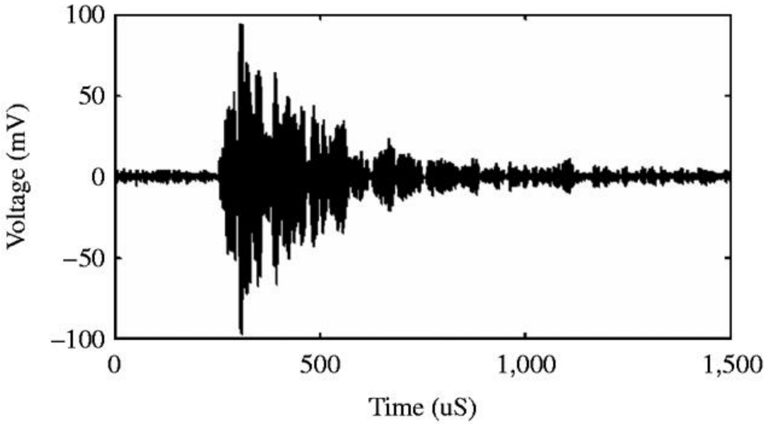
Acoustic Emission (AE) refers to the generation of transient elastic waves produced by a sudden redistribution of stress in a material, usually in locations of defects or discontinuities.



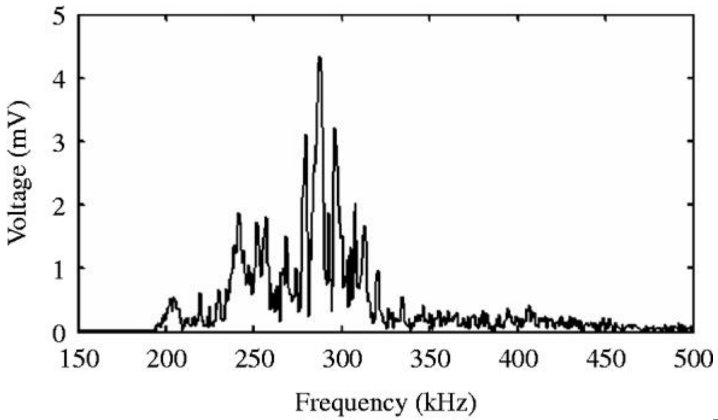
AE sensors

4. Acoustic emission

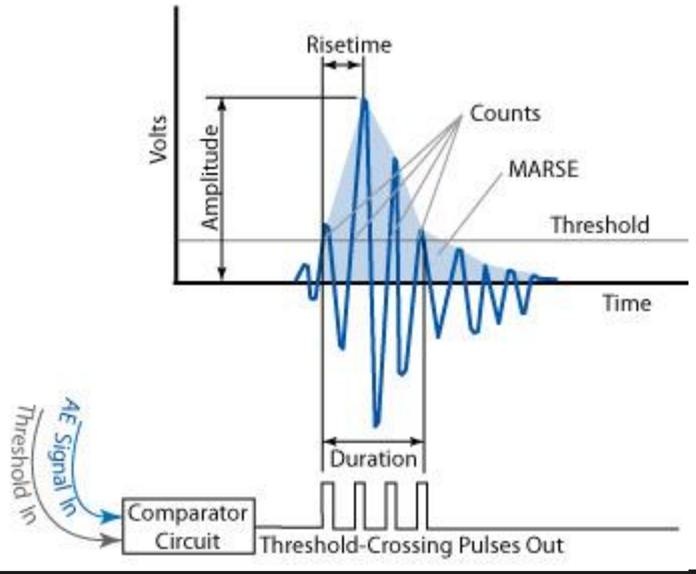
Typical waveform (burst type)



Power spectrum



Feature extraction

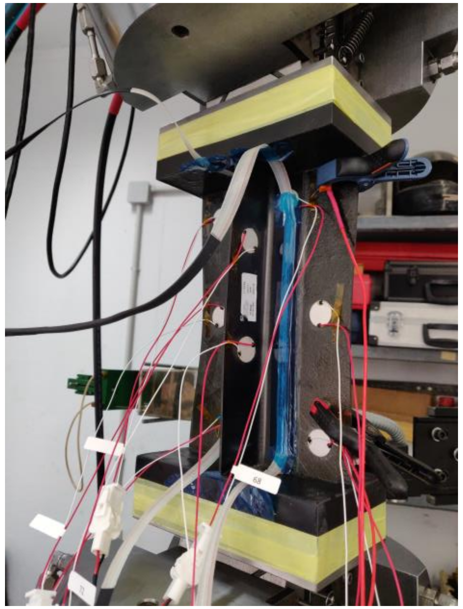


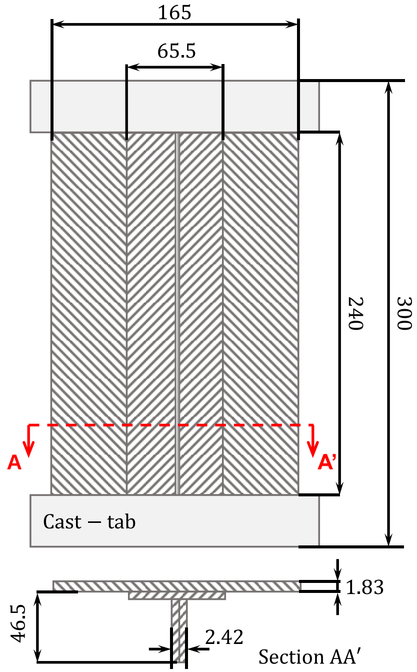
Typical features

AE feature	Symbol	Unit
Duration	DUR	us
Counts	CNT	#
Amplitude	AMP	dB
Counts to peak	CNP	#
Risetime	RT	us
Energy	E	pJ
Absolute energy	ABE	fJ
Signal strength	SS	pVs
Rise angle	RAN	deg
Decay angle	DAN	deg
Average frequency	AF	kHz
Initiation frequency	INF	kHz
Reverberation frequency	REVF	kHz
FFT amplitude	FFTAMP	–
FFT peak frequency	FFTPF	kHz

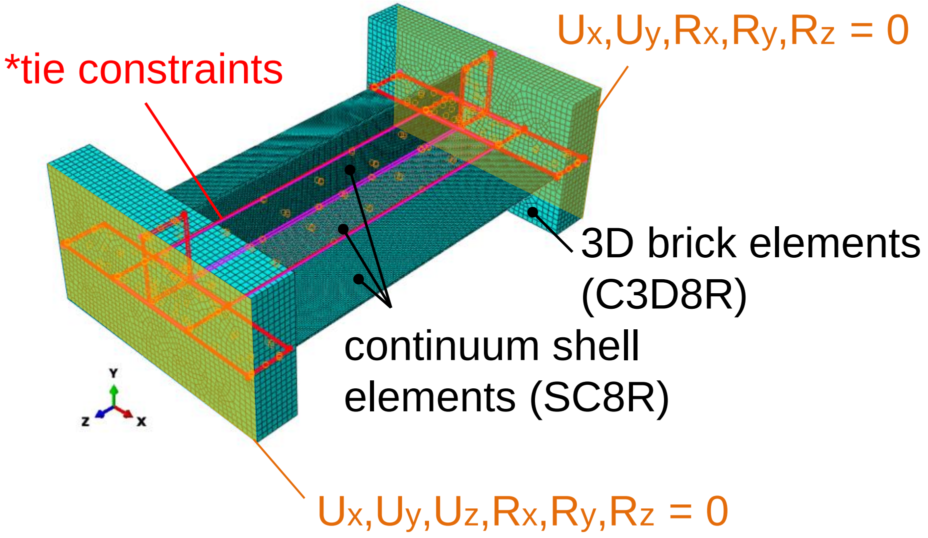
CASE STUDY I:
Digital twin based SHM

2. Digital twin development





Physical twin



Digital twin

1. Linear buckling analysis

↓

Eigenvalues & buckling modes

↓

Initial imperfections

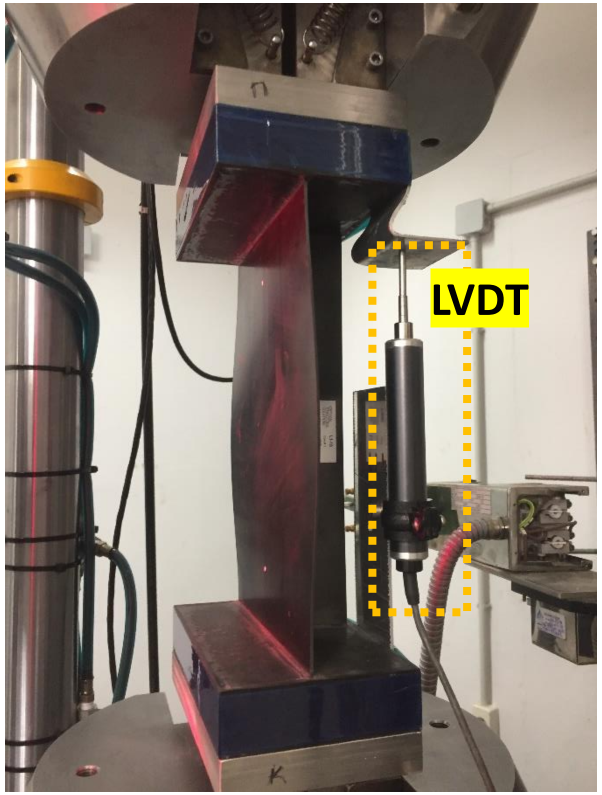
↓

2. Nonlinear analysis Abaqus/Standard (N-R solver)

↓

Simulated strain field

3. Experimental verification (1)

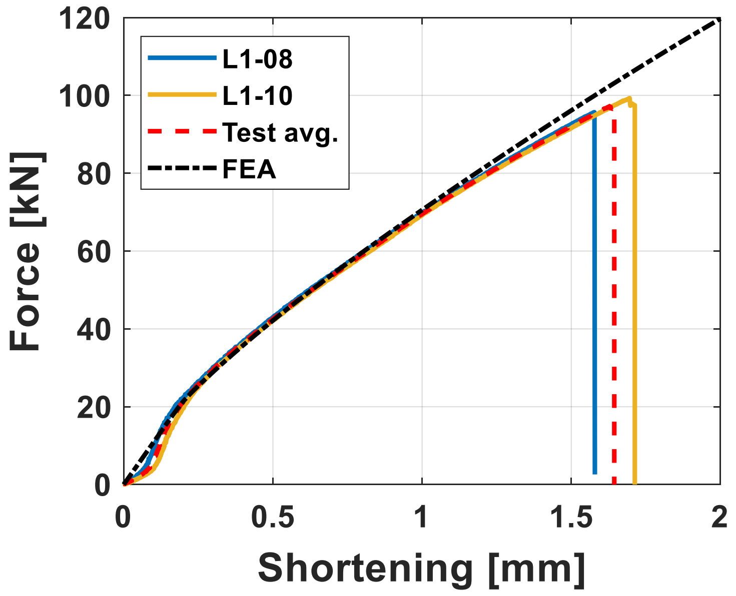


Specimen response during post-buckling regime

Quasi-static uniaxial compression

test:

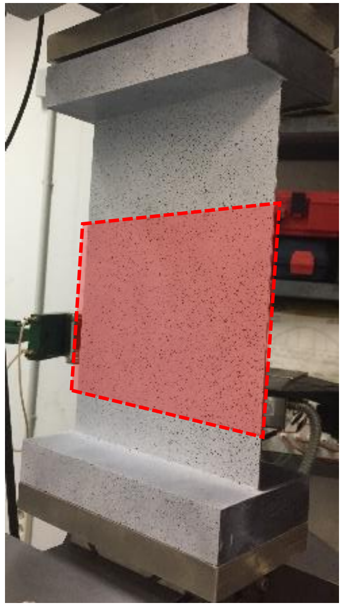
- Displacement rate 0.5 mm/min
- Instron 8802 test machine with load capacity ± 250 kN
- LVDT for panel shortening measurements
- Buckling ~20.0 kN
- Avg. collapse load 97.5 kN



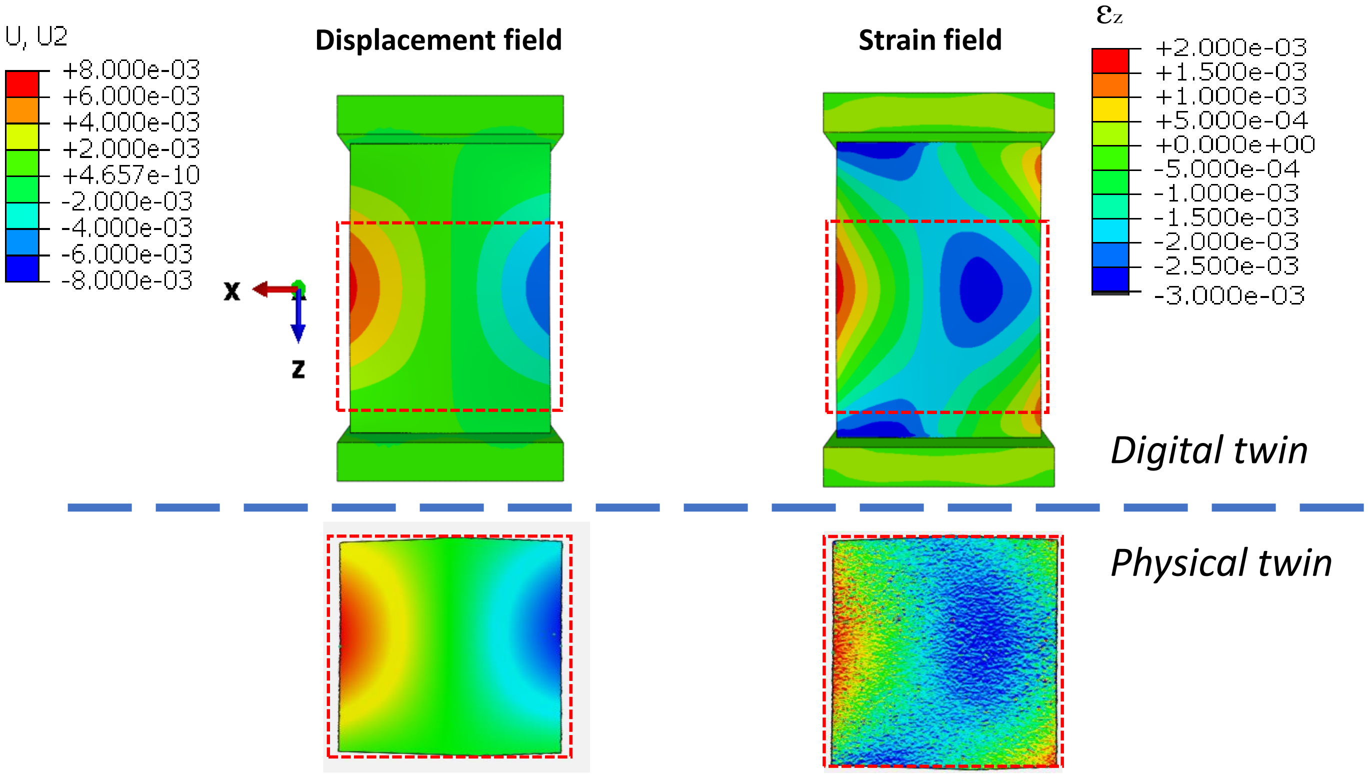
Experimental and numerical force-shortening curves

3. Experimental verification (2)

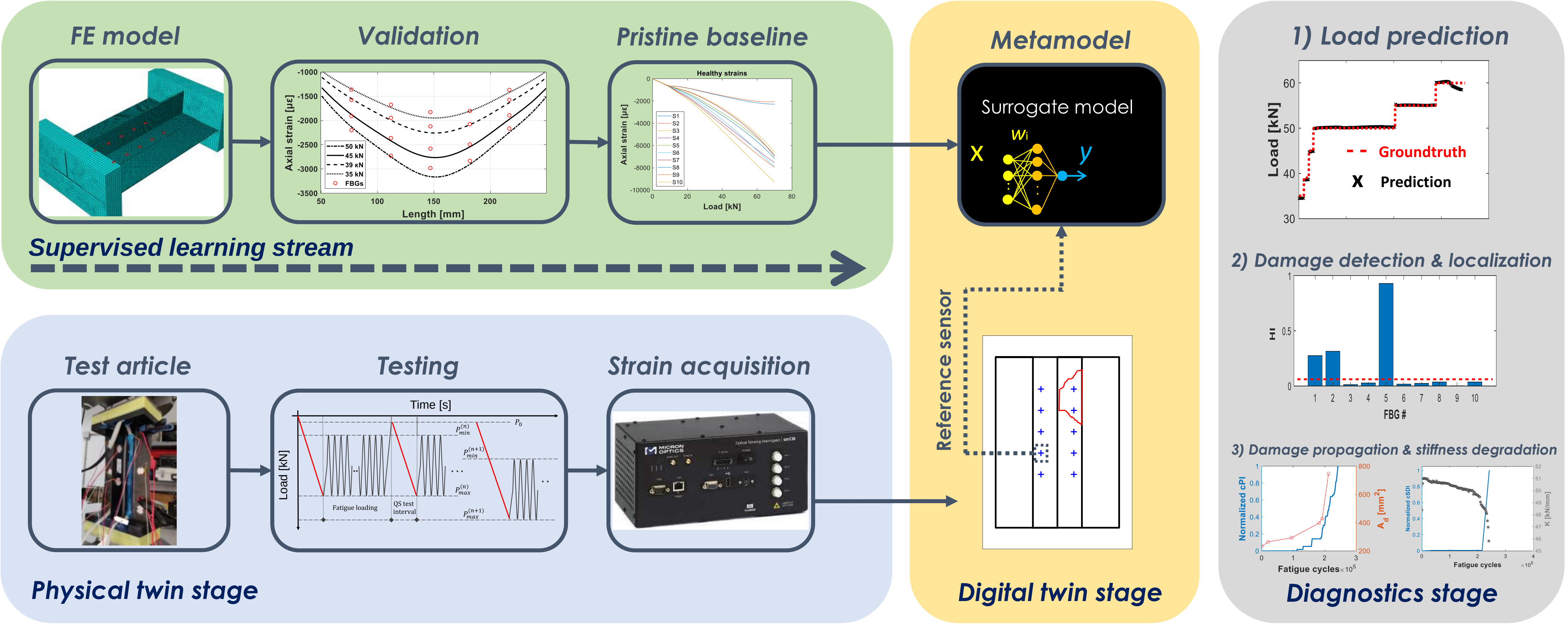
Digital Image Correlation (DIC) measurements



Speckle pattern

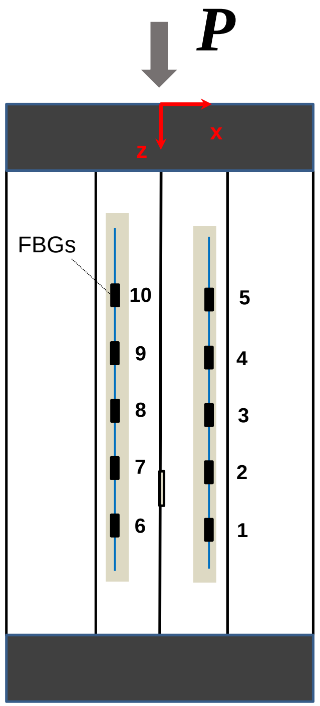


4. DT-based damage diagnosis



4.1 Surrogate modeling

A surrogate model is trained with input-output pairs provided by the DT.



1. Meta-model's variables: $\boldsymbol{\mathcal{X}} = \{\underbrace{\boldsymbol{x}^{(i)}, \boldsymbol{z}^{(i)}}_{\text{FBG spatial coordinates}}, \underbrace{\boldsymbol{P}^{(i)}}_{\text{Load}}\}_{i=1}^{N}$

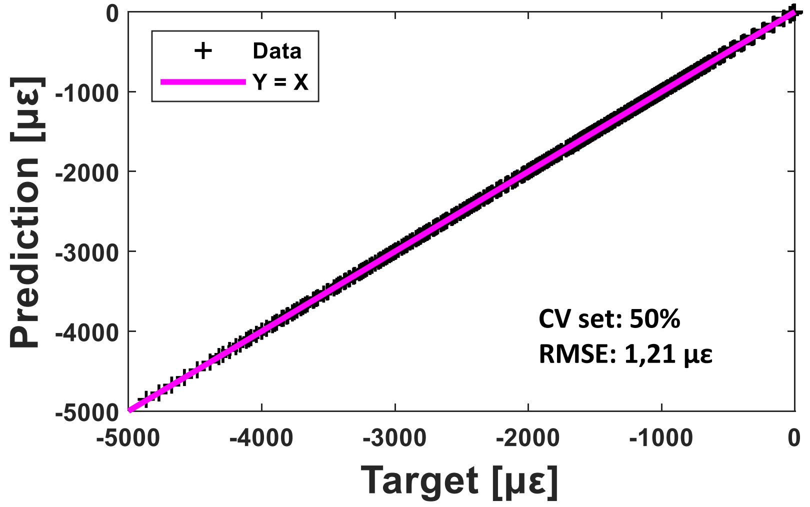
2. Radial Basis Function (RBF) surrogate:

$$\boxed{\widetilde{\mathcal{M}}(\boldsymbol{\mathcal{X}}^{(j)}) = \sum_{i=1}^{N} w_i \psi(||\boldsymbol{\mathcal{X}}^{(j)} - \boldsymbol{\mathcal{X}}^{(i)}||) = \boldsymbol{y}^{(j)}}$$

- fixed basis: $\psi(\rho) = \rho^3$

3. Learning dataset: $\left\{\boldsymbol{\mathcal{X}}^{(i)}; \boldsymbol{y}^{(i)}\right\}$, *i=1,..,N*

- *N=1040* strains, i.e., 100 loads $P \in [0,70]$ kN



Accuracy of the trained surrogate model

4.2 Strain-based feature extraction

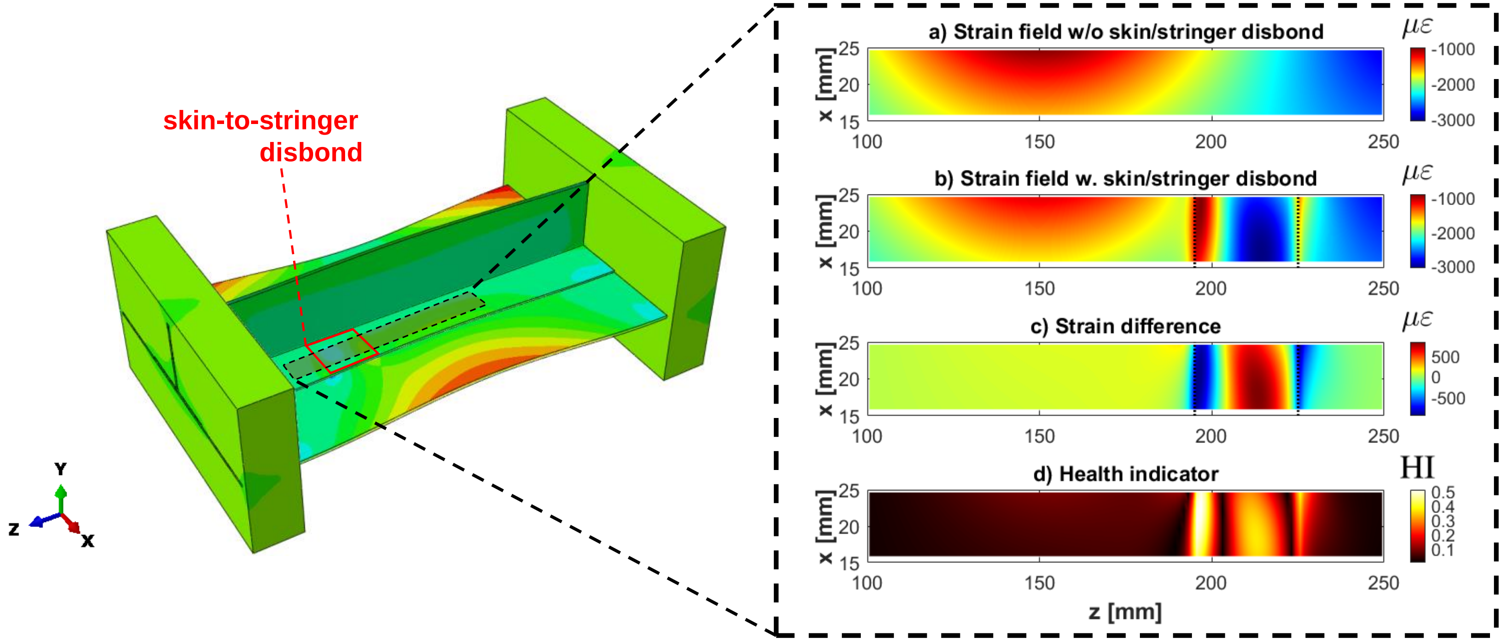
DT-based Health Indicator (HI):

$$\mathrm{HI}_i = \left| \frac{\varepsilon_{ref}^{(i)} - \varepsilon_t^{(i)}}{\varepsilon_{ref}^{(i)}} \right|$$

i=1,…,10 : FBG label

$\varepsilon_{ref}^{(i)}$: DT's strain at the pristine state

$\varepsilon_t^{(i)}$: experimental strain during testing



Strain modification in the vicinity of skin-to-stringer disbonds at -50 kN

<u>Important</u>: HI strongly related to the boundary conditions, e.g., load.

Load derives from the minimization of the following squared ℓ^2-norm objective function *F*:

$$P = \underset{P}{\operatorname{argmin}}\, F(x^{(r)}, z^{(r)}, P) = \underset{P}{\operatorname{argmin}} \left\{ ||\widetilde{\mathcal{M}}(x^{(r)}, z^{(r)}, P) - \boldsymbol{y}^m||^2 \right\}$$

$\boldsymbol{y}^m$: strain measurement by the reference FBG

Iterative estimation of *P* utilizing gradient descent:

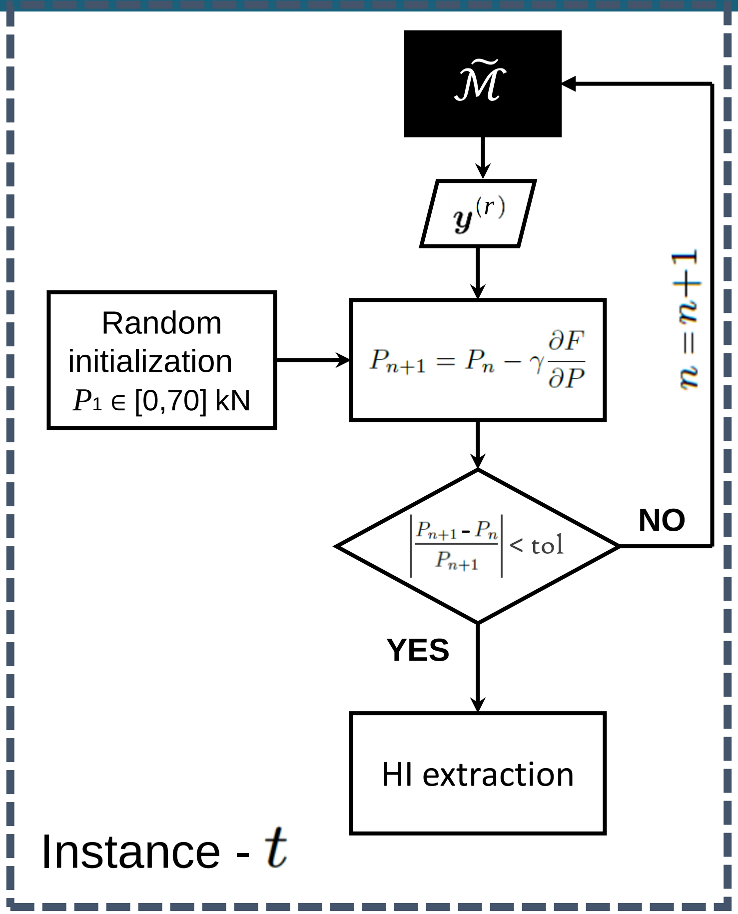
$$P_{n+1} = P_n - \gamma \frac{\partial F}{\partial P} \quad , \qquad \gamma \text{ : step size}$$

Derivative term with central differences:

$$\frac{\partial F}{\partial P} = \frac{1}{\epsilon} \left[\widetilde{\mathcal{M}}(x, z, P) - \boldsymbol{y}^m \right] \cdot \left[\widetilde{\mathcal{M}}(x, z, P + \epsilon) - \widetilde{\mathcal{M}}(x, z, P - \epsilon) \right]$$

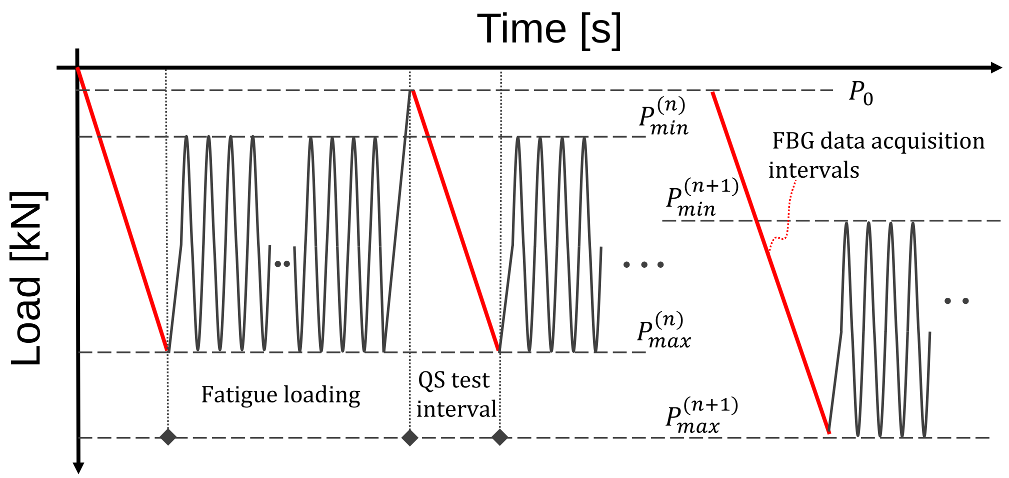
ϵ : small perturbation

Highlight: Load is predicted by a sensor far from damage utilizing information from the pristine DT.



Gradient-descent optimization algorithm

5. Evaluation of the methodology



Test plan definition

- Block loading compression-compression fatigue
- FBG strains recorded during quasi-static test intervals every 500 cycles

Details of the fatigue tests

SSP	Damage type	Damage location [x,z] (mm)	Initial damage area $(mm)^2$	P_{min} (kN)	P_{max} (kN)	Consecutive cycles	Failure cycles
Panel #1	I - 10 J	[22.5,200]	1397.9	-4.0 -4.5 -5.0	-40.0 -45.0 -50.0	10,000 177,000 30,000	217,000
Panel #2	I - 7.4 J	[32.5,105]	232.5	-4.0 -4.5 -5.0 -5.5	-40.0 -45.0 -50.0 -55.0	10,000 80,000 90,000 63,000	243,000

I. *Damage detection and localization*

$$\mathrm{DI}_i = \begin{cases} 1, & \text{if } \mathrm{HI}_i > \textit{threshold} \\ 0, & \text{if } \mathrm{HI}_i \leq \textit{threshold} \end{cases}$$

II. *Damage type identification (boxplot statistics)*

a) Type 1: Damage propagation

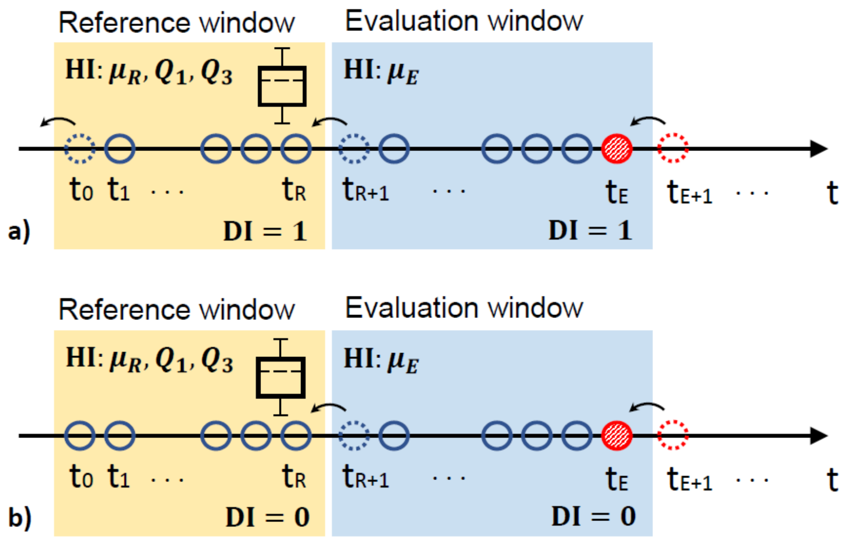
$$\mathrm{PI}_i(t_E) = \begin{cases} 1, & \text{if } \mu_E > Q_3 + 1.5(Q_3 - Q_1) \\ & \text{or } \mu_E < Q_1 - 1.5(Q_3 - Q_1) \\ 0, & \text{otherwise} \end{cases}$$

b) Type 2: Stiffness degradation

$$\mathrm{SDI}_i(t_E) = \begin{cases} 1, & \text{if } \mu_E > Q_3 + 1.5(Q_3 - Q_1) \\ & \text{or } \mu_E < Q_1 - 1.5(Q_3 - Q_1) \\ 0, & \text{otherwise} \end{cases}$$

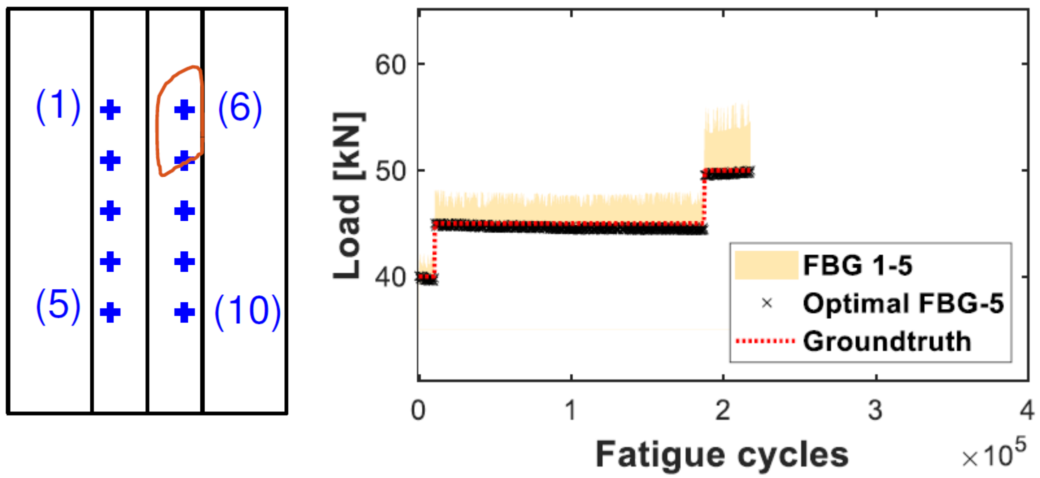
a) Sensors detecting local damage (DI=1) evaluate potential propagation

b) Sensors not detecting local damage (DI=0) evaluate potential stiffness degradation (global effect)

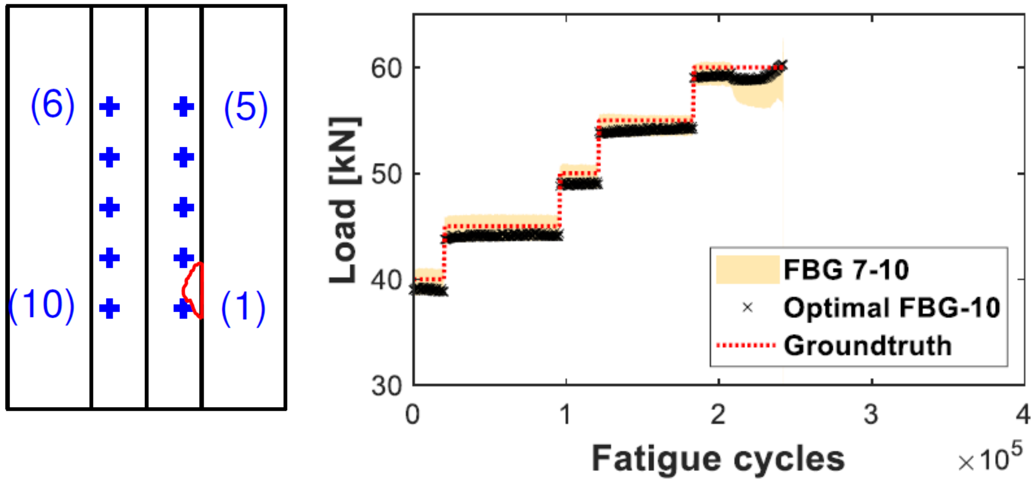


6. Results: Load predictions

Impacted panel #1



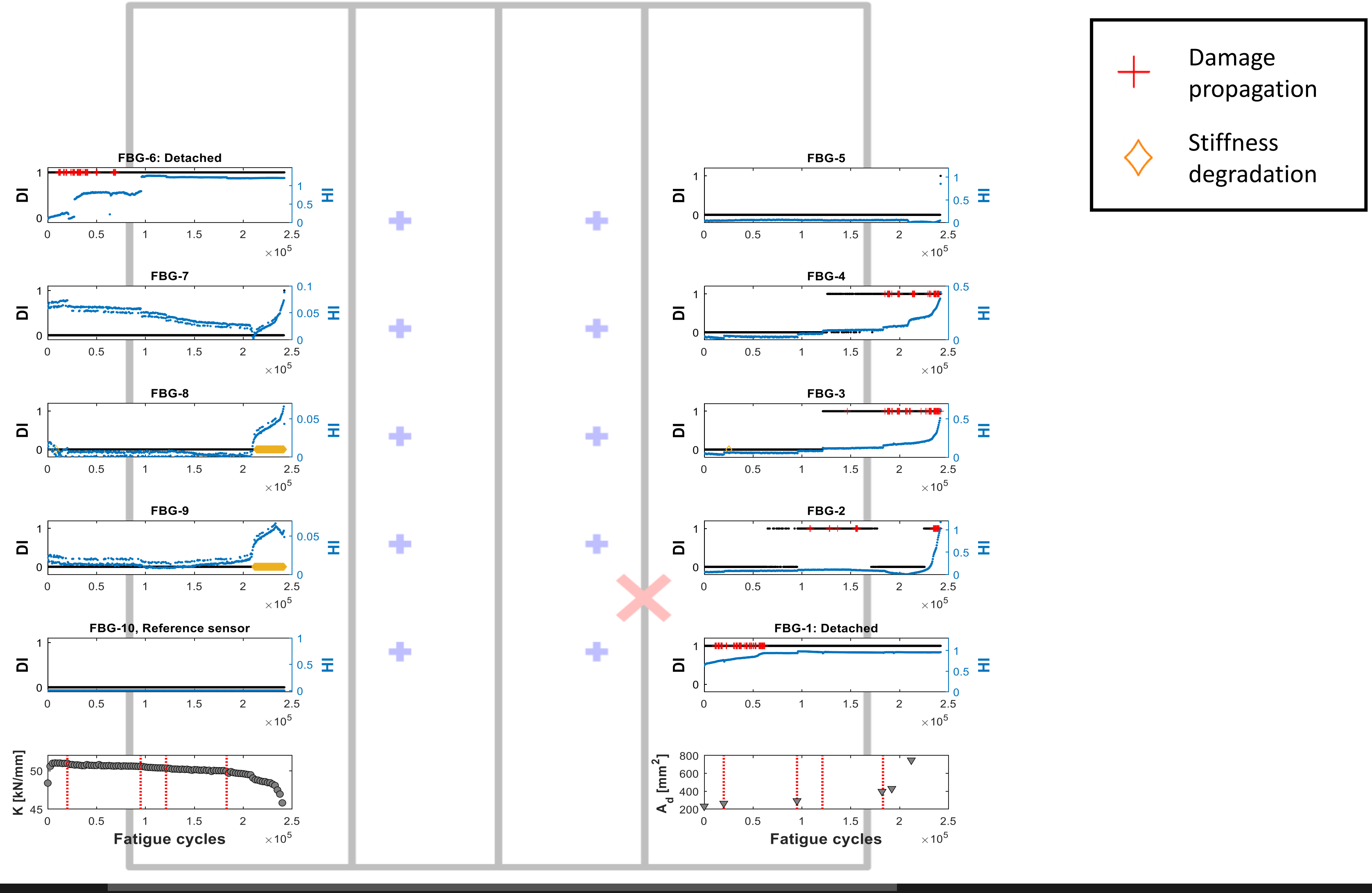
Impacted panel #2



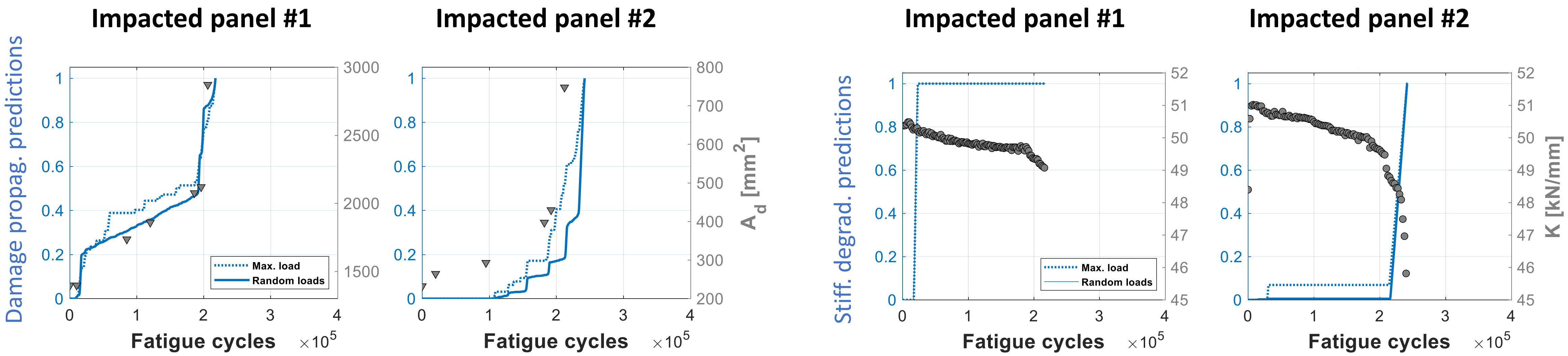
- Groundtruth loads reflect to the maximum load during each quasi-static test.

6. Results: Multi-level diagnostics

Impacted panel #2



6. Results: Cumulative predictions



A_d: Damaged area (measured with DolphiCam)

K: Experimentally measured stiffness

Concluding remarks

1. A structural DT of a pristine single-stringer composite panel was efficiently established in terms of a verified finite element model
2. Exploitation of a RBF surrogate model, trained with deterministic strain data from the finite element model, enabled the DT-based damage diagnosis concept
3. Damage diagnosis was realized with a strain correlation between the DT's and corresponding static strains extracted from the actual specimen via permanently affixed FBGs
4. Damage-unaffected FBGs were effectively utilized as load evaluators by iteratively estimating the load with a gradient descent optimization algorithm
5. The proposed methodology revealed the presence of a skin-to-stringer disbond and monitored the forthcoming fatigue disbond growth

CASE STUDY II:

Remaining Useful Life Prognostics in complex structures

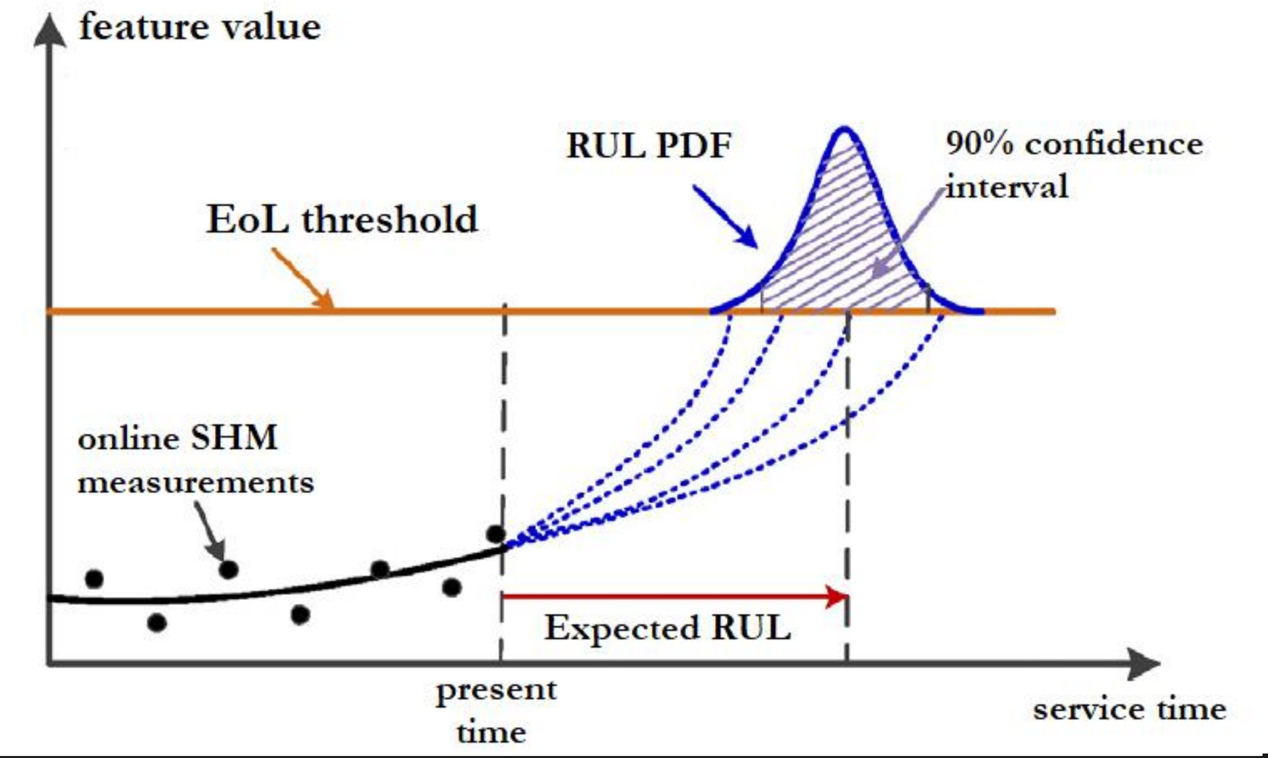
Prognostics

Prognosis (prɒgnoʊsɪs)

A **prognosis** is an estimate of the future, a forecast, foreknowledge (in Greek)

Central concept: **RUL =** Remaining Useful Life

SHM data-driven prognosis

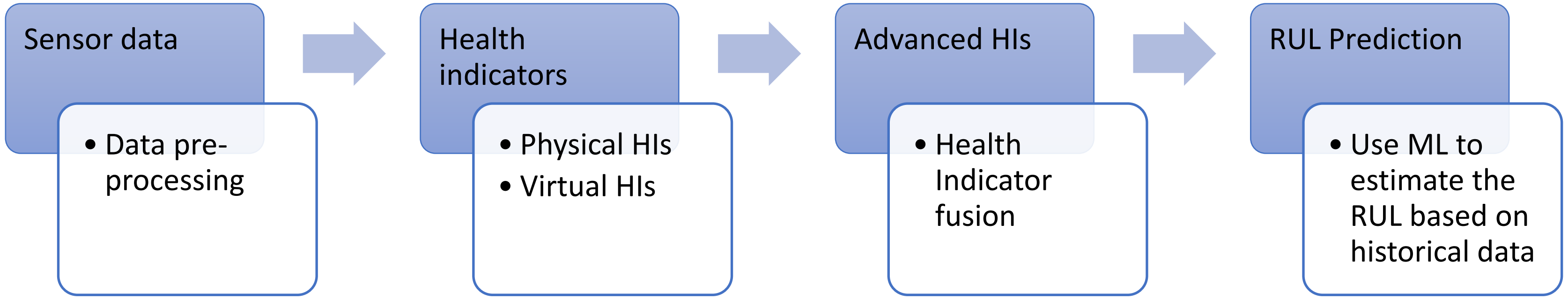


Problem Statement: RUL prediction

- **Data-driven prognostics** require historical data to train ML models to predict the RUL

- The **accuracy of the prediction** is dependent on the degradation features (**Health Indicators - HIs**)

- **Key attributes**
  - ❖ **Monotonicity**
  - ❖ **Prognosability**



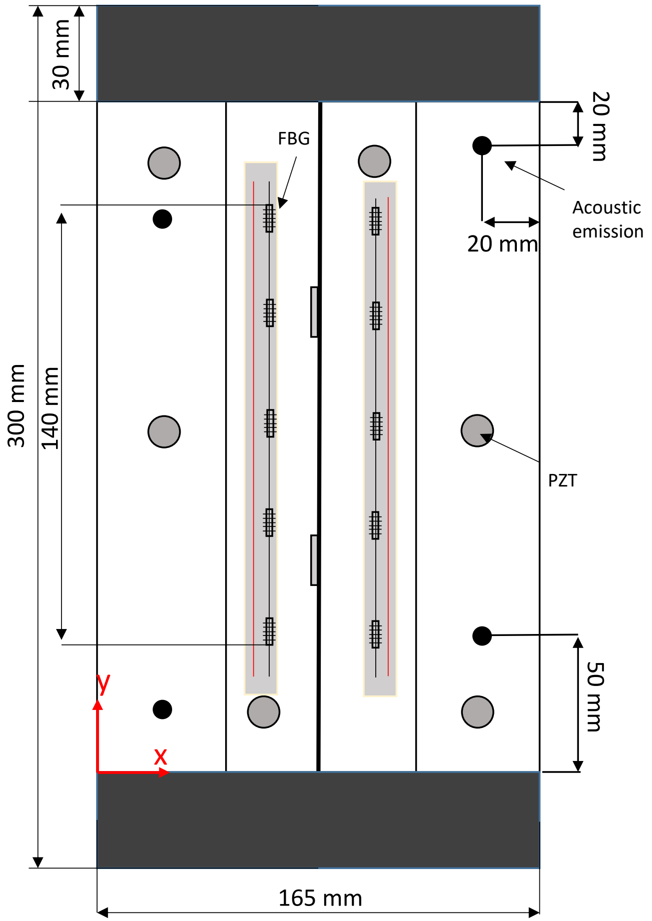
Generic Methodology

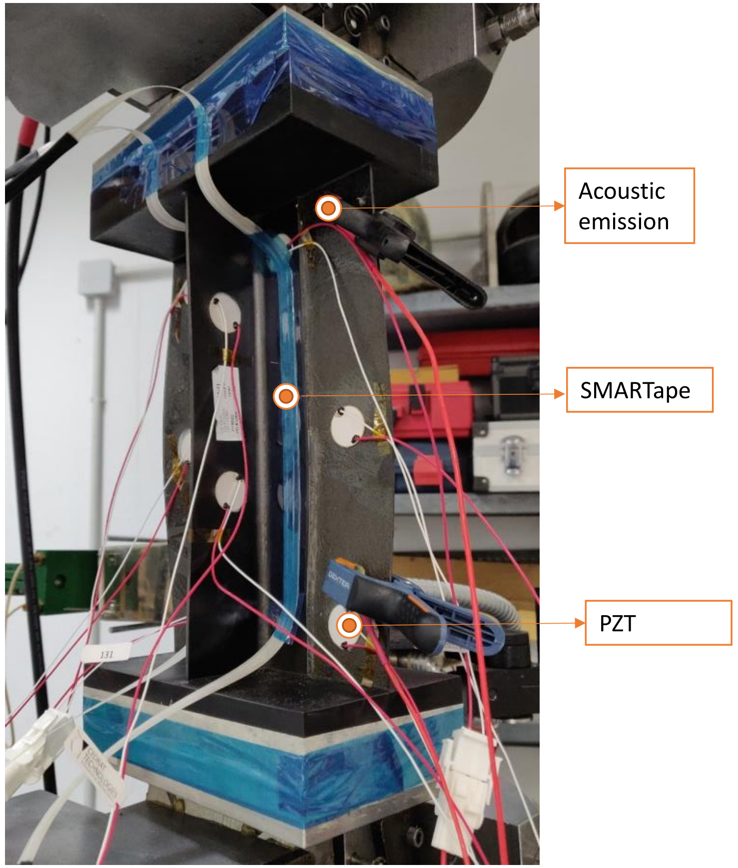
Experimental Campaign(1): Panel geometry

- **Single T-shaped Stiffened Panels**
- Layup:
- Skin: $[45/-45/0/45/90/-45/0]_S$
- Stiffener: $[45/-45/0/45/-45]_S$

- Dimension:
- 300x165x1.85 mm^3 (Nominal)
- 240x165x1.85 mm^3 (Free length)

- Sensors:
- **FBG strain sensors**
- Acoustic emission sensors
- PZT lamb wave sensors

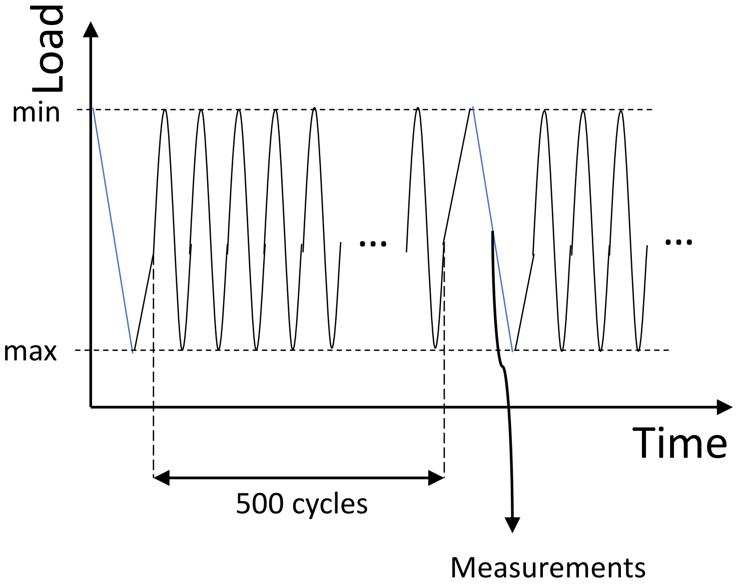




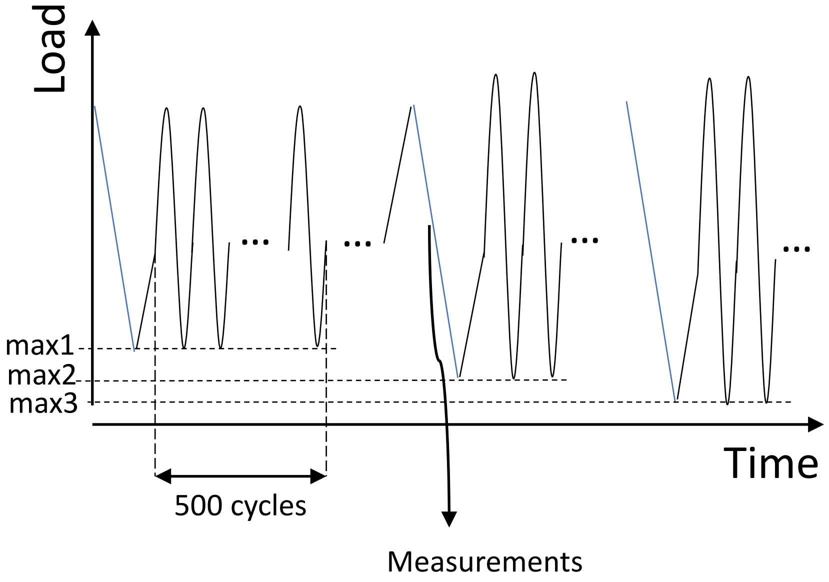
Experimental Campaign(2): Fatigue experiments – Raw strain data

- 3 different fatigue scenarios were investigated with increased loading complexity:

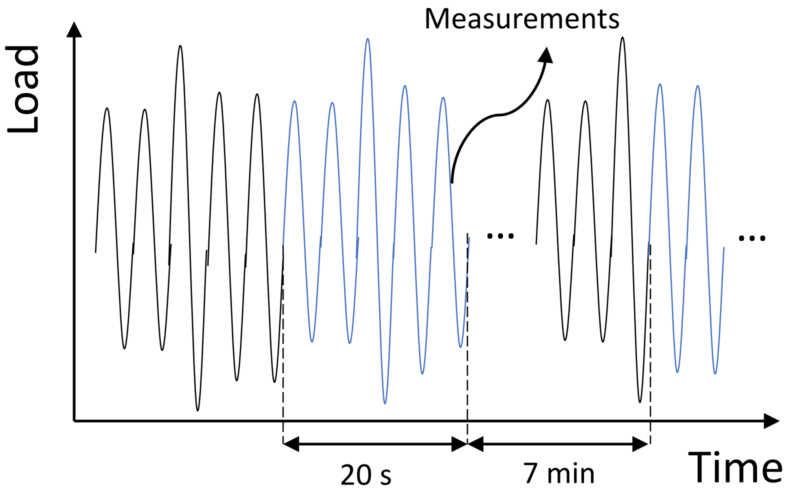
Constant Amplitude Fatigue



Variable Amplitude Fatigue



Random Amplitude Fatigue (spectrum)



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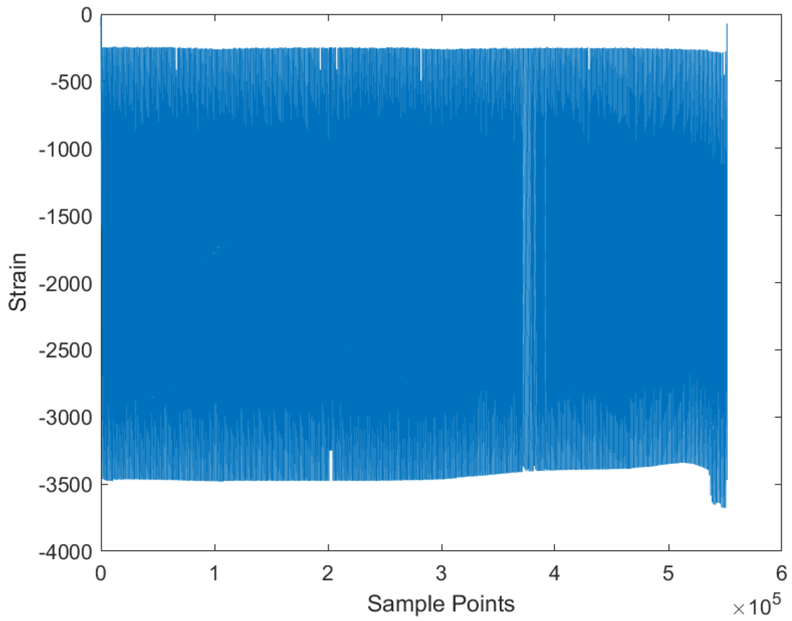
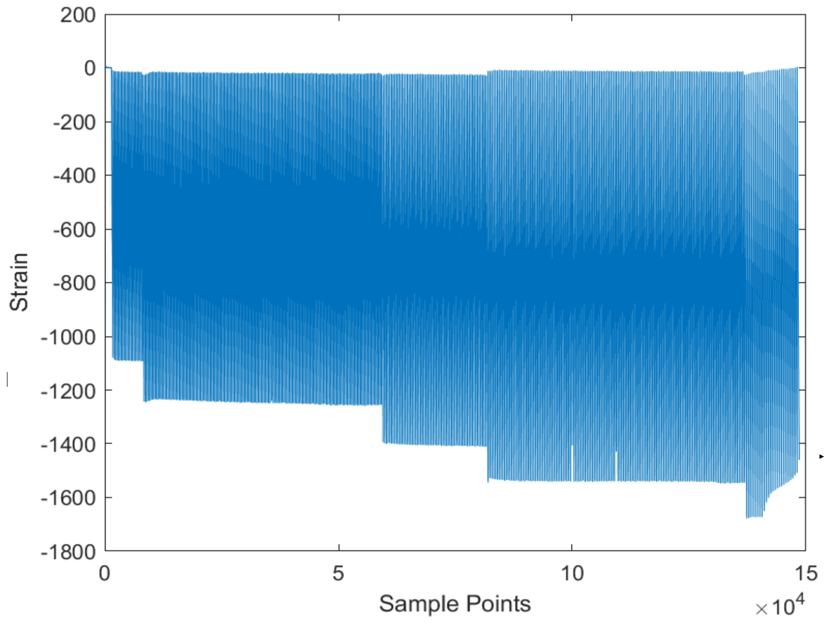
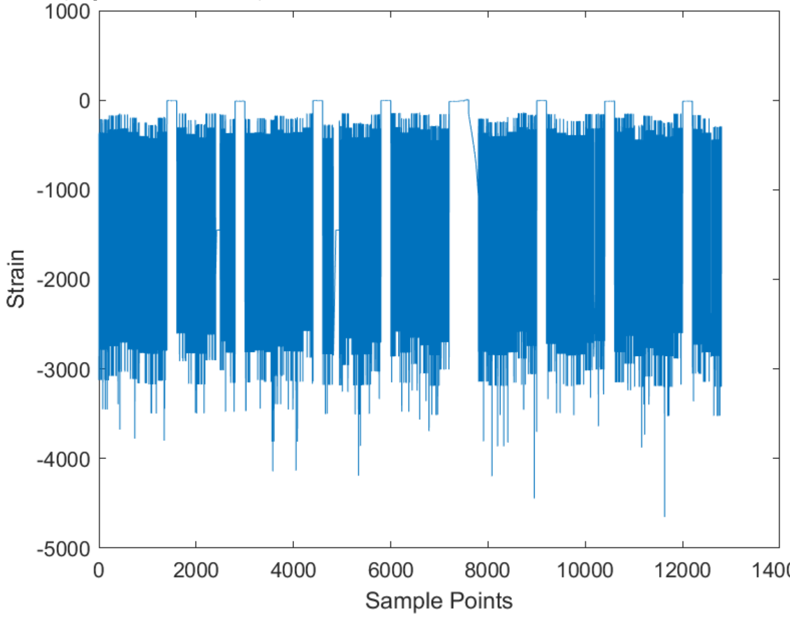
Constant Amplitude Fatigue



Variable Amplitude Fatigue



Random Amplitude Fatigue (spectrum)



Health Indicators(1): Physical HIs

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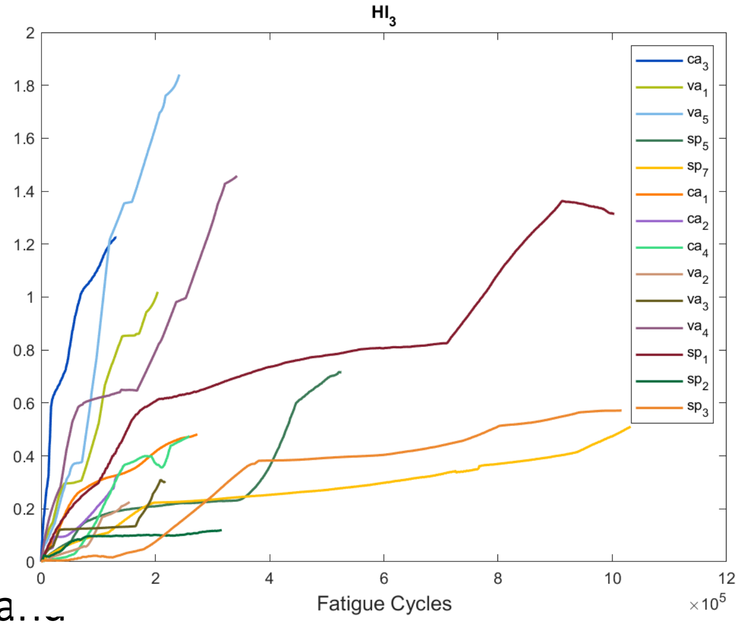
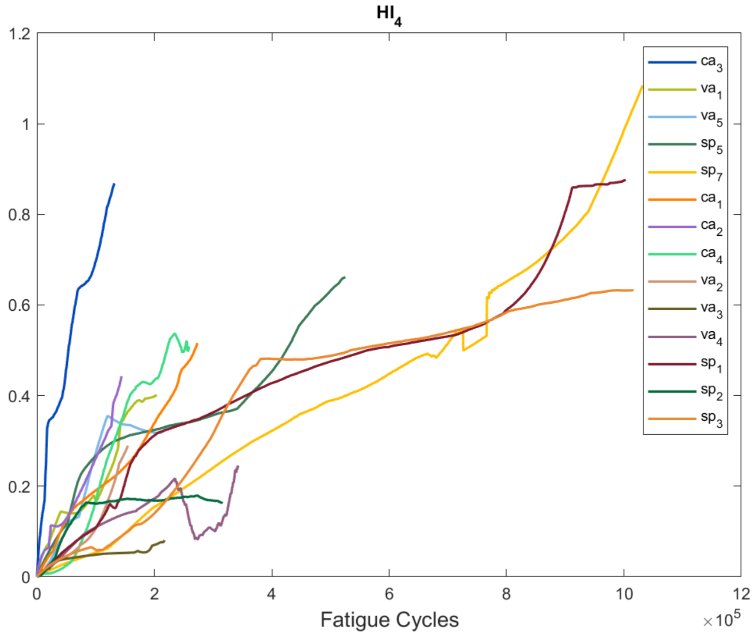
- HIs correlated to physical measurements
- Extracted from simple expressions on strain data

- $HI_3(t) = \sqrt{\sum_{i=1}^{N} \left| 1 - \frac{\varepsilon^i(t)}{\varepsilon^i_{ref}} \right|^2}$

- $HI_4(t) = \sqrt{\sum_{i=1}^{N} \left(\mathrm{HI}_2^i(t) \right)^2}$,
- Where $HI_2^i(t) = \frac{\varepsilon^i(t)}{\frac{1}{n}\sum_1^n \varepsilon^i(t)} - \frac{\varepsilon^i(t=0)}{\frac{\sum_1^n \varepsilon^i(t=0)}{n}}$





n=1,..,5 number of sensor at each foot a…
N=1,…,10 total number of sensors

Health Indicators(2): virtual HI

- HIs not directly correlated to physical measurements
- PCA based feature extraction

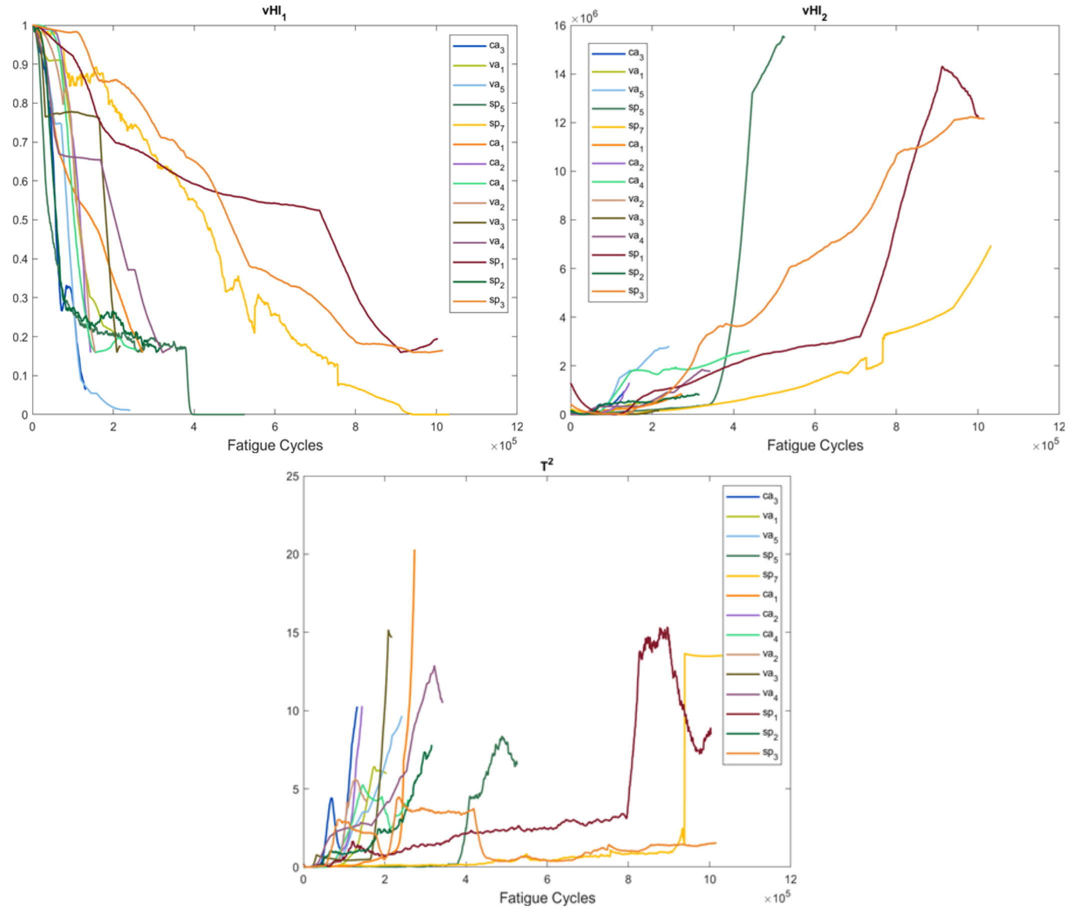
$$vHI_1 = \exp\left(-\frac{(d_L - d_{Lmin})^2}{\sigma_L}\right),$$

Where, $\sigma_L = -\frac{(d_{Lmax}-d_{Lmin})^2}{2}\left[\frac{1}{\log_{10}\varepsilon}+\frac{1}{\log_{10}(\varepsilon+\delta)}\right]$ and ε=δ=0.01

SPC metrics *

$$vHI_2(t) = Q = \sum_1^N \left(x_i(t) - x_{r_i}(t)\right)^2,$$

$$T^2(t) = \sum_1^N \frac{\tau_i^2(t)}{\lambda_i}$$

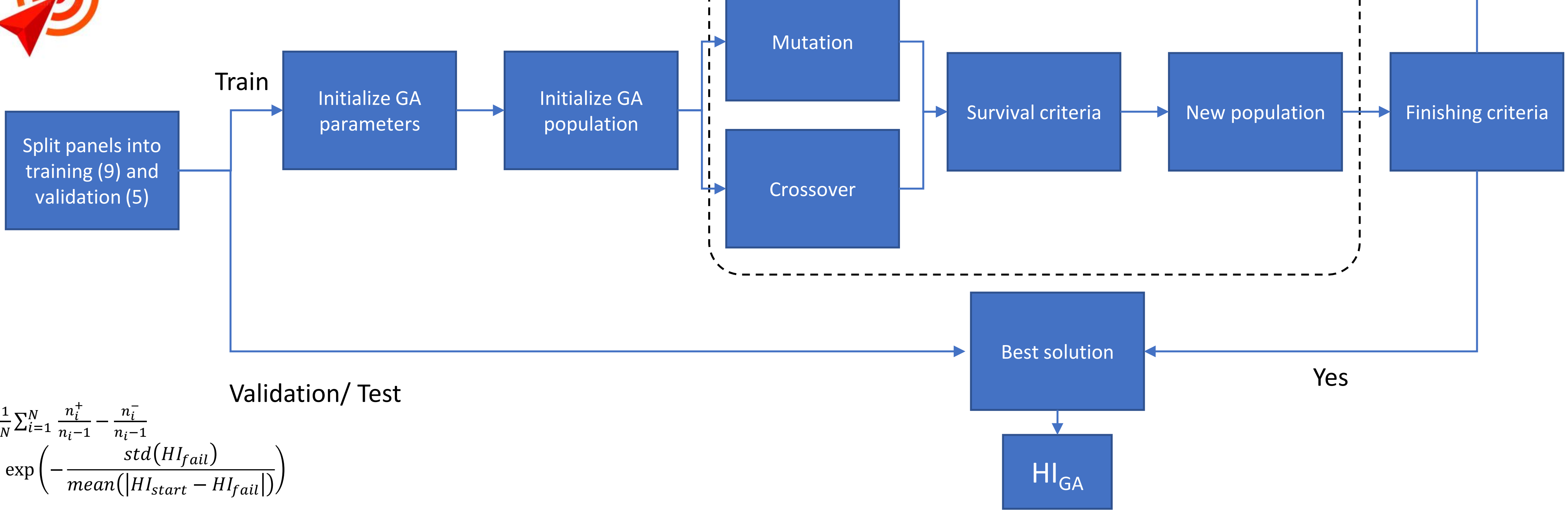


* T. Loutas et al., *IEEE Transactions on Industrial Electronics*, vol. 67, doi: 10.1109/TIE.2019.2926048
Kourti T. MacGregod J., Chemom Intell Lab Syst 1995;28:3–21. http://dx.doi.org/10.1016/0169-7439(95)80036-9

Health Indicator fusion(1)

- Genetic Algorithms are utilized to fuse the HIs:

Maximize: $F = monotonicity + prognosability$ *



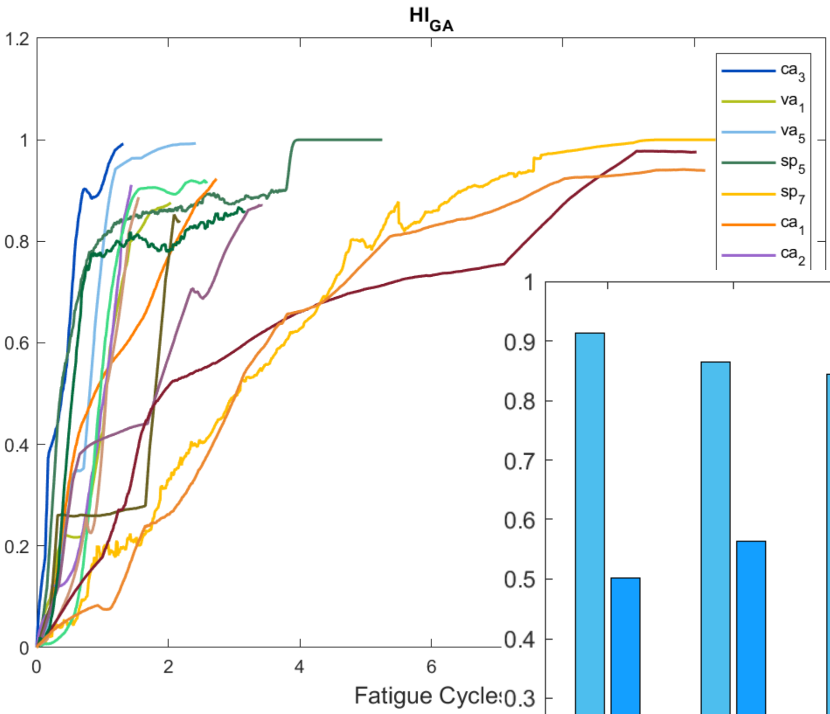
$$*Monotonicity = \frac{1}{N}\sum_{i=1}^{N} \frac{n_i^+}{n_i - 1} - \frac{n_i^-}{n_i - 1}$$

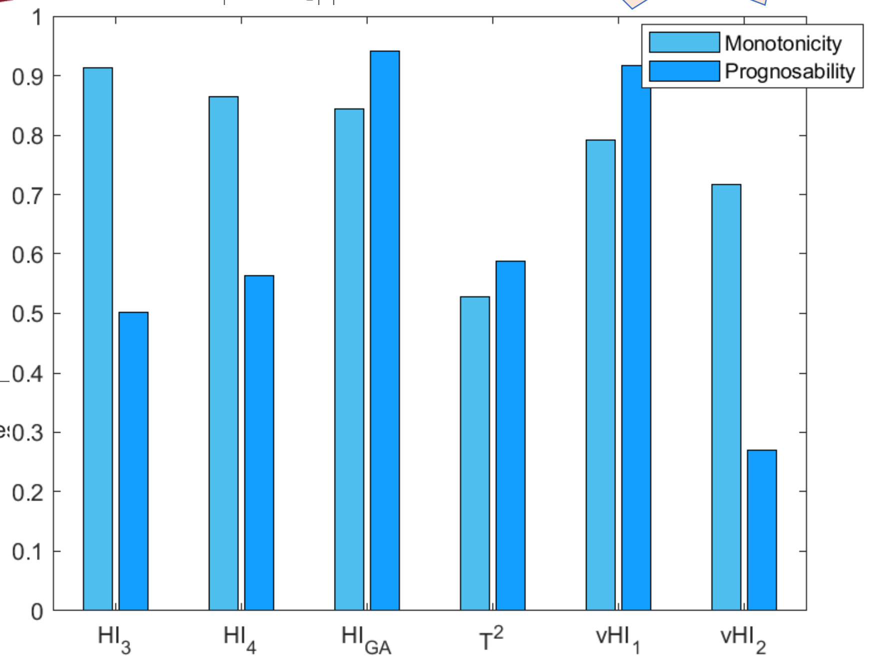
$$Prognosability = \exp\left(-\frac{std\left(HI_{fail}\right)}{mean\left(\left|HI_{start} - HI_{fail}\right|\right)}\right)$$

Health Indicator Fusion(2)

- *Accepted solution:*
- $HI_{GA} = vHI_1\left(vHI_2 - \frac{HI_4+0.5HI_5}{HI_4}\right) - 1$

- Repeatability (50 runs):
- - average monotonicity: 0.90±0.026
- - average prognosability: 0.96±0.024





Enhanced prognosability monotonicity

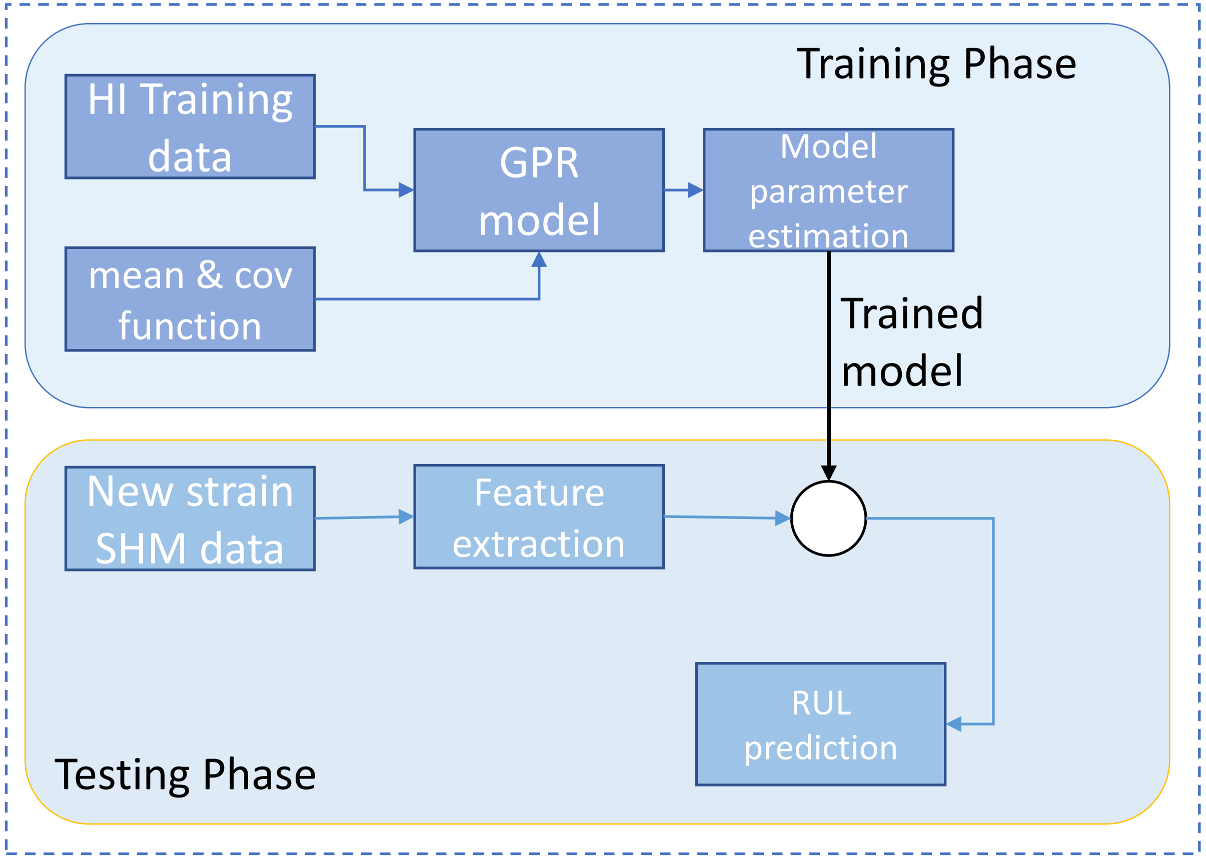
RUL predictions (1): Procedure

- Gaussian Process regression was used for the RUL estimation task
- 1 panel from the test set was used to tune the GP parameters:
  - Linear mean function:

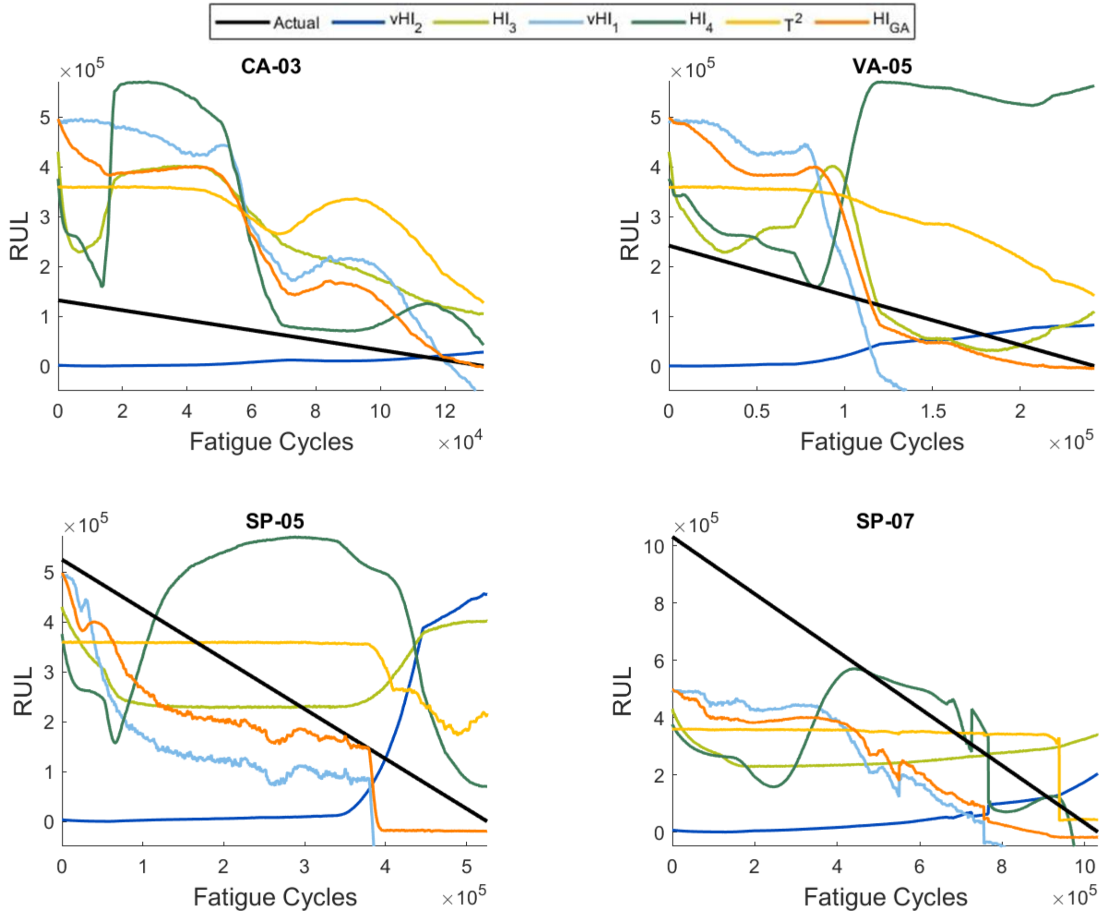
$$m(x) = ax + b$$

  - Matern 5/2 covariance function:

$$k(r) = \sigma_f^2 \left(1 + \frac{\sqrt{5}r}{\sigma_l} + \frac{5r^2}{3\sigma_l^2}\right) \exp\left(-\frac{\sqrt{5}r}{\sigma_l}\right)$$



RUL predictions(2): Results

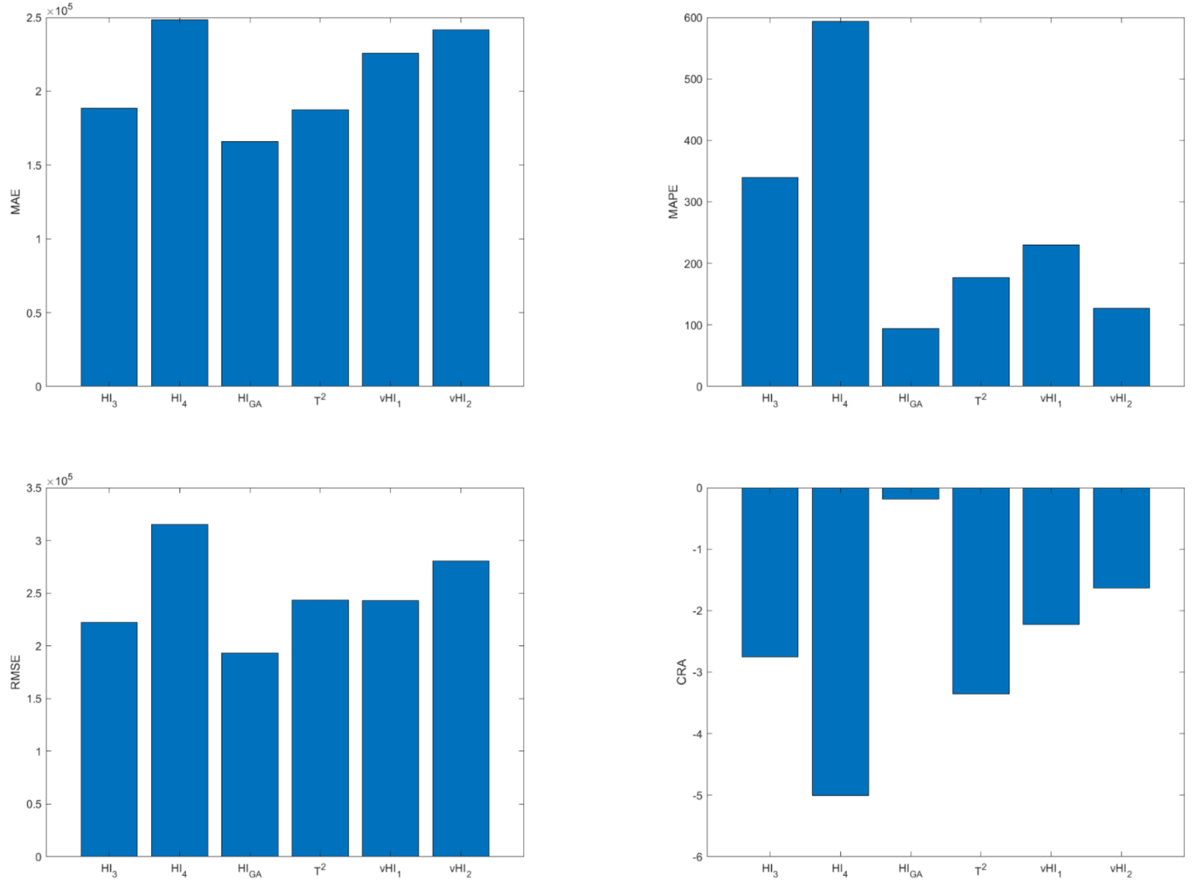


- HI_{GA} converges to the true RUL in all cases
- vHI_1 shows the second best predictions
- HI_3 shows poor performance for SP panels
- HI_4 shows good performance only for CA-03
- T^2 in most cases does not converge to the true RUL
- vHI_2 shows the worst performance, incapable of converging to the true RUL

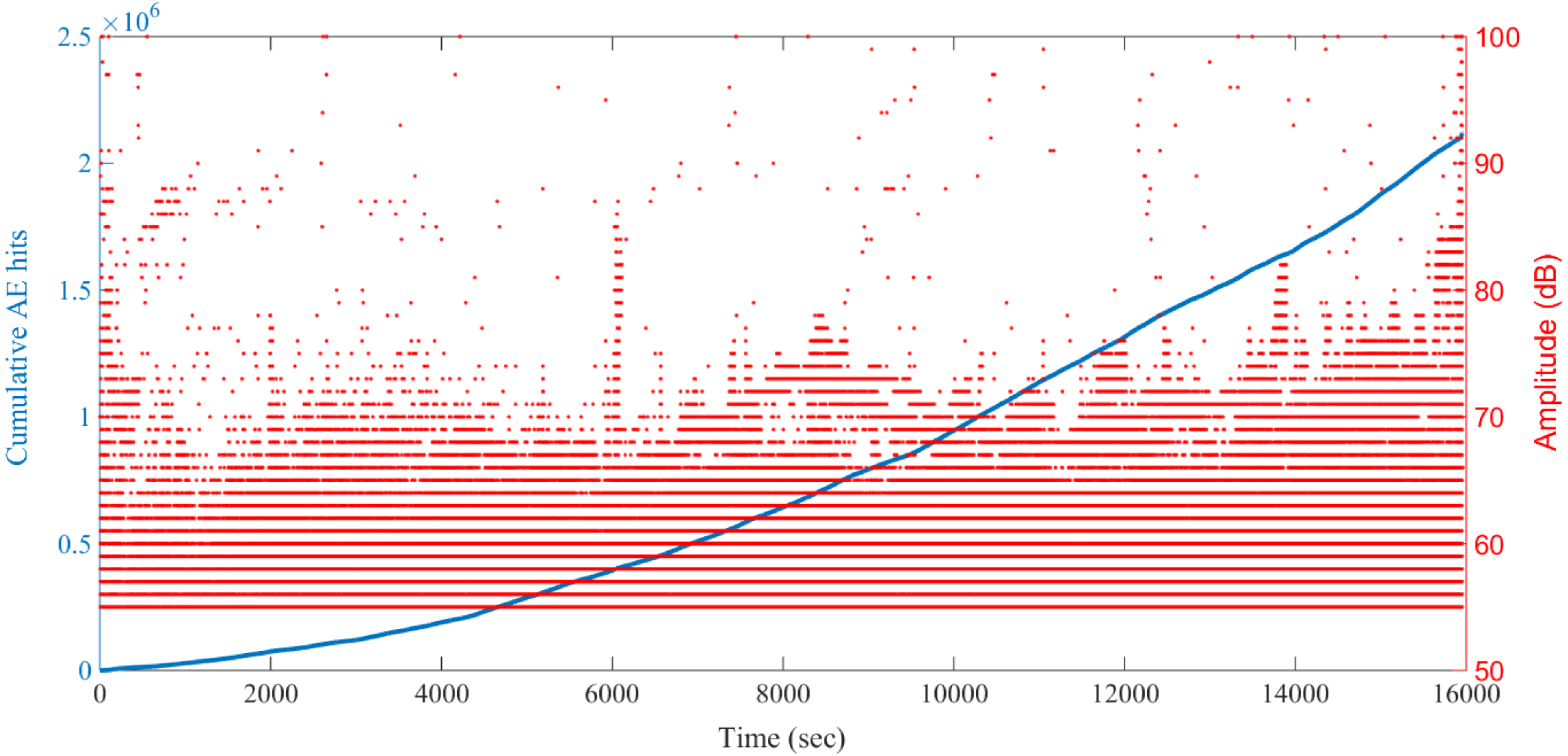
RUL prediction: Performance metrics

- Classical metrics were employed to validate the prognostic performance
  - Mean Absolute Error (MAE)
  - Mean Absolute Percent Error (MAPE)
  - Root Mean Squared Error (RMSE)
  - Cumulative Relative Accuracy (CRA)

HI_{GA} outperforms in every metric

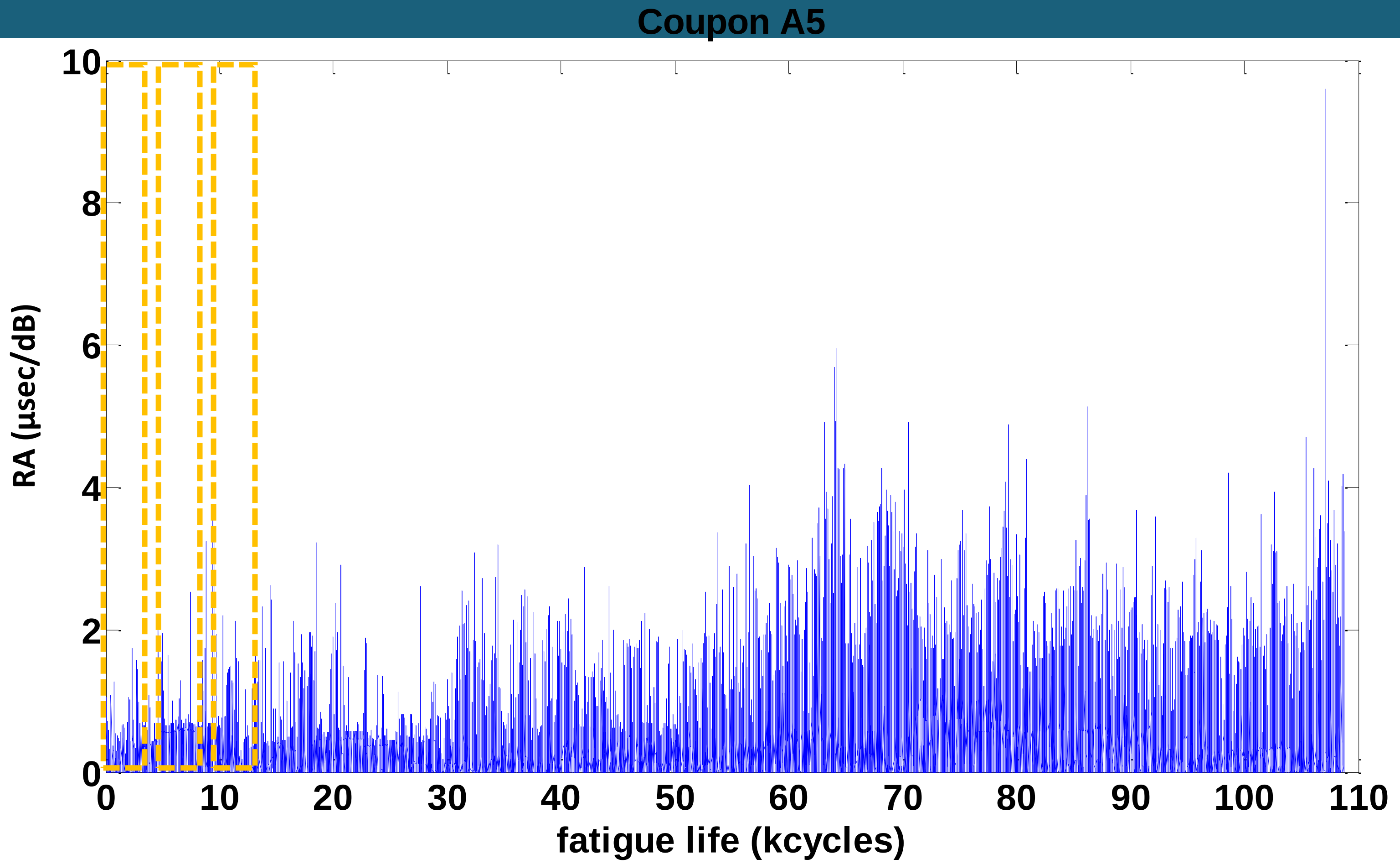


AE raw data



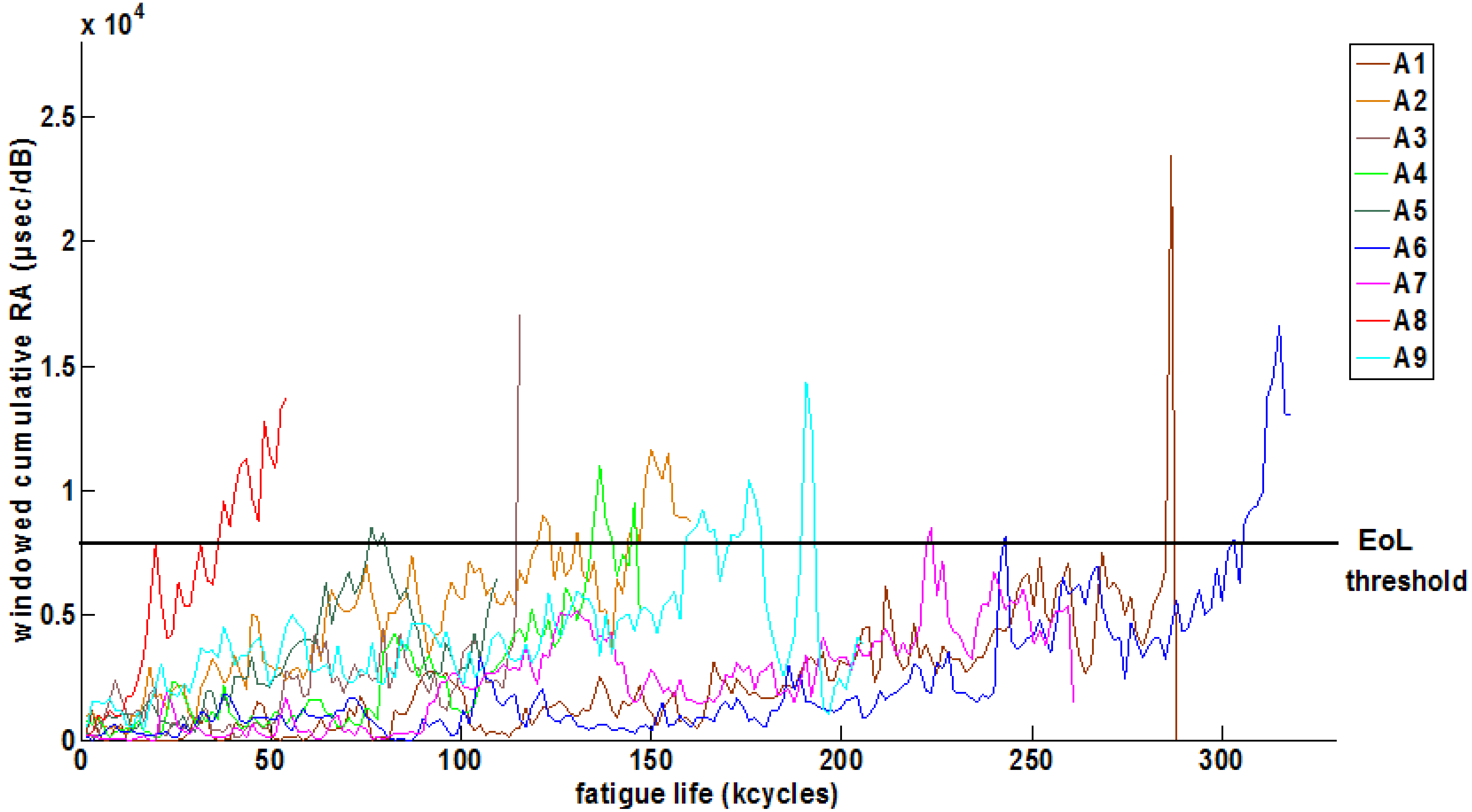
~2,2 million AE hits!!
Too many and not periodically distributed

HI extraction



A windowed CRA (cumulative risetime/amplitude) feature is calculated in periodic windows of 2.5 minutes or 1500 cycles

Resulted degradation histories



A few tens or hundreds points each degradation history!!

EoL threshold needed – final state has to be unique

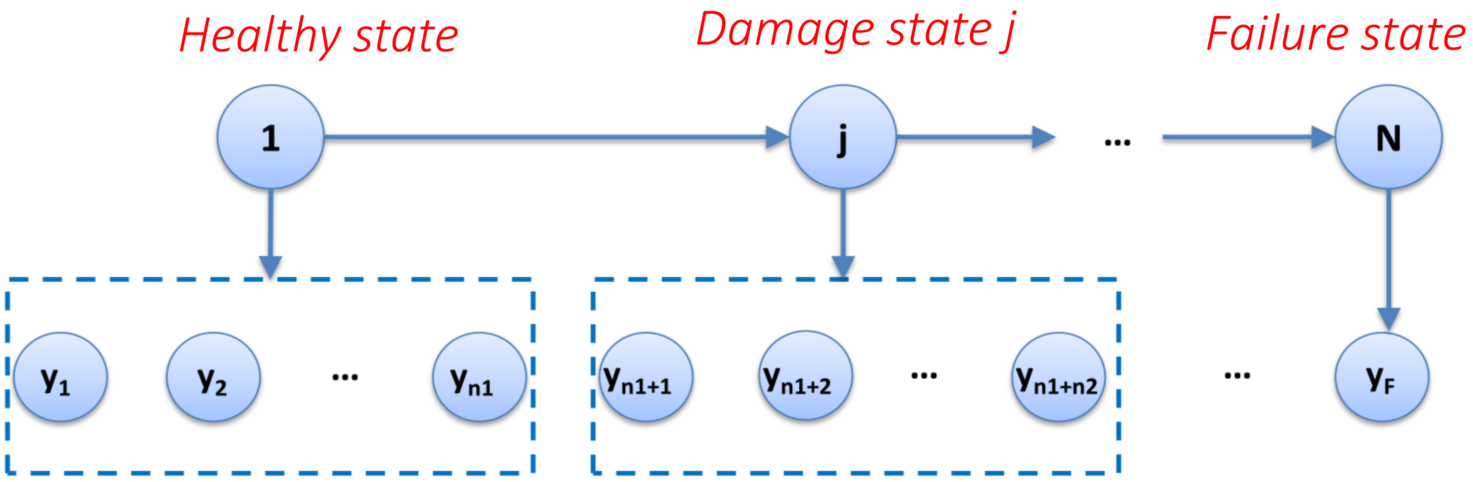
Algorithms for RUL prediction

- ML/AI algorithms (Neural Networks, Gaussian processes, Gradient Boosting etc)

- Statistical models (Hidden Semi-Markov models, Proportional Hazards model etc)

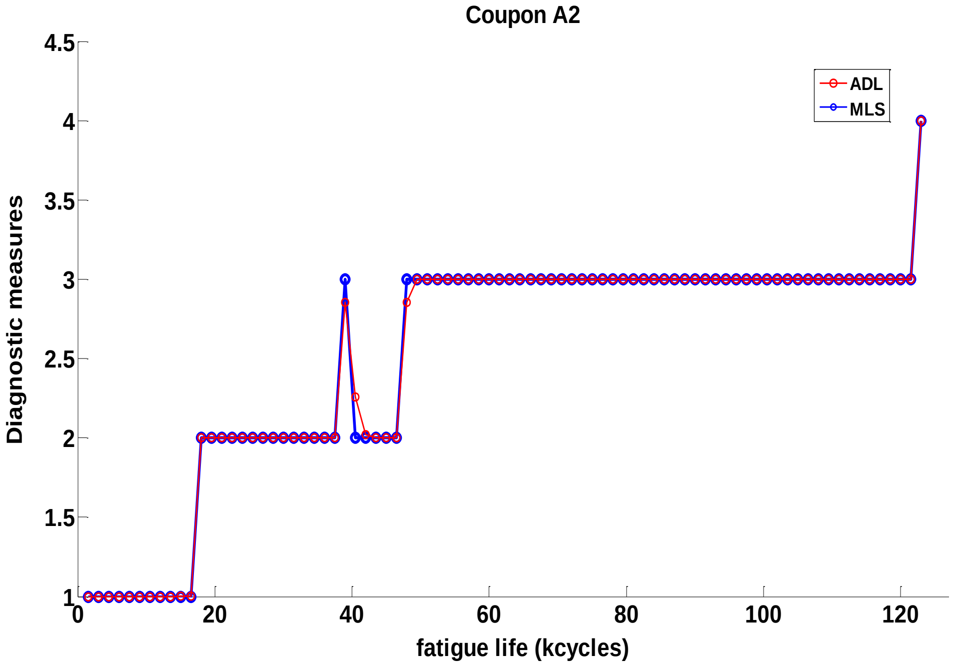
Focus: Hidden State Semi Markov model

- ✓ *Damage evolution in composites is modeled as a doubly stochastic hidden Markov process that manifests itself via structural health monitoring (SHM) observations*
- ✓ *NHHSMM (an extension of the Hidden semi-Markov Models to account for non-homogeneity i.e. age dependence in state transitions) is utilized to model damage progression*

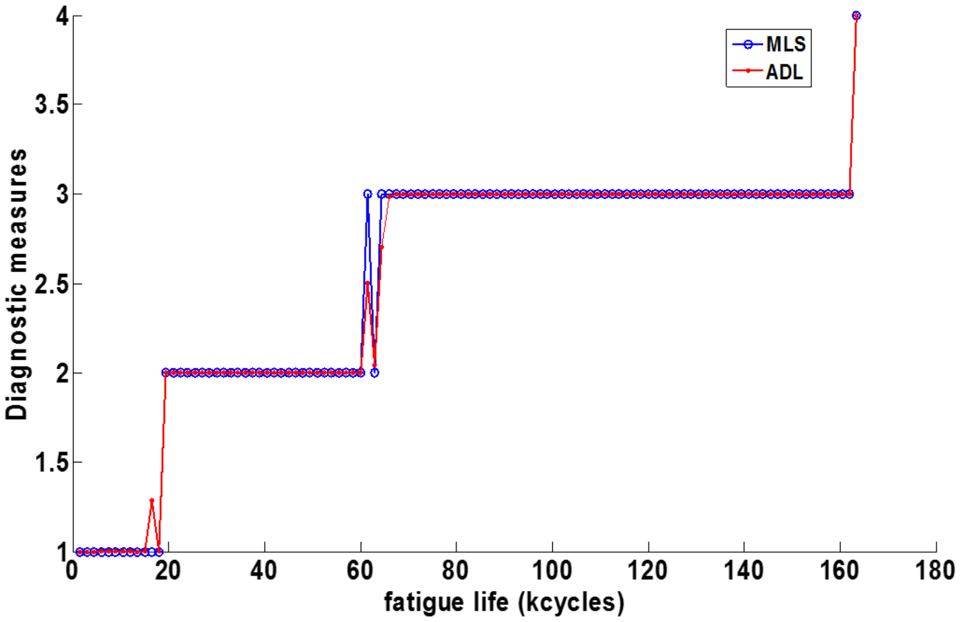


Observation sequence $y_{1:F}$ i.e. SHM data and j possible degradation state j=2,…,N-1

Diagnostics – Health state identification



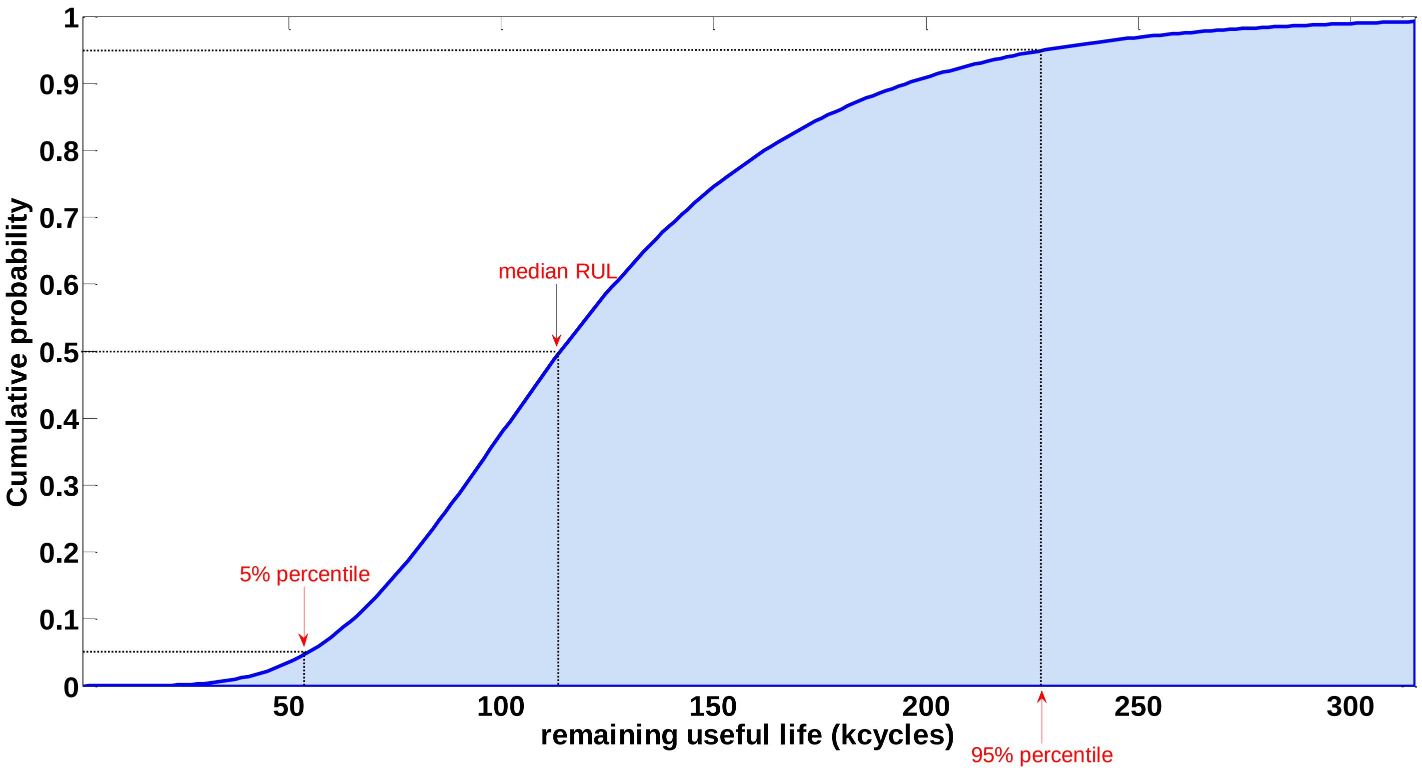
ADL and MLS for coupon A2



ADL and MLS for coupon A9

A real time 3-D visualization tool such as X-ray CT would be required in order to monitor in detail the developed damage mechanisms and their synergies and determine to what extent of damage these health states correspond to.

Prognostic results – probabilistic aspect



Cumulative distribution function for RUL at t_p=1.5 kcycles of coupon A9

The target in prognostics is the estimation of the conditional (on SHM data) reliability and finally the Remaining Useful Life (RUL) of the system.

- Reliability function:

$$R\left(t \middle| y_{1:t_p}, L > t_p, \boldsymbol{M}\right) = Pr\left(L > t \middle| y_{1:t_p}, L > t_p, \boldsymbol{M}\right)$$

- The CDF and mean of RUL:

$$Pr\left(RUL_{t_p} \leq t \middle| y_{1:t_p}, \boldsymbol{M}\right) = 1 - R(t + t_p \,|\, y_{1:t_p}, \boldsymbol{M})$$

$$\widehat{RUL}\left(t \middle| y_{1:t_p}, L > t_p, \boldsymbol{M}\right) = \int_0^\infty R\left(t + \tau \middle| y_{1:t_p}, L > t_p, \boldsymbol{M}\right) d\tau$$

Focus - Bayesian Neural Networks

An alternative machine learning approach handles the RUL estimation as a nonlinear regression task mathematically described as:

$$y(\boldsymbol{x}) = RUL(\boldsymbol{x}) = f(\boldsymbol{x}, \boldsymbol{\theta}) + \boldsymbol{e}$$

Where $\boldsymbol{w}$ the network weight and bias parameters

$$p(\boldsymbol{w}|\boldsymbol{D}) \sim p(\boldsymbol{D}|\boldsymbol{w})p(\boldsymbol{w})$$

$$p(\boldsymbol{D}|\boldsymbol{w}) = \prod_{i=1}^{N} p(y_i|\boldsymbol{x}, \boldsymbol{w}) = \prod_{i=1}^{N} (2\pi/b)^{-\frac{1}{2}} \exp\left[-\frac{b}{2}\{y_i - f(x_i, \boldsymbol{w})\}^2\right]$$

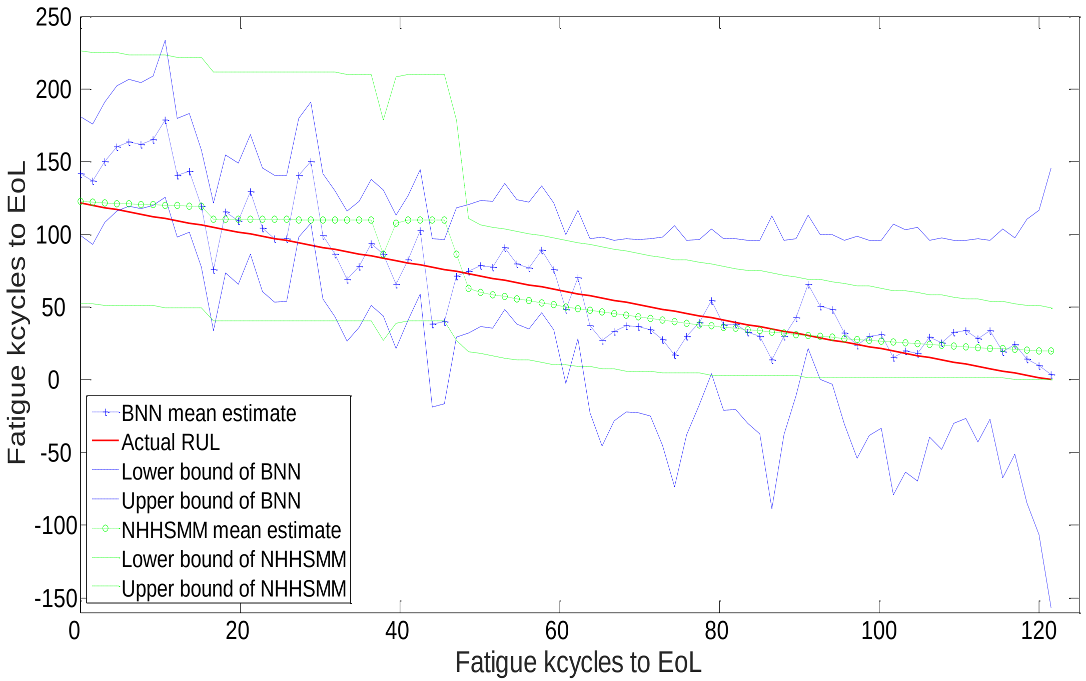
$$p(y_{new}|x_{new}, \boldsymbol{D}, a, b) = \int p(y_{new}|x_{new}, \boldsymbol{w}, b)\, p(\boldsymbol{w}|\boldsymbol{D}, a, b) d\boldsymbol{w}$$

MCMC

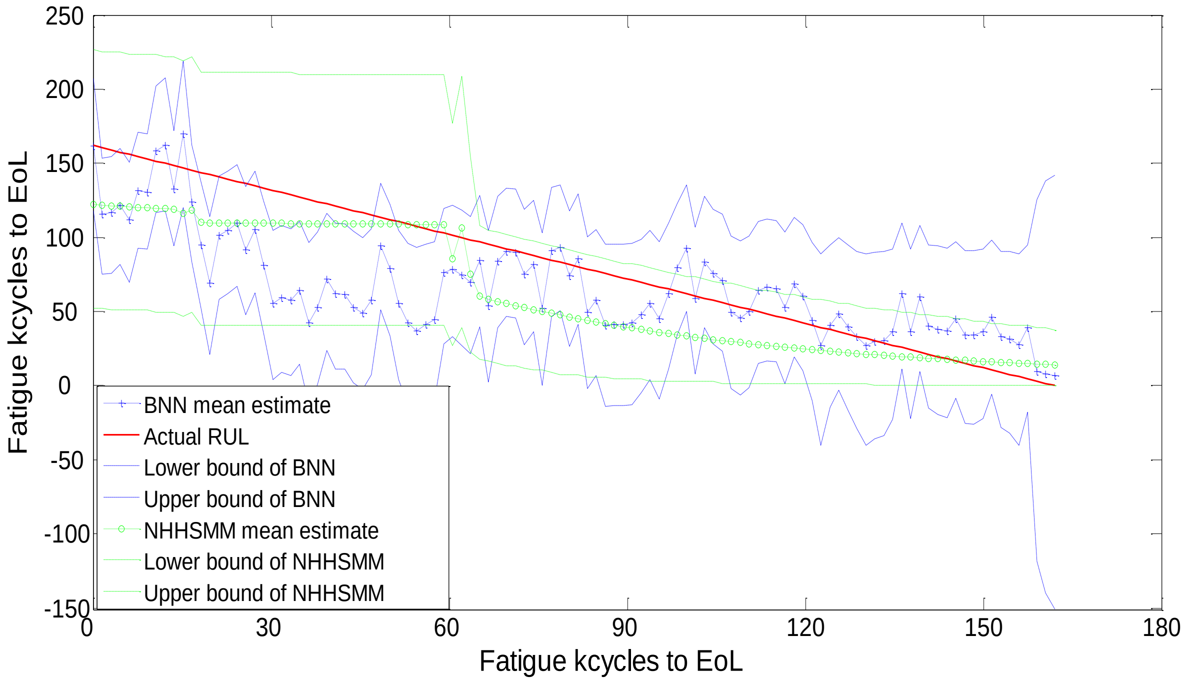
$$p(y_{new}|x_{new}, \boldsymbol{D}) \approx \frac{1}{m} \sum_{i=1}^{m} p(y_{new}|x_{new}, w_i)$$

Hybrid Monte-Carlo algorithm

Results – RUL estimates



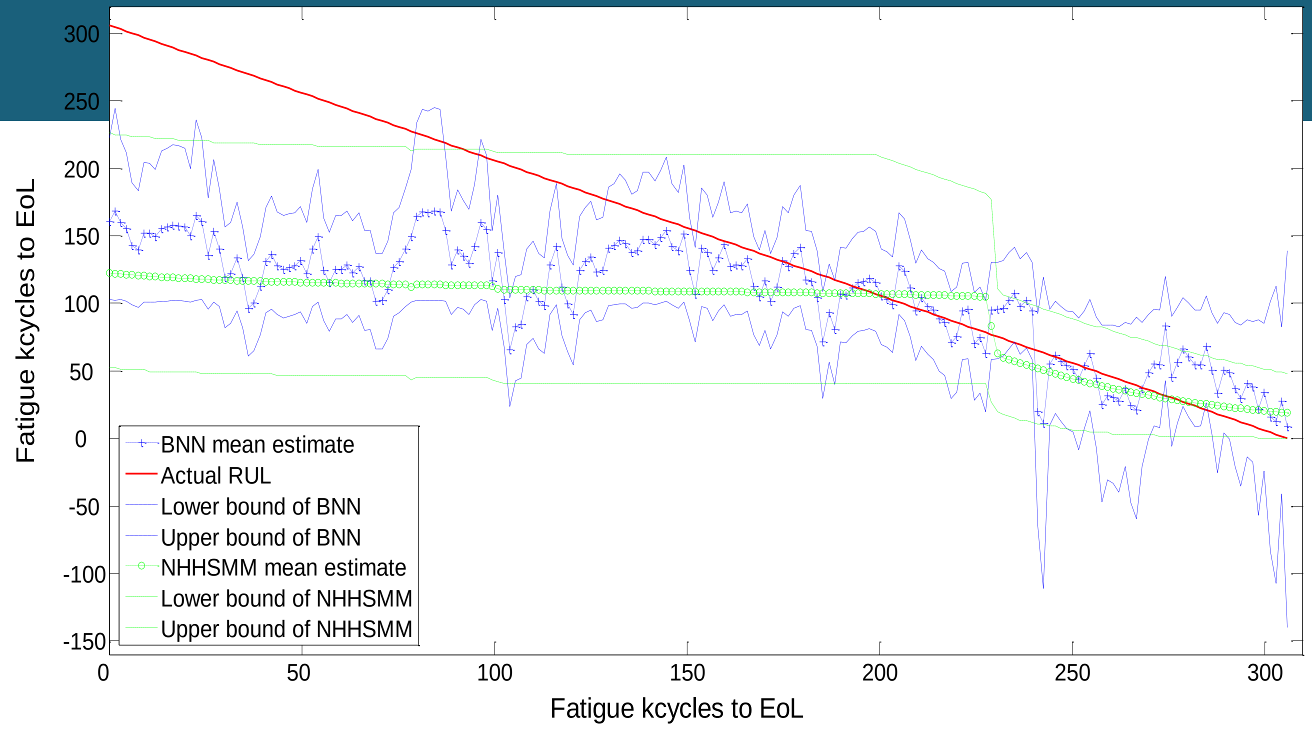
Mean and median estimations of RUL with 90% confidence intervals for coupon A2



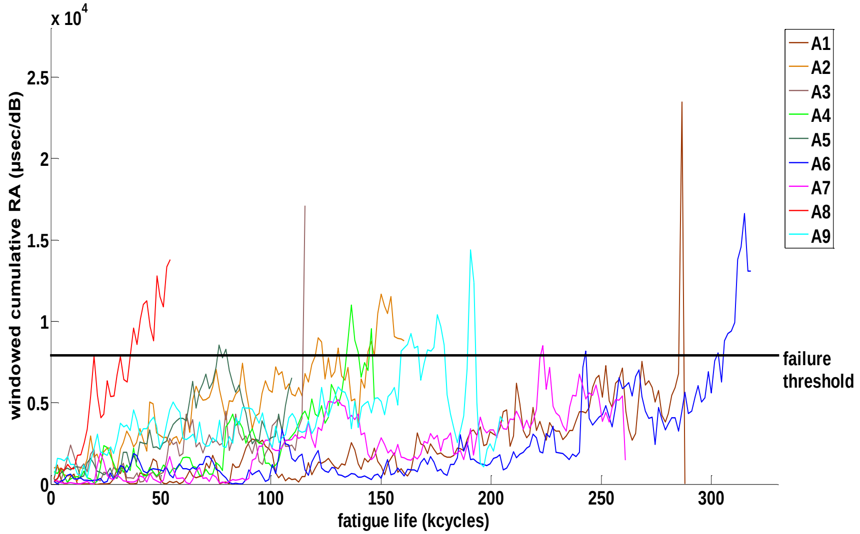
Mean and median estimations of RUL with 90% confidence intervals for coupon A9

- ✓ Both models give very good predictions even from early on
- ✓ NHHSMM predictions are smoother – BNN predictions more “volatile”
- ✓ CIs get more narrow as more AE data come into play for the NHHSMM model

Loutas et al., Composite Structures, 2016

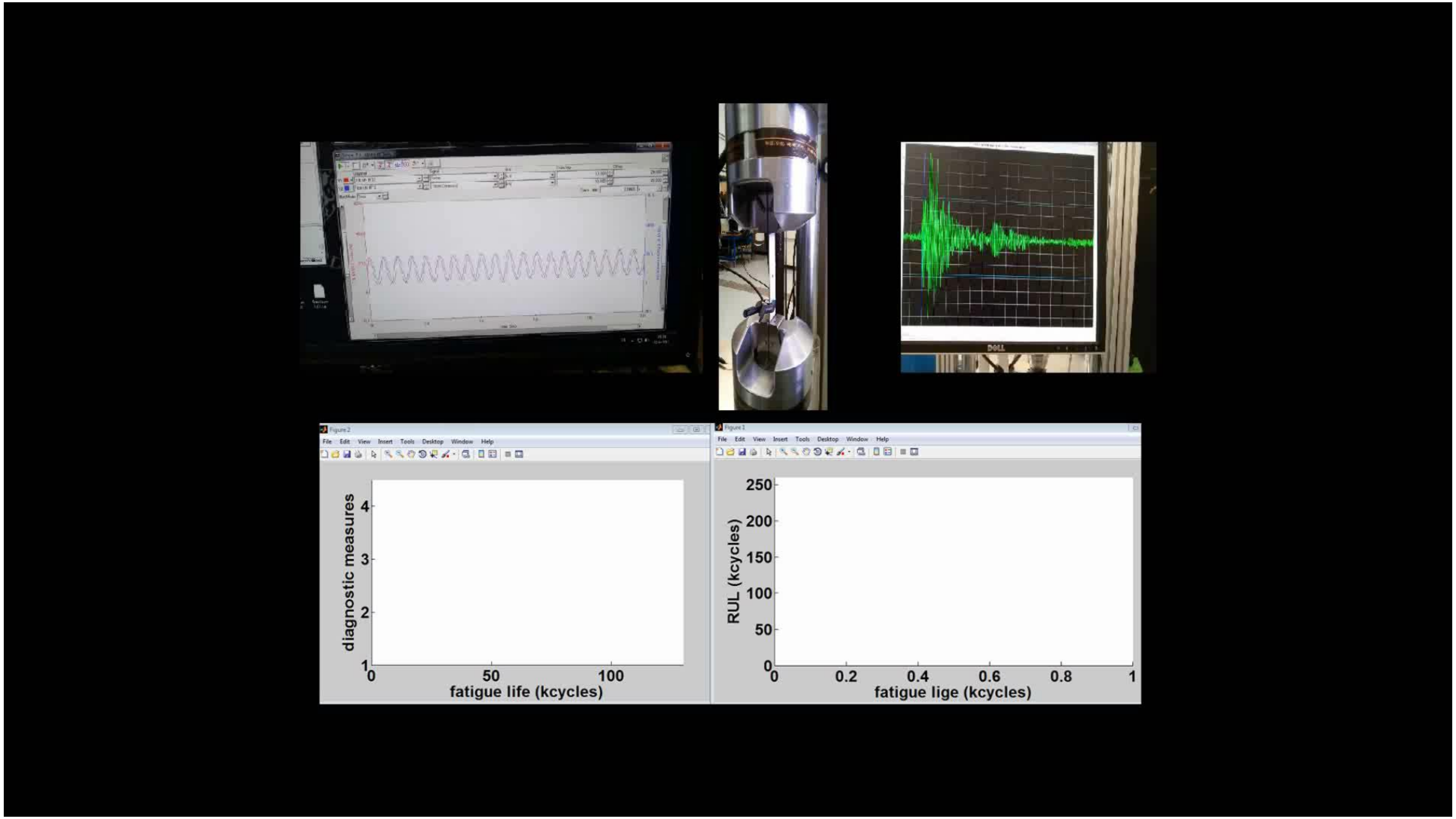


Mean and median estimations of RUL with 90% confidence intervals for coupon A6

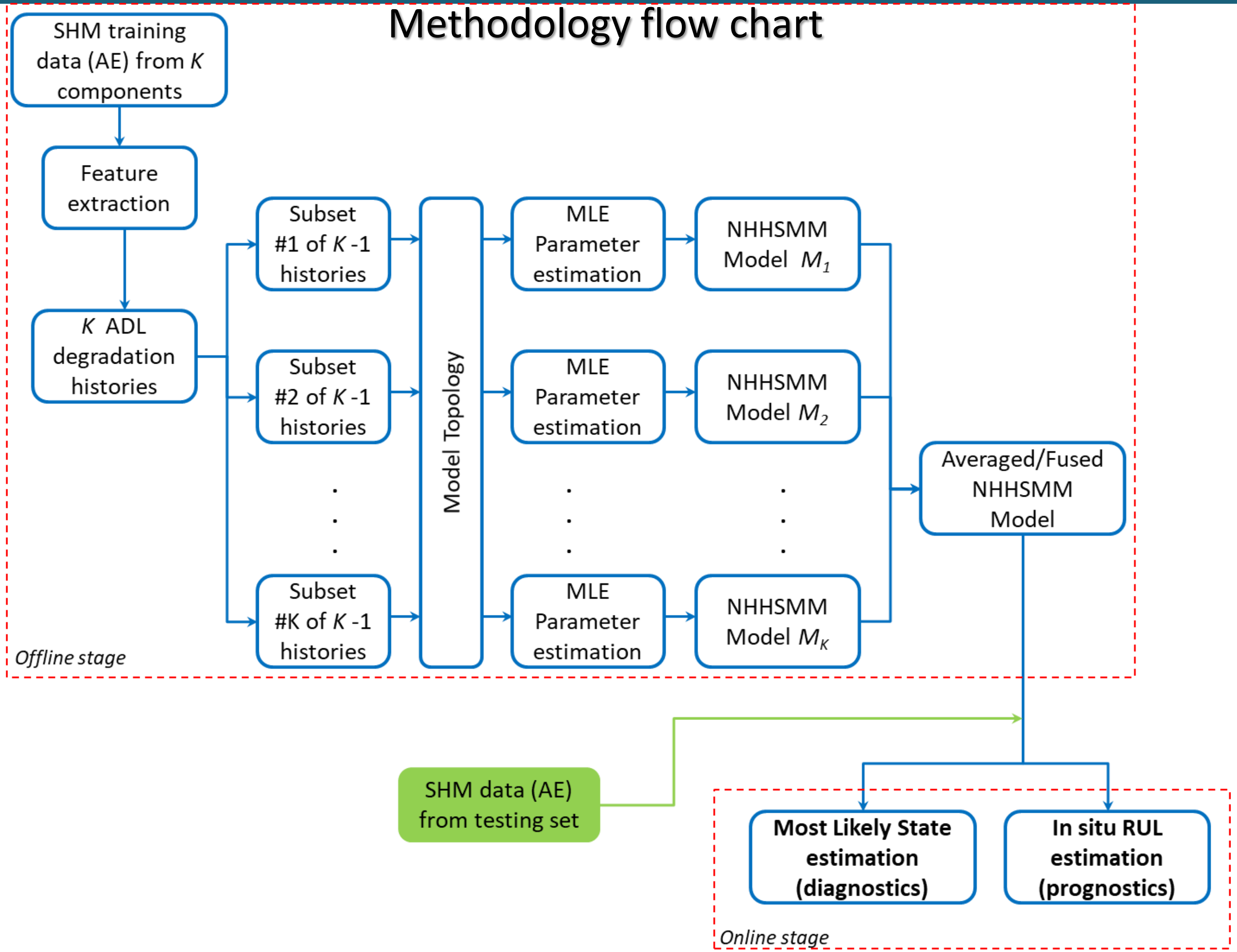


Outlier data-set, still predictions start to converge to the ground truth after mid-life

Demonstration video



Methodology flow chart



Current challenges for SHM (in aeronautics)

- ✓ *Extra cost, non-quantified benefits, weight penalty*
- ✓ *Lack of robust diagnostic/prognostic methodologies under changing environment or extreme loadings*
- ✓ *Validation / Verification / Standardization*
- ✓ *Long-term sensors reliability/durability*
- ✓ *Lack of databases for various damage types*
- ✓ *Lack of run-to-failure data*
- ✓ *End-of-Life threshold determination*
- ✓ *Scarcity of ground truth measurements*

Work in progress: ReMAP & MORPHO H2020 projects

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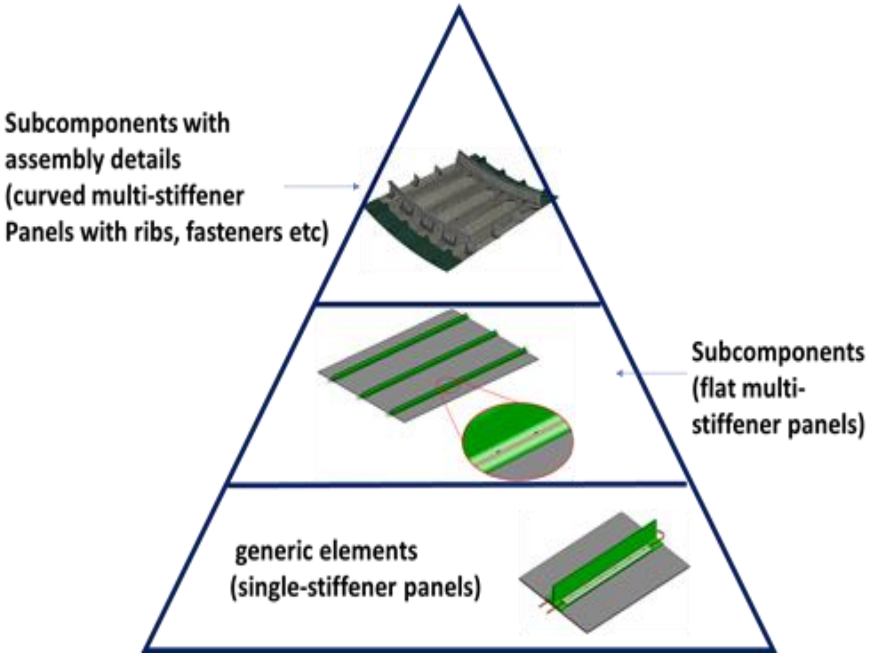
Research questions

- How feasible is confident RUL estimation based on SHM data in generic element and subcomponent level?
- How reliable are data-driven prognostic methodologies when applied to complex structures under realistic fatigue loads?
- How anomalous operations phenomena, such as impacts and low velocity collisions, can affect the RUL?



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 769288

Happy to discuss!