What is your mobile's battery percentage?

When will your mobile shut down?

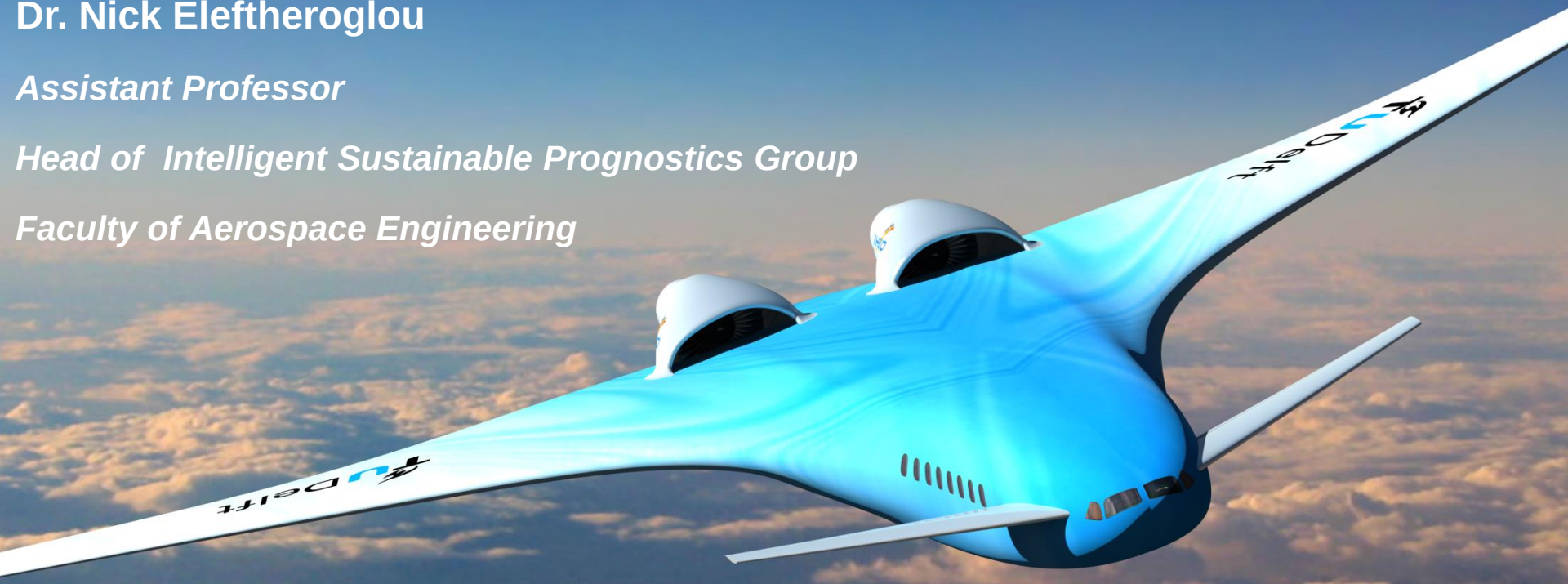
Exploring the Power of Markov Models for Comprehensive Prognostics

Dr. Nick Eleftheroglou

Assistant Professor

Head of Intelligent Sustainable Prognostics Group

Faculty of Aerospace Engineering



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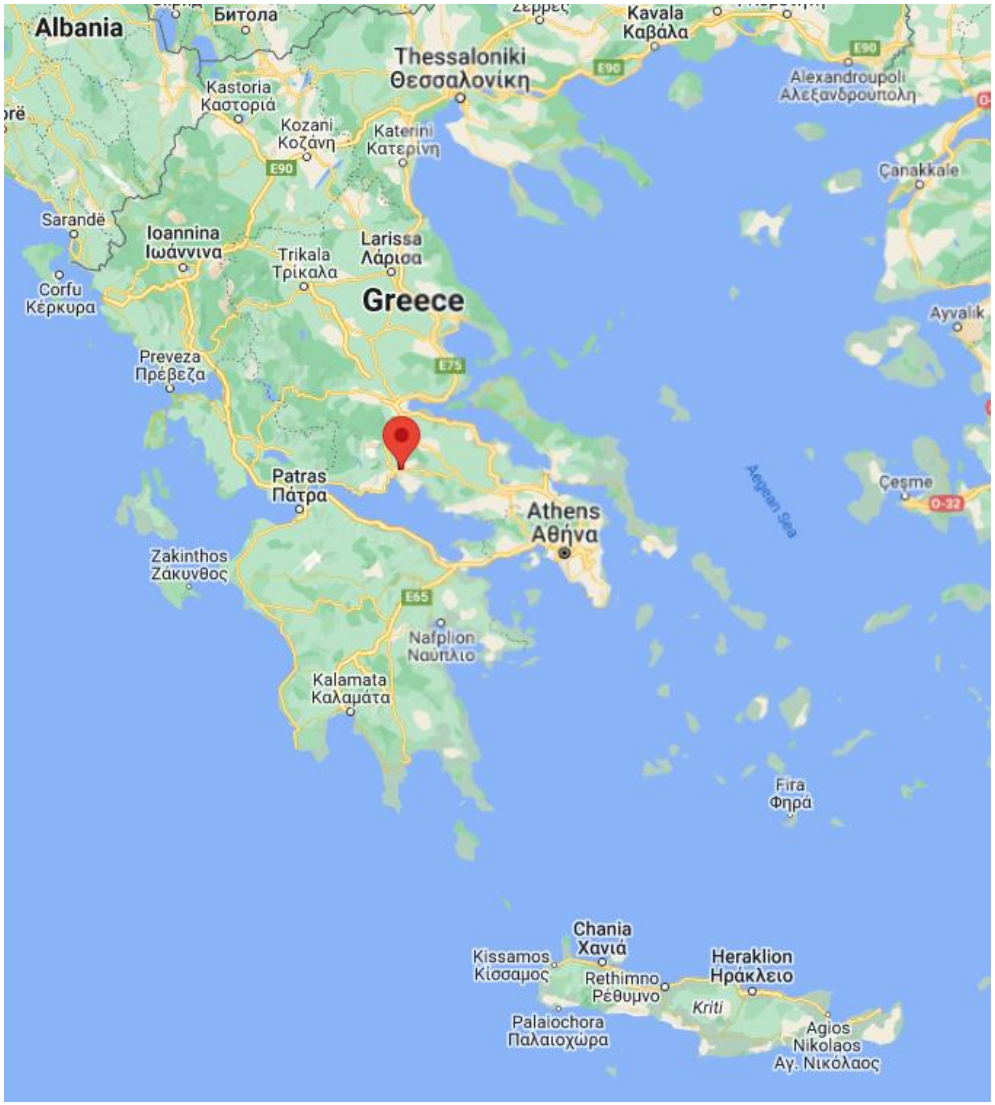
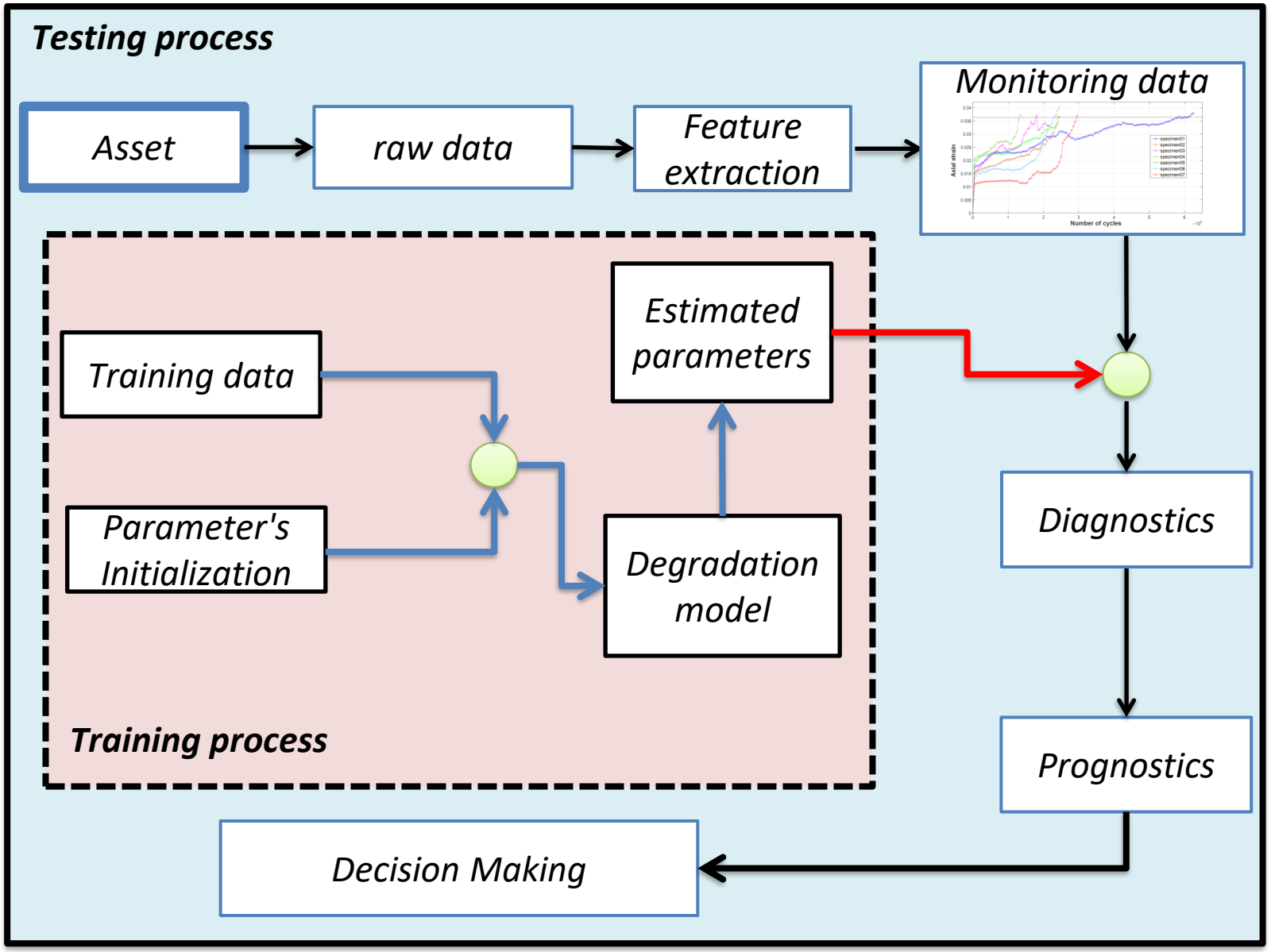
25 Apr 2024

iSP for Operations & Maintenance

Prognosis ‘*Πρόγνωσις*’



PHM - Prognostics & Health Management

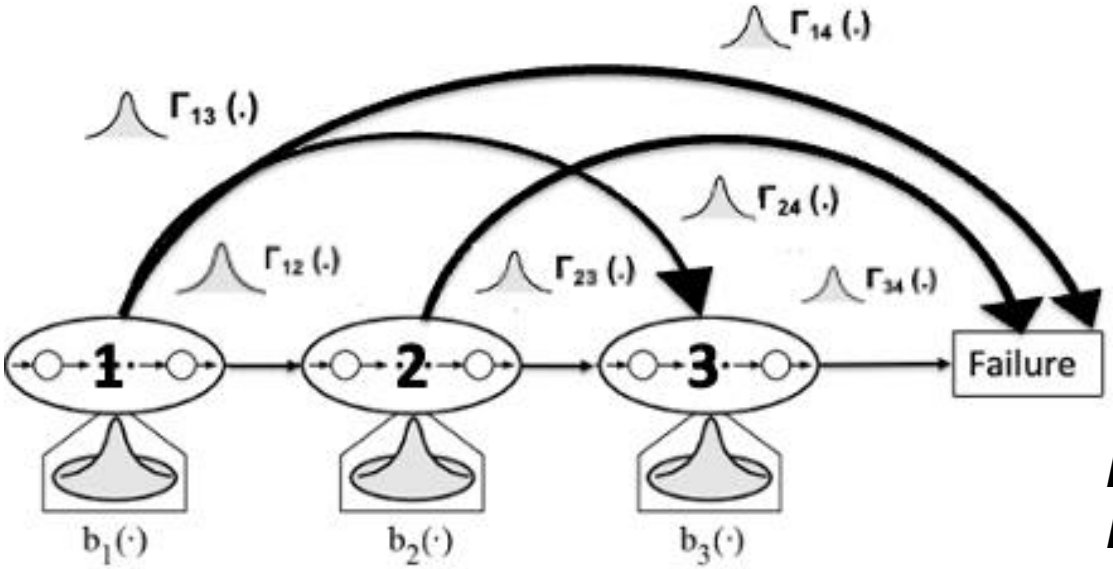


Degradation Model

NON-HOMOGENOUS **HIDDEN** **SEMI**

MARKOV MODEL

is a stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event



Initialization

Number of damage states (N)

Possible transitions

B: observation process parameters

Γ: degradation process parameters

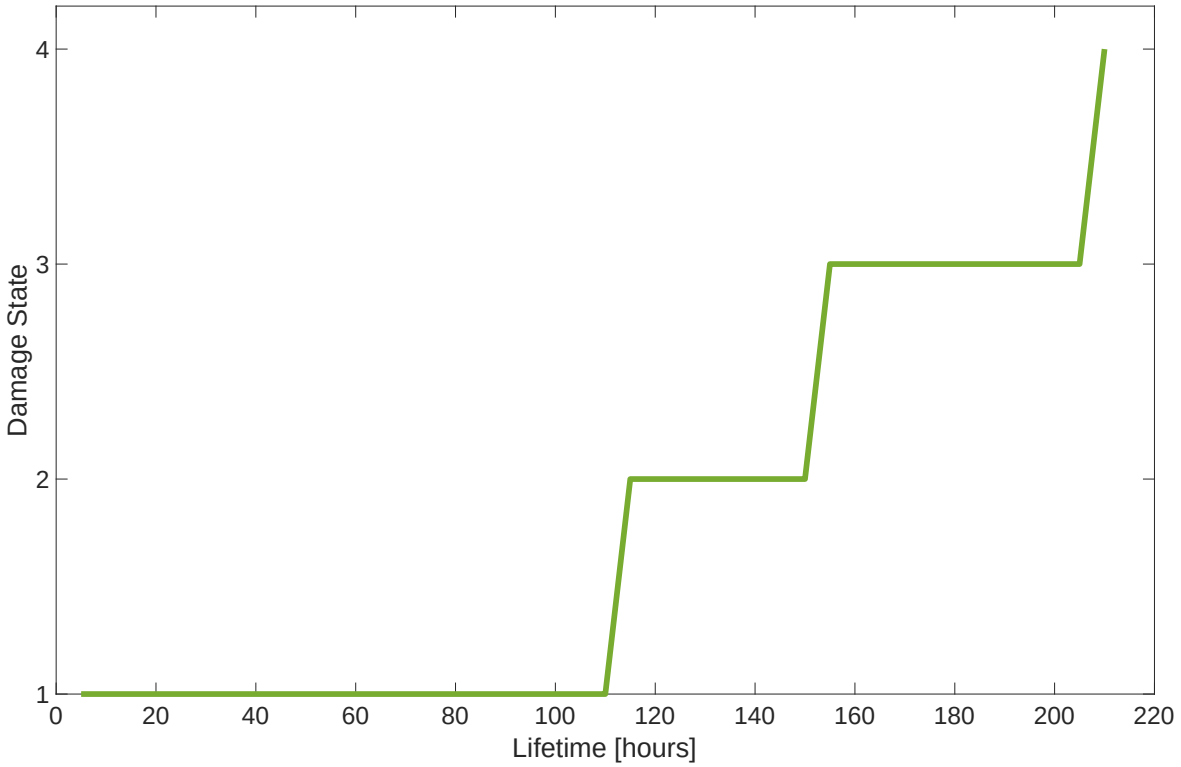
θ = { B, Γ }

$$\boldsymbol{\theta}^* = arg\max_{\theta}\left(\sum_{k=1}^{K} log\left(Pr\left(\boldsymbol{y}^{(k)}\middle|\boldsymbol{\theta}\right)\right)\right)$$

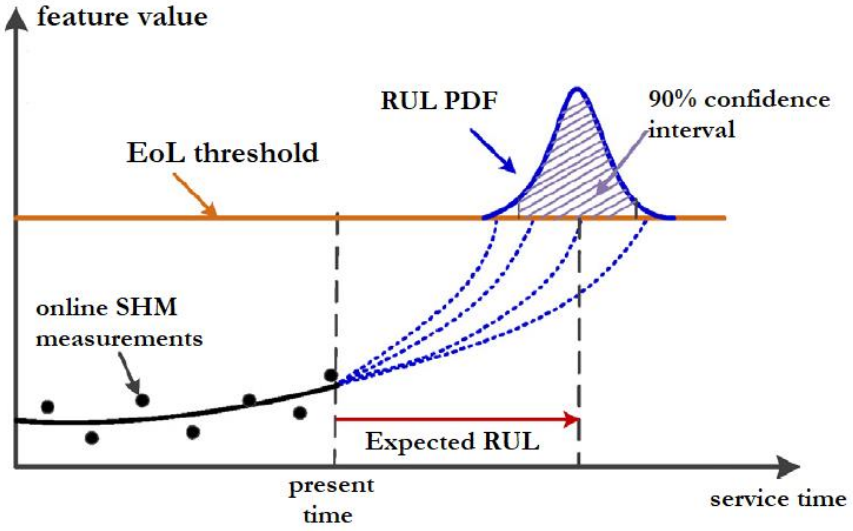
Diagnostics

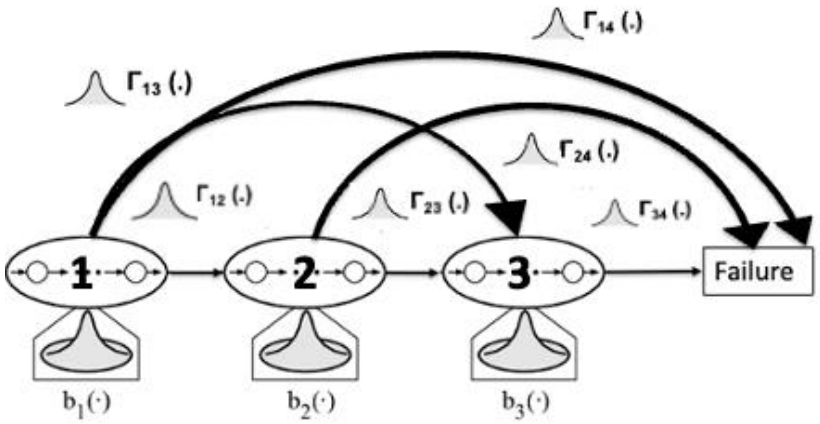
Assess the current damage state ***conditional*** on the available data (**y**) and the trained model parameters $\boldsymbol{\theta}^*$:

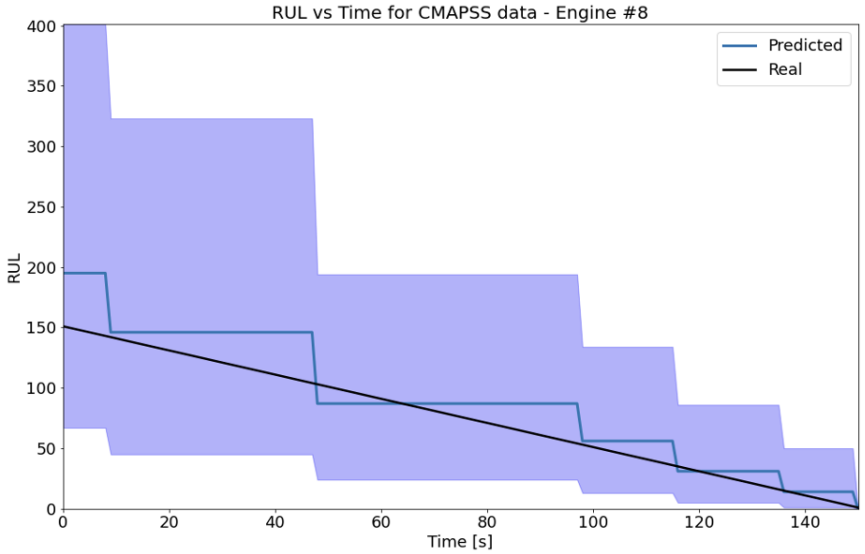
$$\mathrm{MLS}(\mathrm{t}|y_{1:\mathrm{t}}, \boldsymbol{\theta}^*) = \underset{\mathrm{i}}{\mathrm{argmax}}\ \Pr(\mathrm{Q_t} = \mathrm{i}|\mathrm{y}_{1:\mathrm{t}}, \boldsymbol{\theta}^*)$$

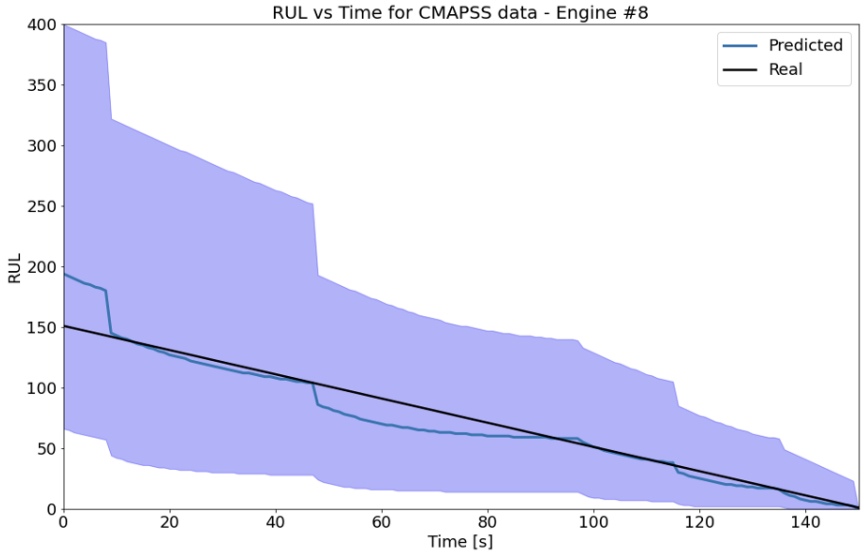


Prognostics









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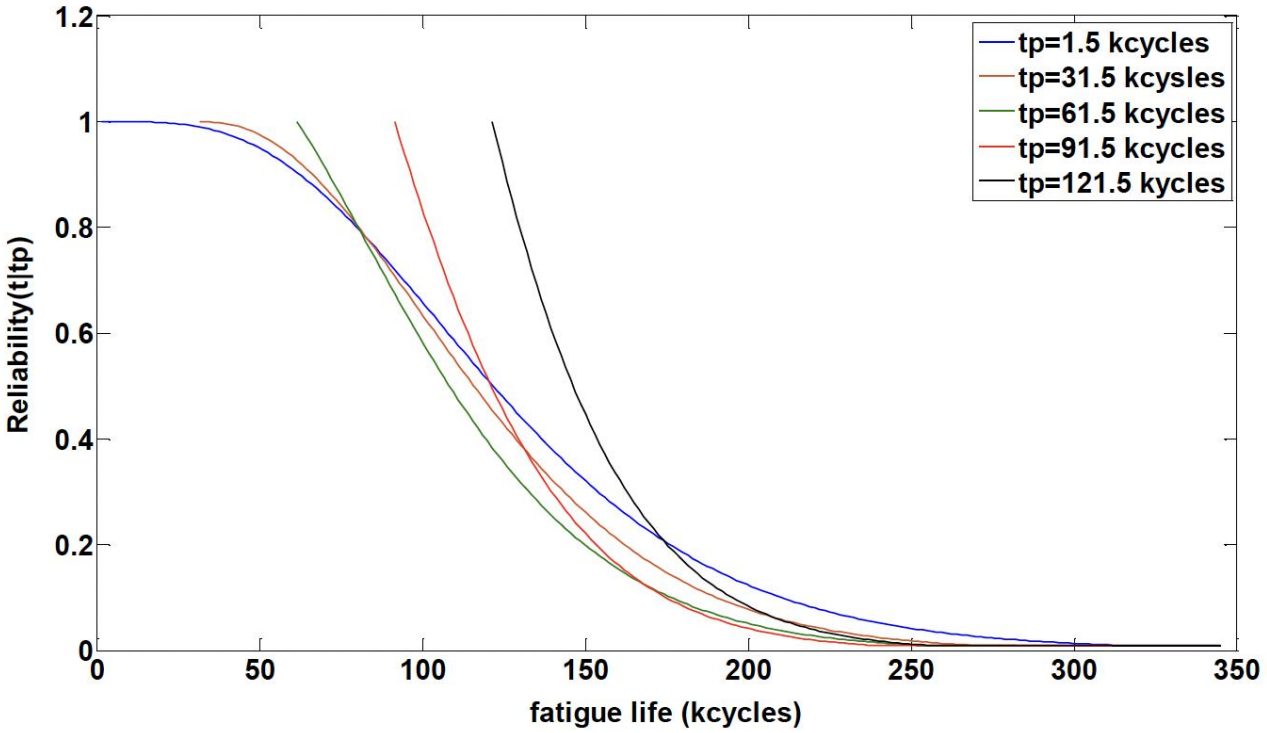
Prognostics

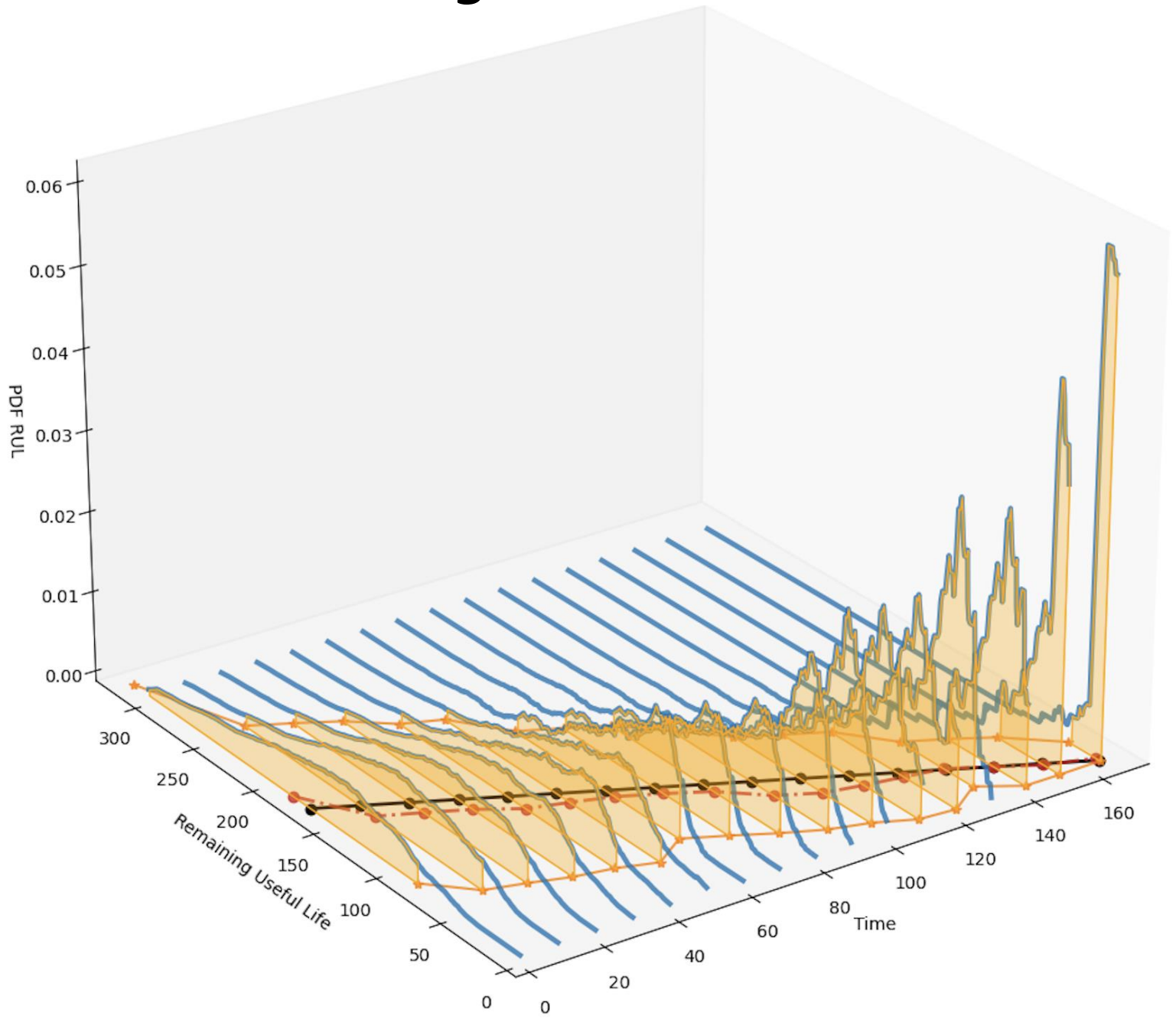
Assess the conditional reliability given the available data (**y**) and the trained model parameters $\boldsymbol{\theta}^*$:

$$\mathrm{R}\left(\mathrm{t}\middle|\mathrm{y}_{1:\mathrm{t_p}}, \mathrm{L} > \mathrm{t_p}, \boldsymbol{\theta}^*\right) = \Pr\left(\mathrm{L} > \mathrm{t}\middle|y_{1:\mathrm{t_p}}, \mathrm{L} > \mathrm{t_p}, \boldsymbol{\theta}^*\right)$$

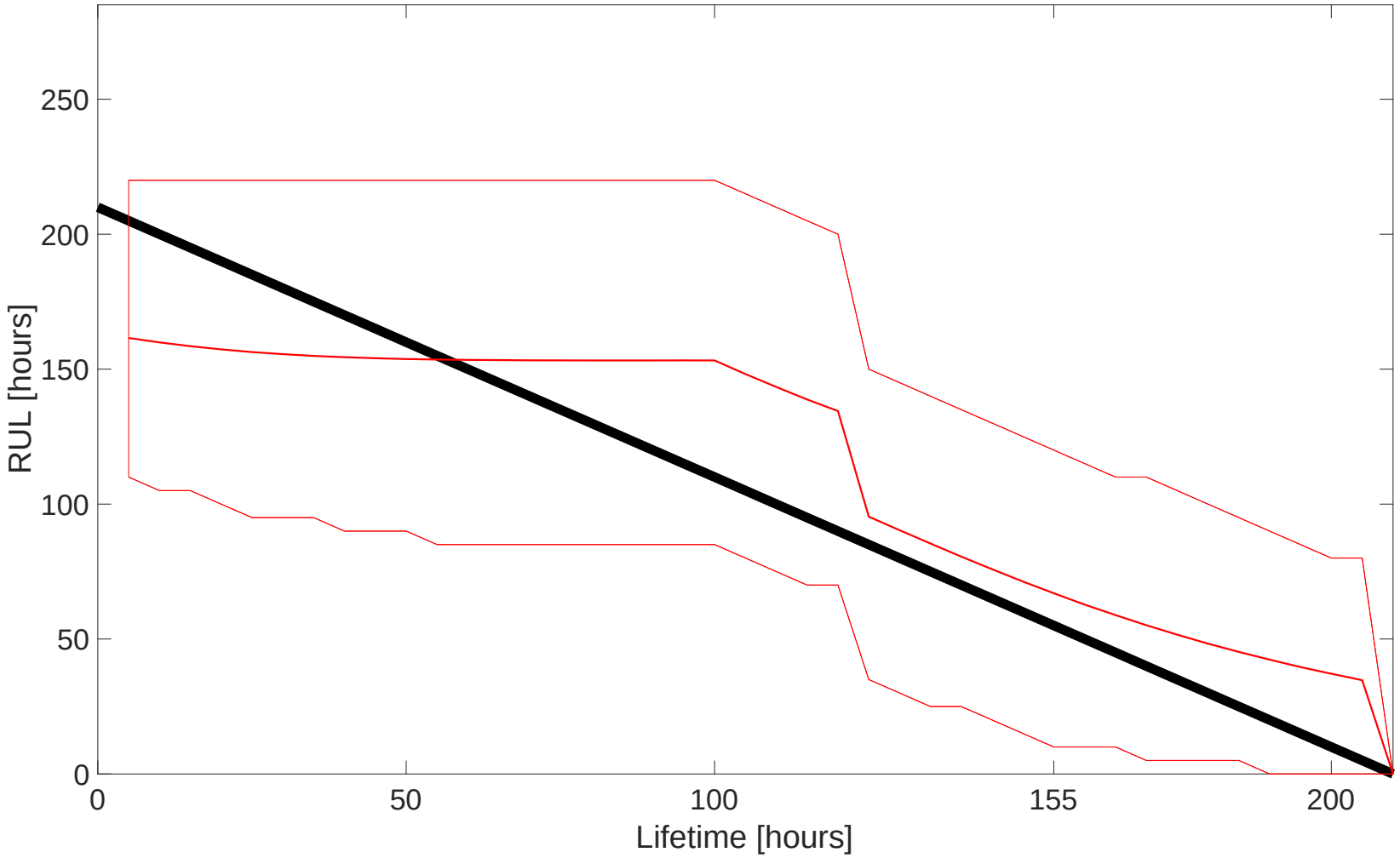
$$\Pr\left(\mathrm{RUL}_{\mathrm{t_p}} \leq \mathrm{t}\middle|y_{1:\mathrm{t_p}}, \boldsymbol{\theta}^*\right) = 1 - \mathrm{R}\left(\mathrm{t} + \mathrm{t_p}\middle|\mathrm{y}_{1:\mathrm{t_p}}, \boldsymbol{\theta}^*\right)$$



Prognostics



Prognostics



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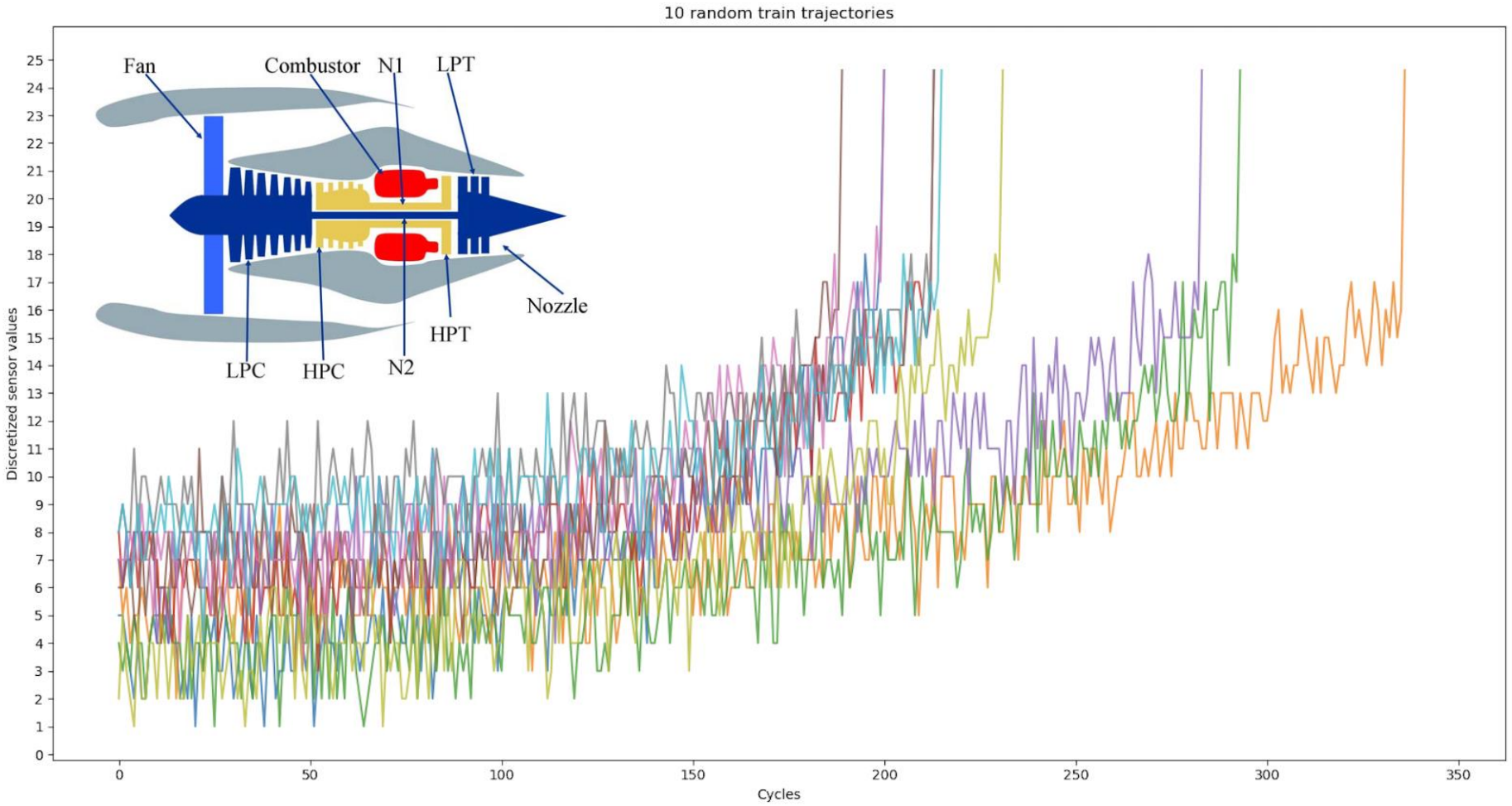
Prognostics of Aircraft Engines



NASA C-MAPSS (Turbofan Engine Degradation Simulation Data Set)

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Prognostics of Aircraft Engines

$$\boldsymbol{\theta}^* = arg\max_{\theta}\left(\sum_{k=1}^{K} log\left(Pr\left(\boldsymbol{y}^{(k)}\middle|\boldsymbol{\theta}\right)\right)\right)$$

B: observation process parameters

Γ: degradation process parameters

θ = { **B**, **Γ** }

HMM

B : non-parametric

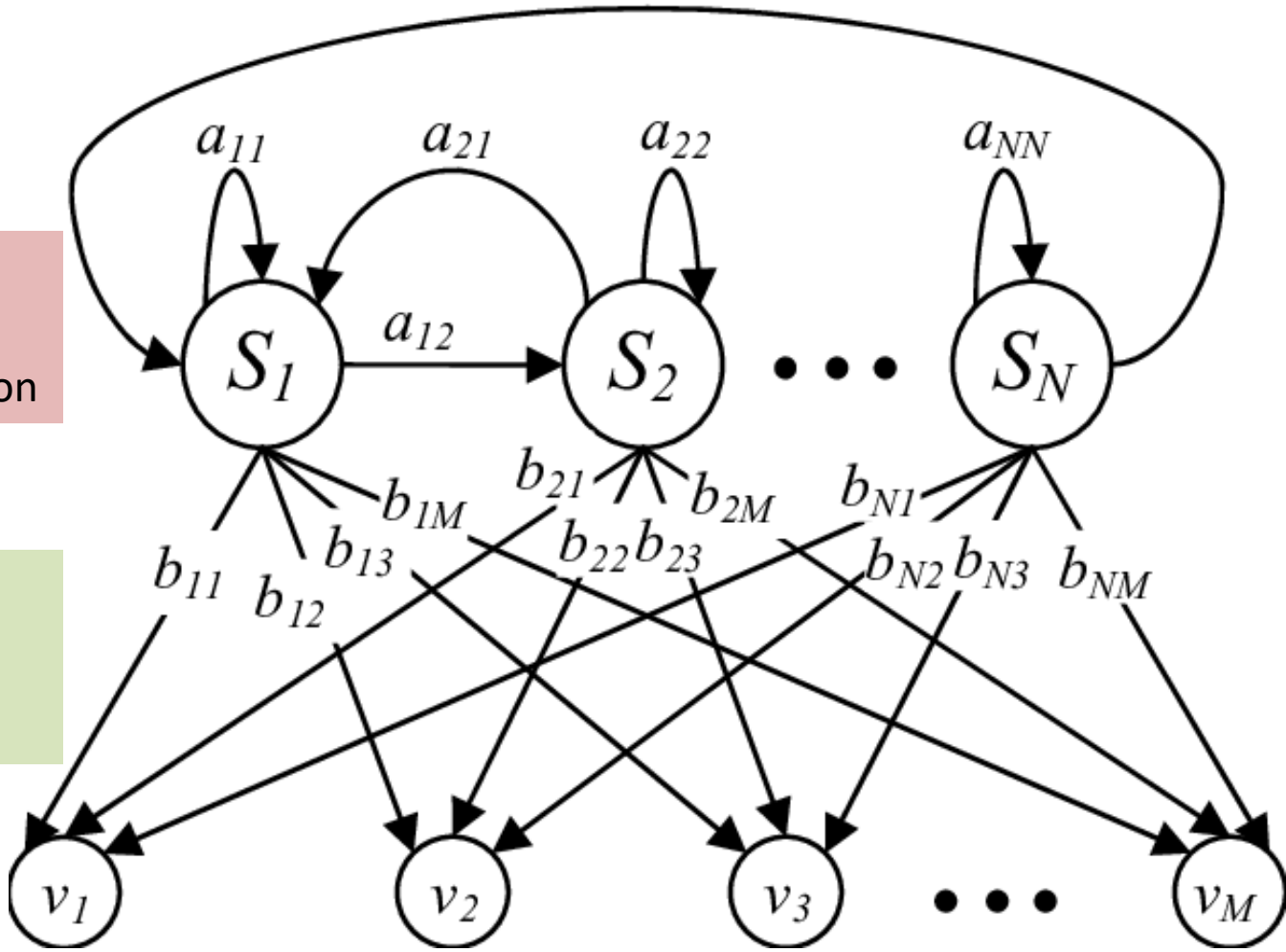
Γ : exponential state duration

$$p_i(d) = (a_{ii})^{d-1}(1 - a_{ii})$$

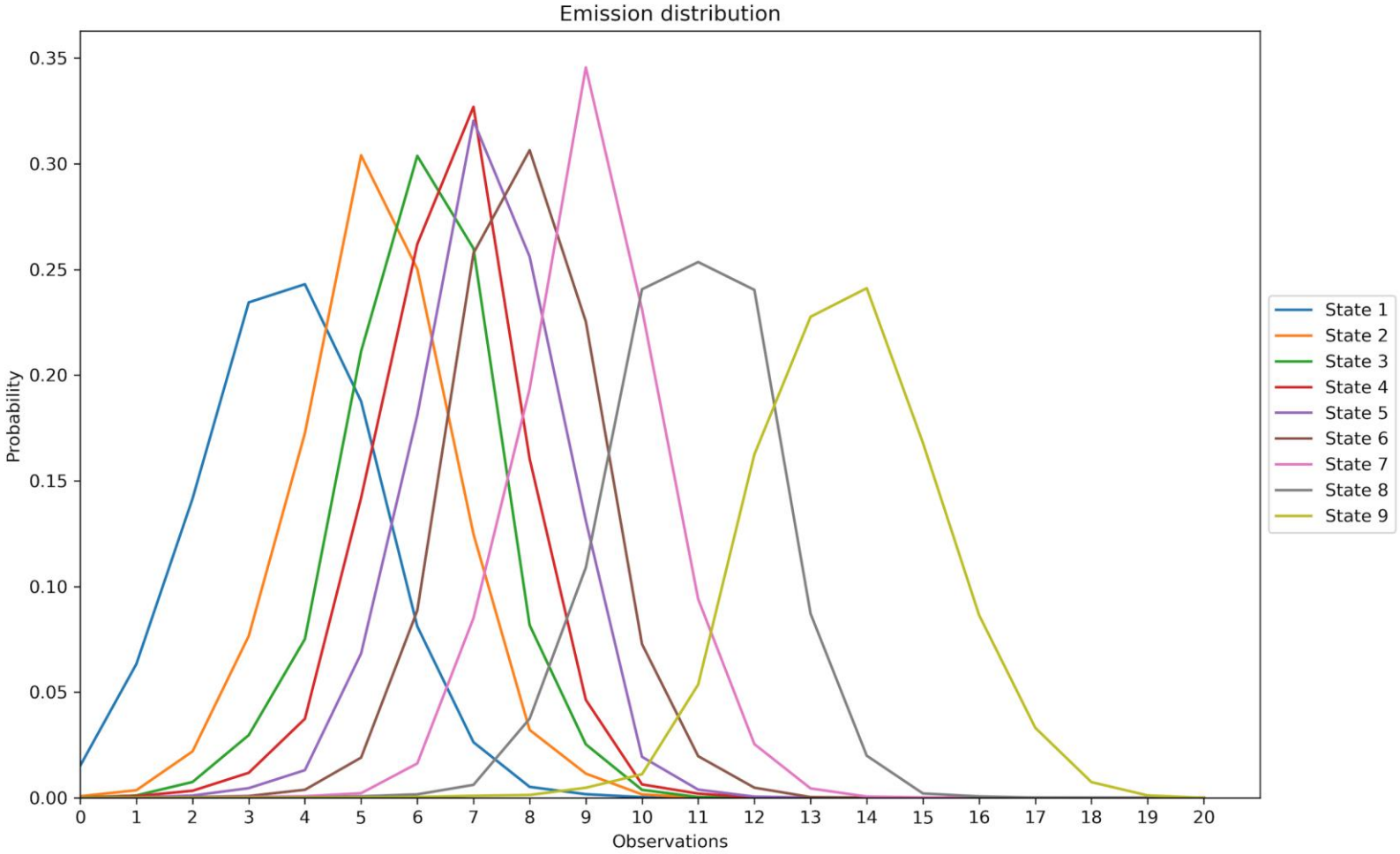
HSMM

B : Gaussian distribution

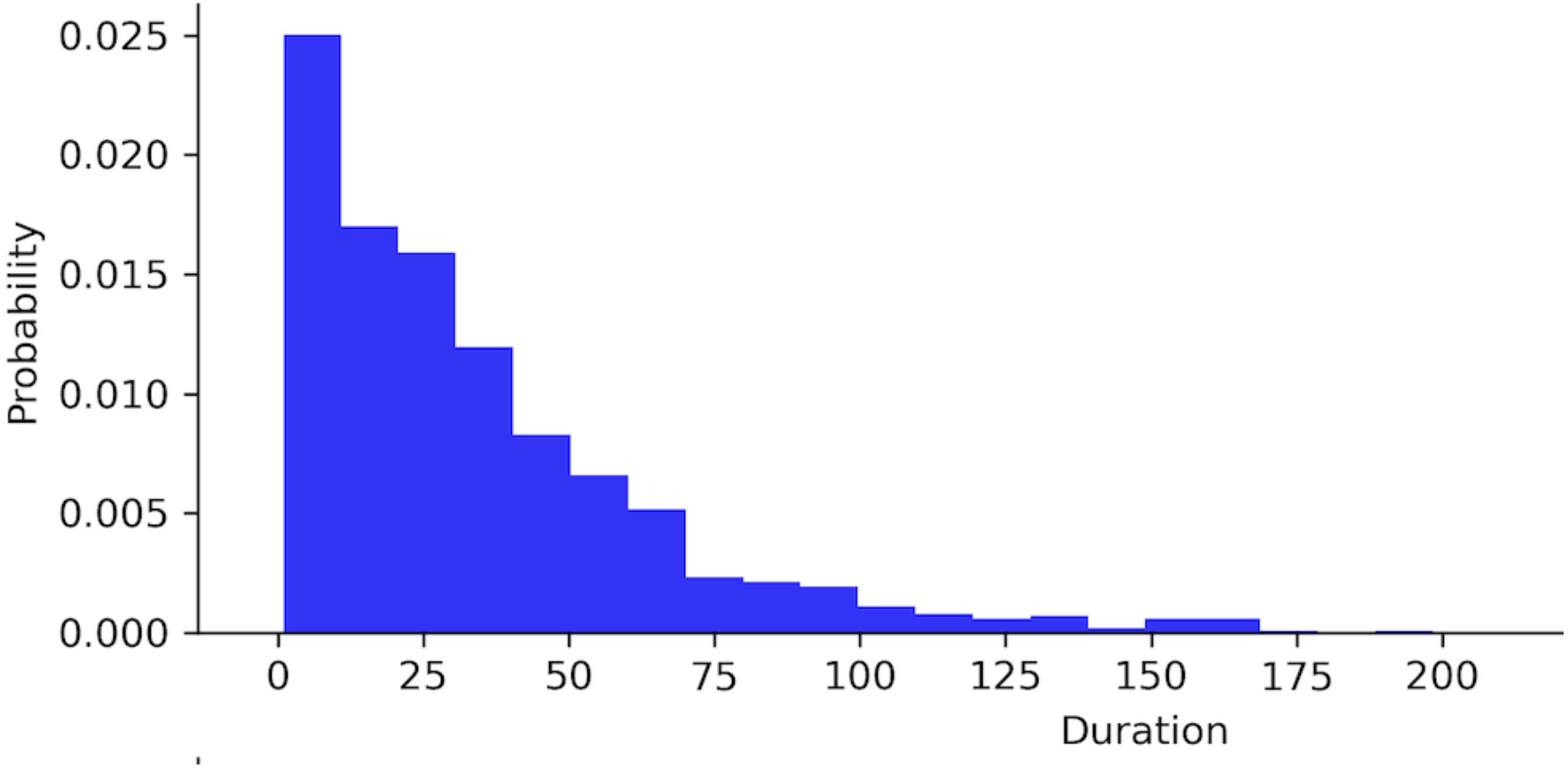
Γ : non-parametric



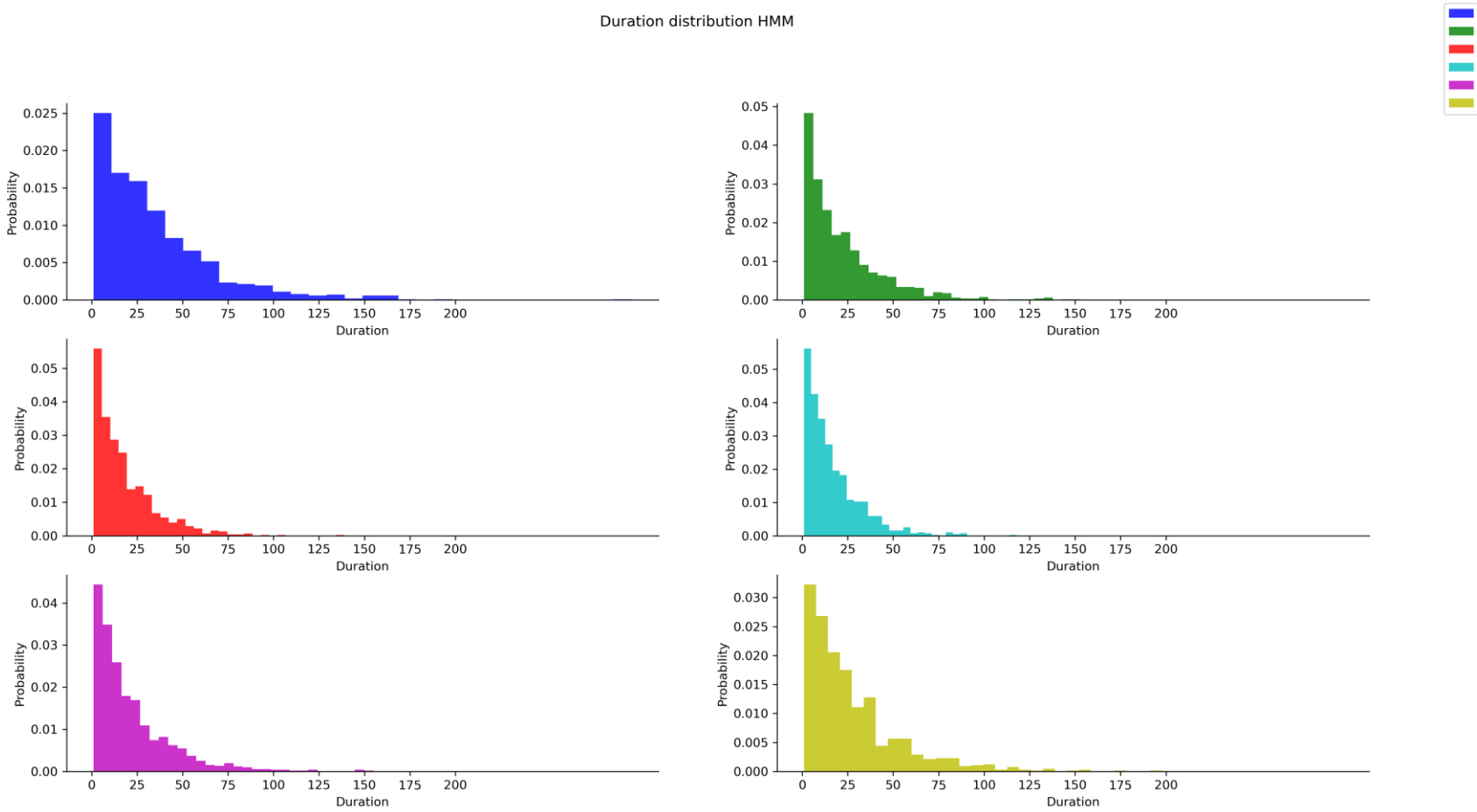
HMM - B


Emission distribution
Probability
Observations
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
State 1
State 2
State 3
State 4
State 5
State 6
State 7
State 8
State 9

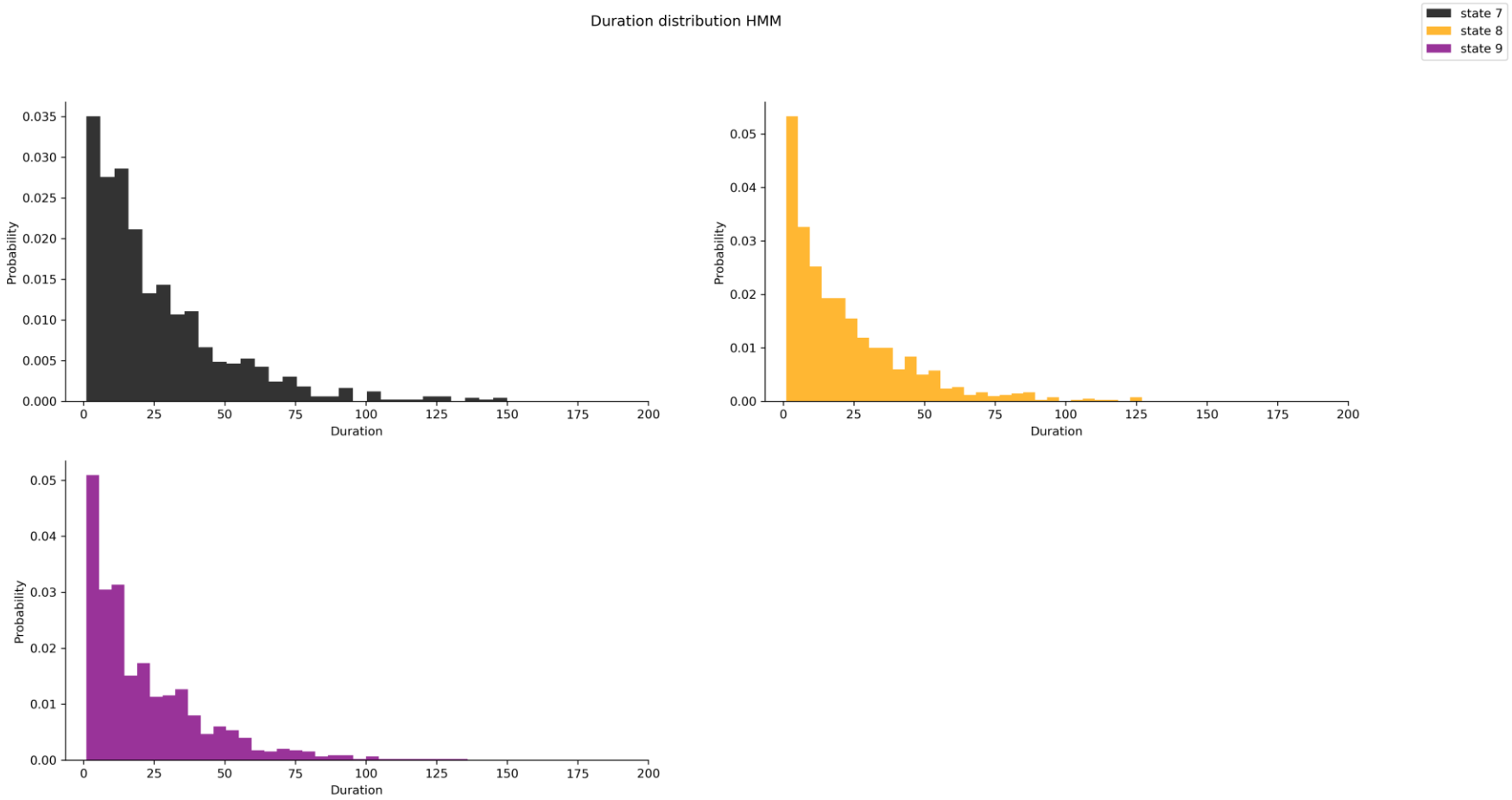
HMM – Γ of S1


0.025
0.020
0.015
0.010
0.005
0.000
Probability
0
25
50
75
100
125
150
175
200
Duration

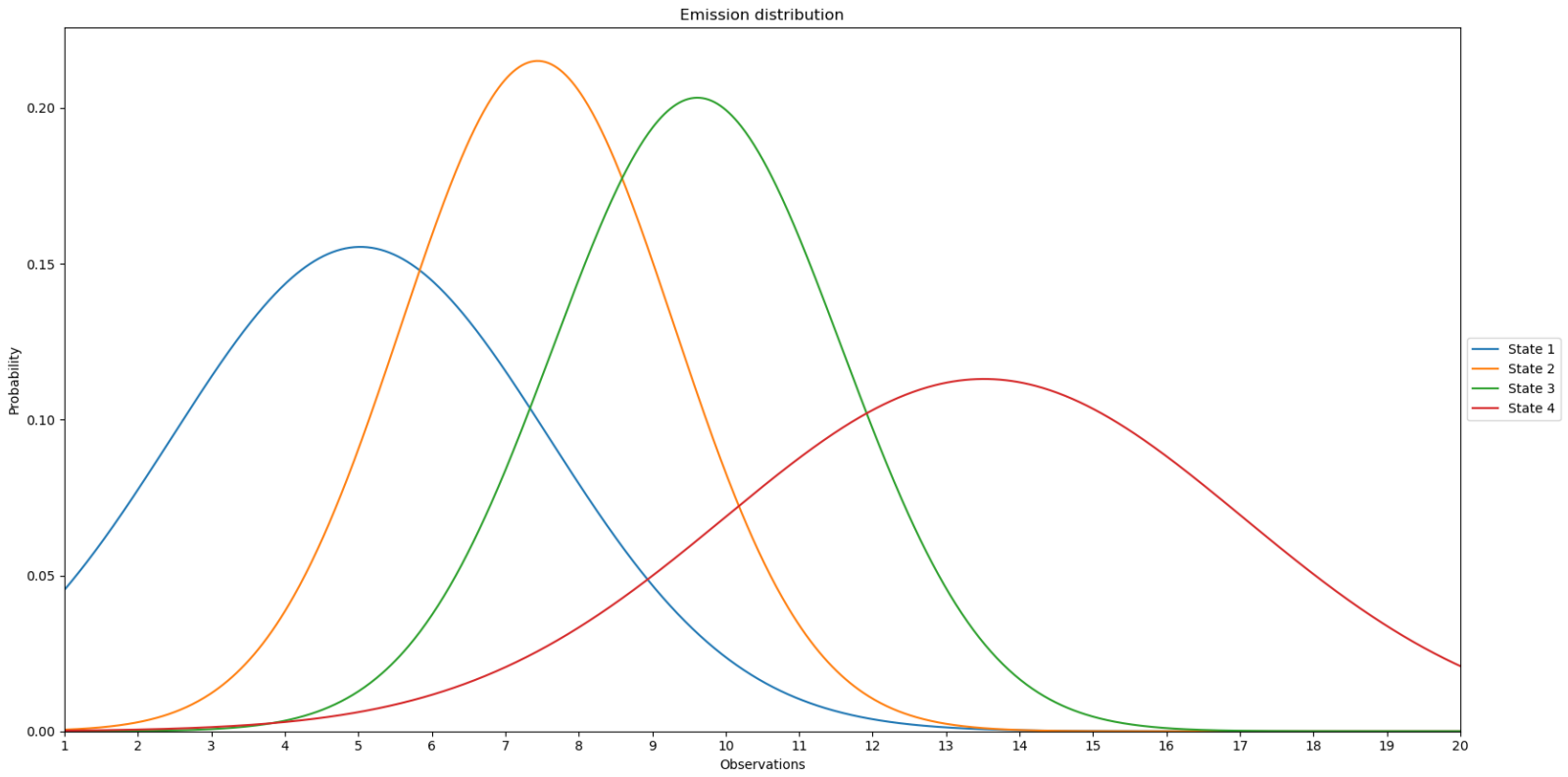
HMM - Γ


Duration distribution HMM
state 1
state 2
state 3
state 4
state 5
state 6
Probability
Duration

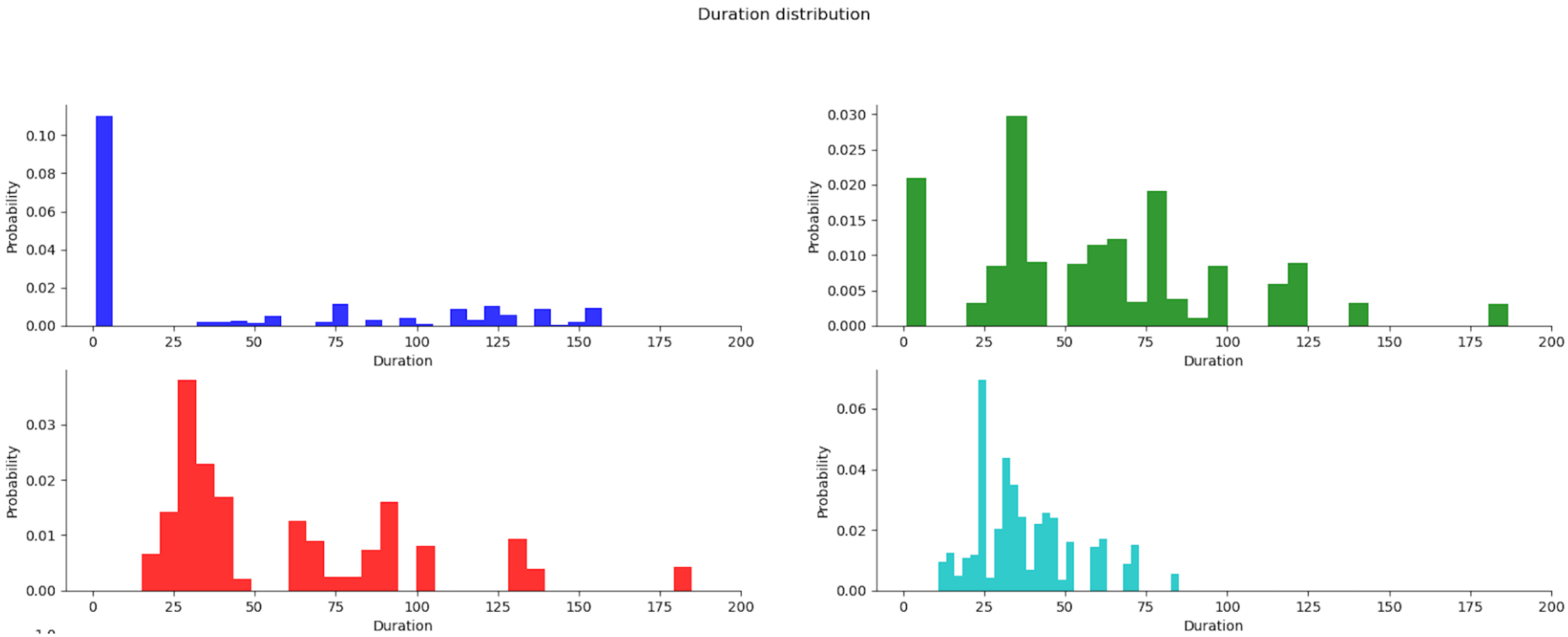
HMM - Γ


Duration distribution HMM
state 7
state 8
state 9
Probability
Duration
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0.05
0.04
0.03
0.02
0.01
0.00
0
25
50
75
100
125
150
175
200

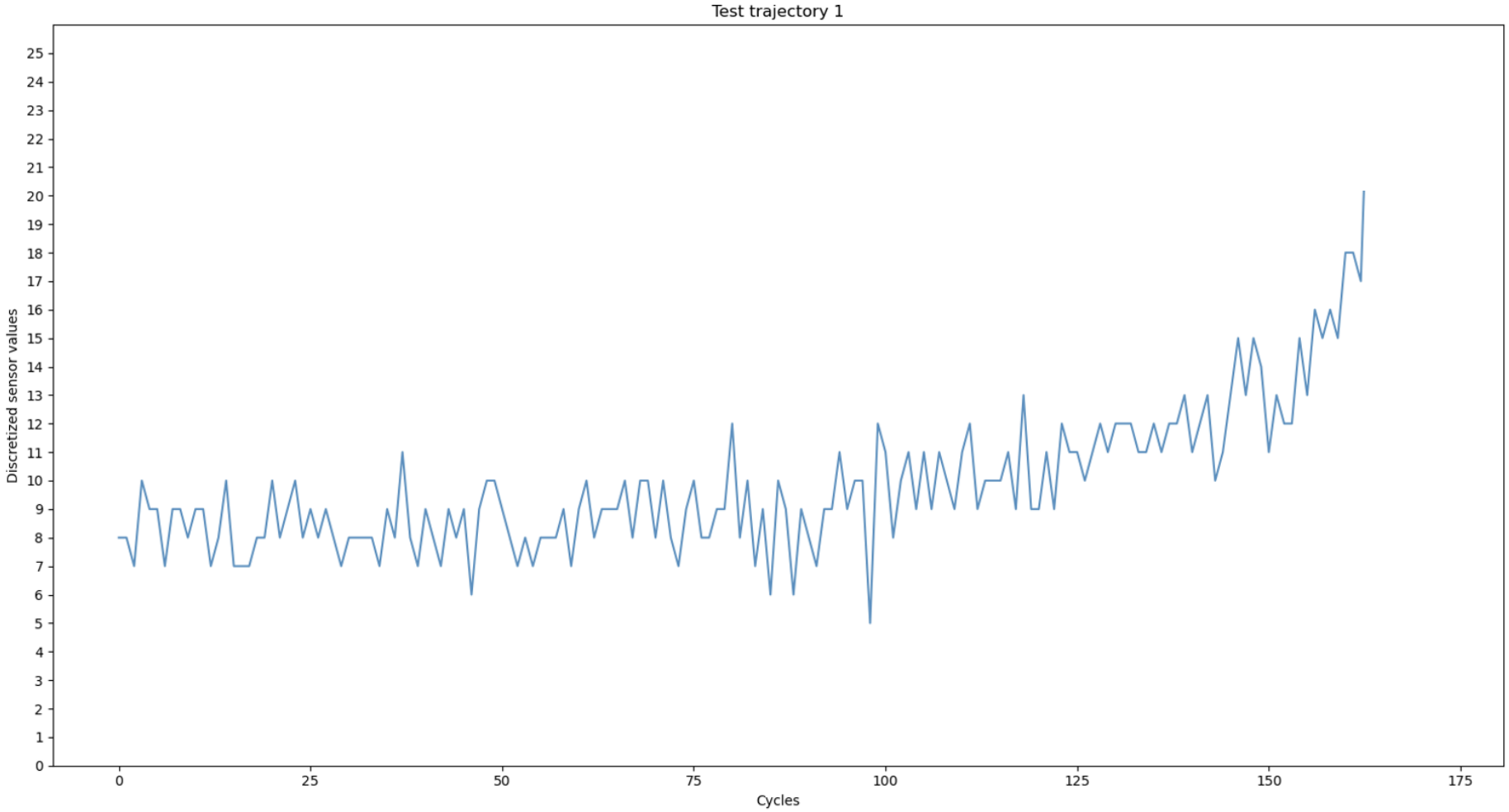
HSMM - B


Emission distribution
Probability
0.00
0.05
0.10
0.15
0.20
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
Observations
State 1
State 2
State 3
State 4

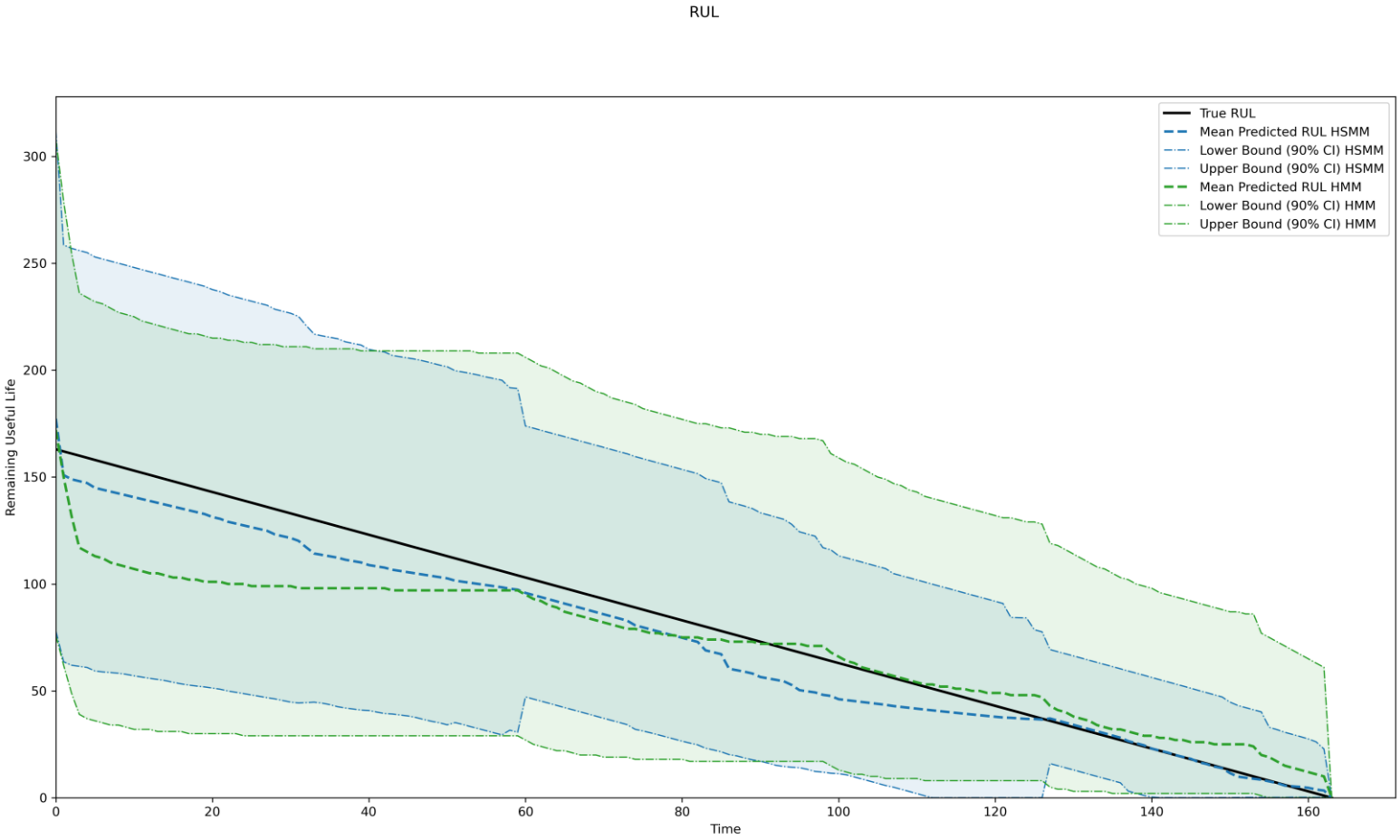
HSMM – Γ


Duration distribution
Probability
Duration
0.10
0.08
0.06
0.04
0.02
0.00
0.030
0.025
0.020
0.015
0.010
0.005
0.03
0.01
0.06
0
25
50
75
100
125
150
175
200

Prognostics of Aircraft Engines – Testing phase



Prognostics of Aircraft Engines – Testing phase



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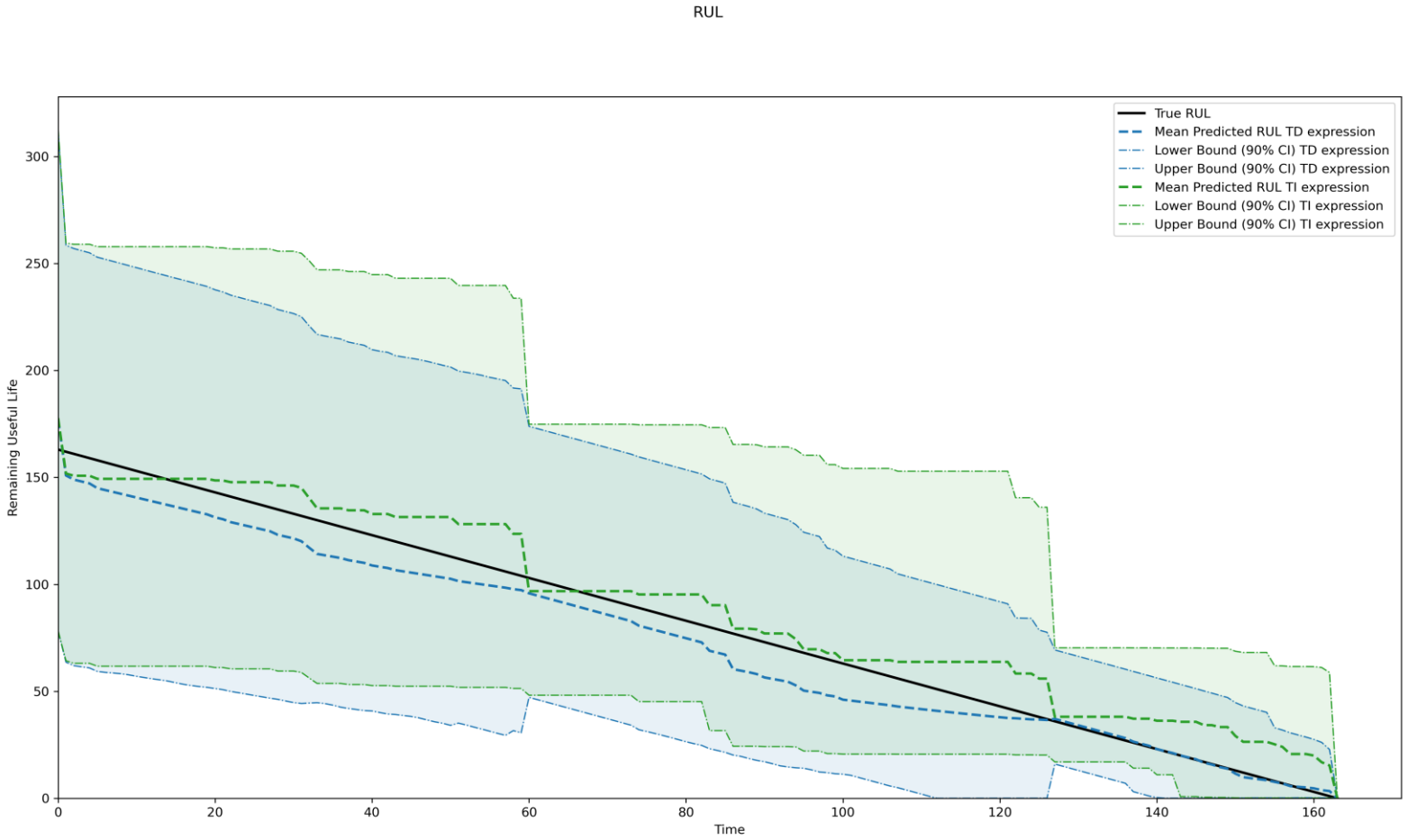
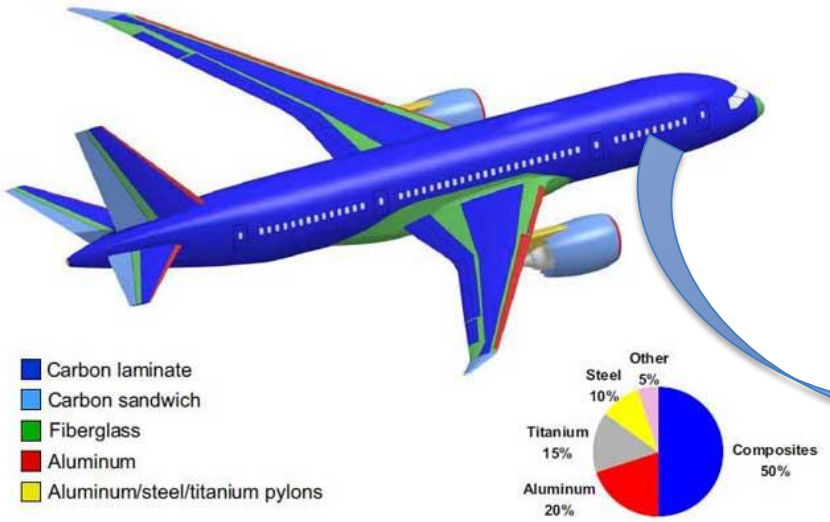
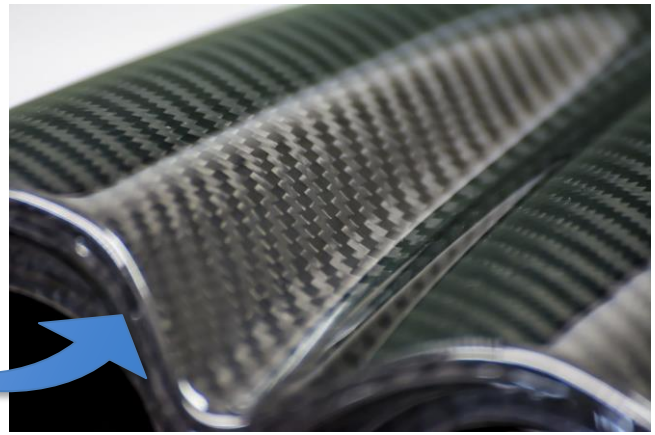
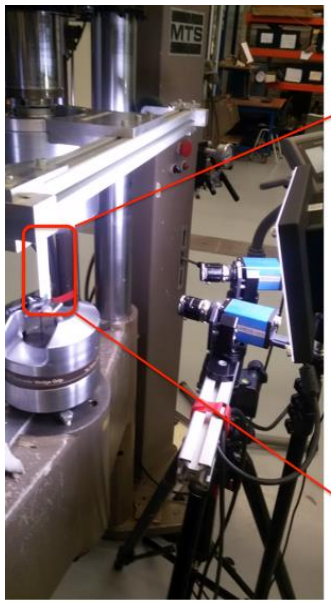
Prognostics of Aircraft Engines – Testing phase

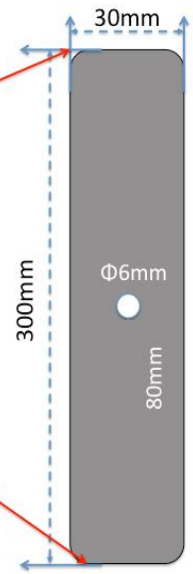


Case-Study Composites







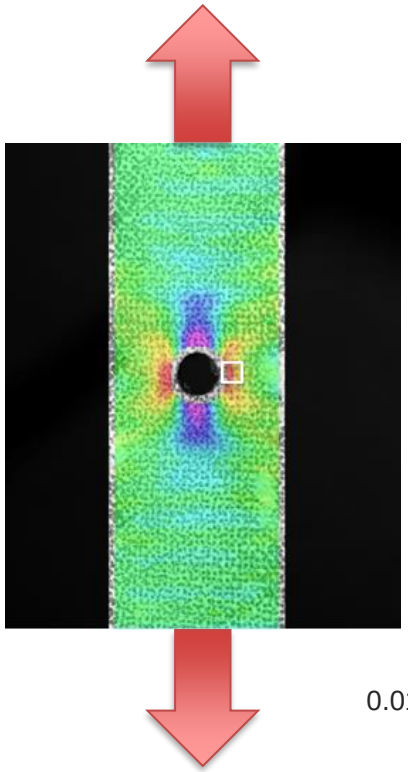


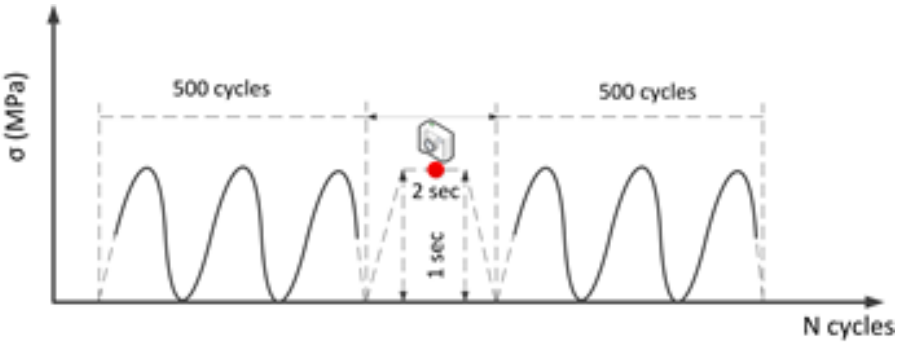
- Heterogeneity
- Anisotropy
- Interfacial effects
- Manufacturing process

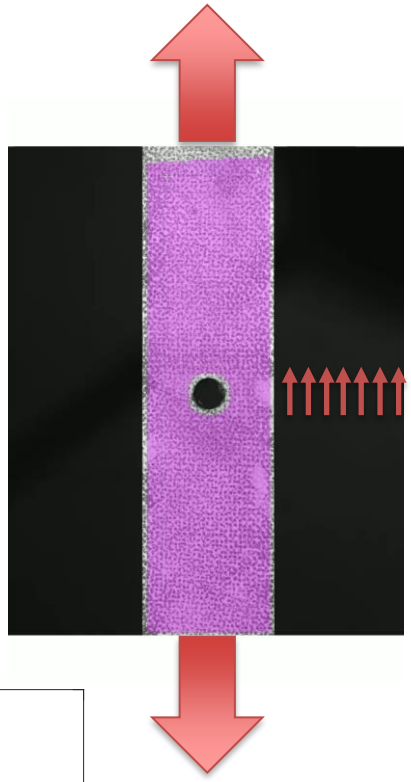
- Lightweight
- High strength-to-weight ratio
- Durability
- Design flexibility
- Tailored properties

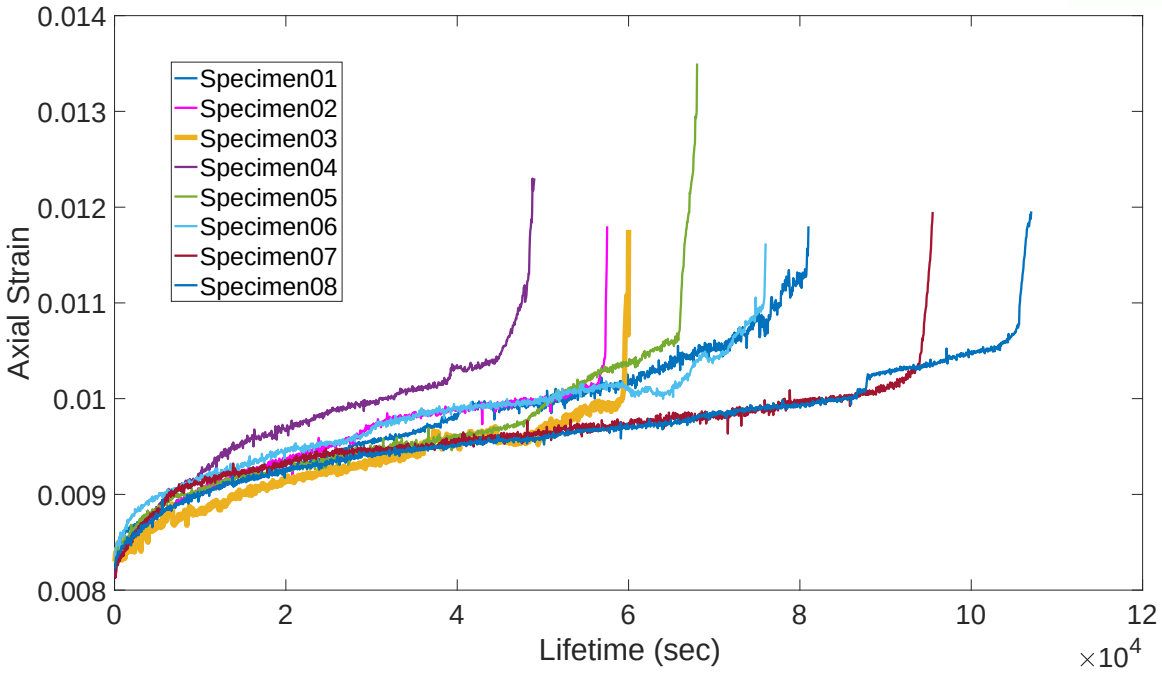
Specimen	Experimental Conditions	Lifetime (hours)
1	R=0.1 f=10 Hz A=36 x 90% kN [0/45/90/-45]2s Prepreg tape Hexply® F6376C-HTS(12K)-5-35%	22.5
2		16.1
3		16.6
4		13.6
5		18.9
6		21.1
7		26.5
8		29.7

Case-Study Composites

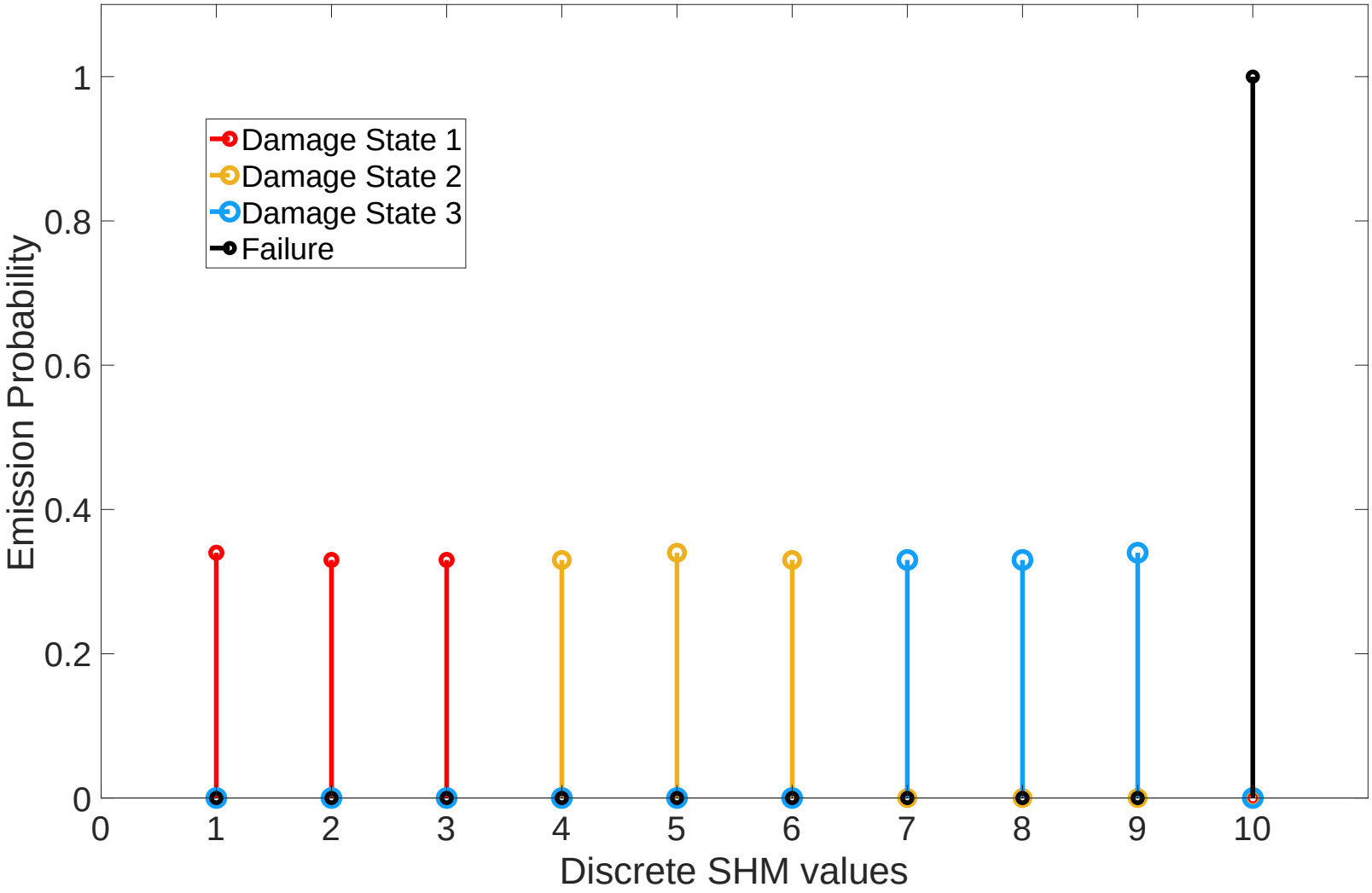




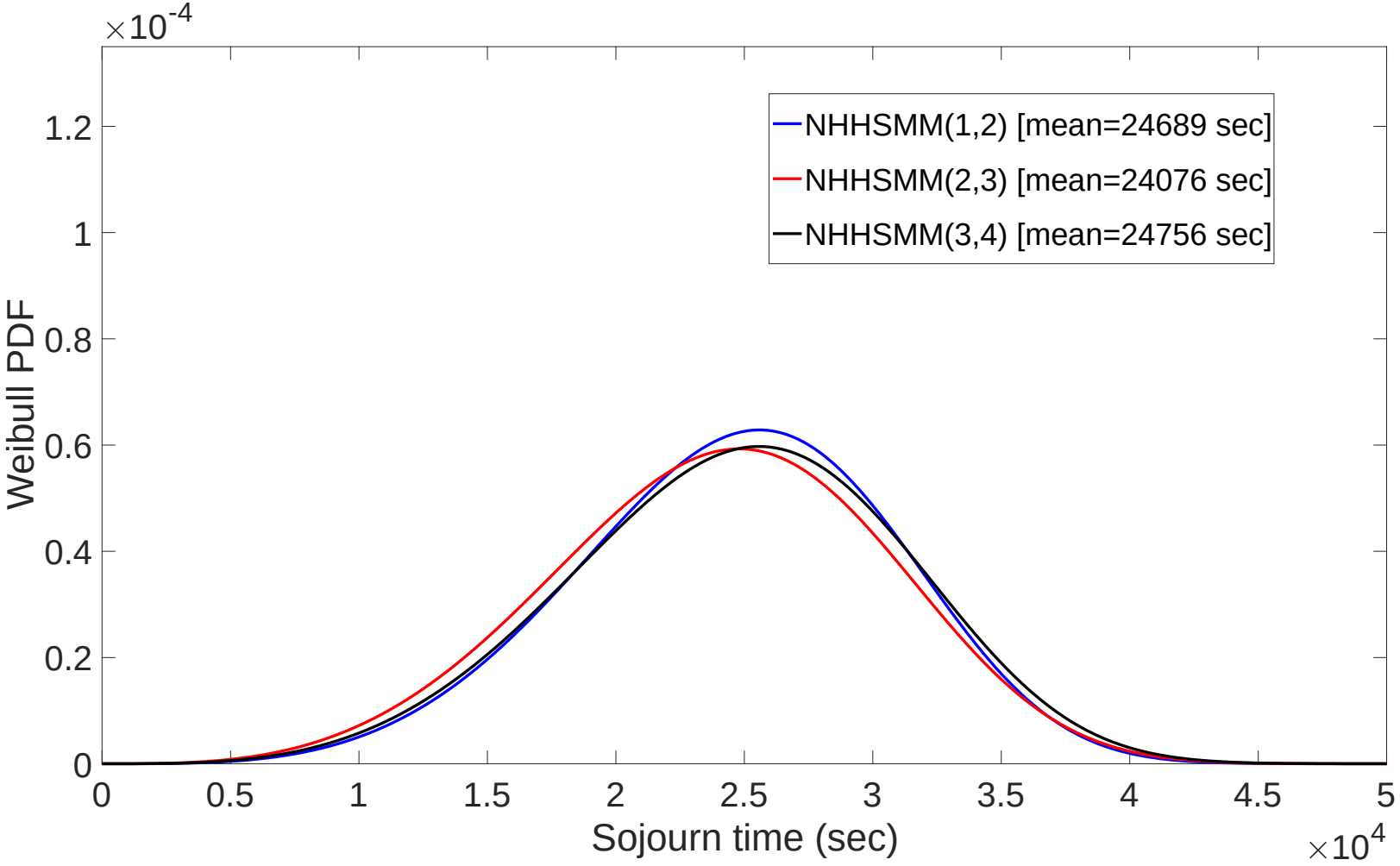




NHHSMM – B


Damage State 1
Damage State 2
Damage State 3
Failure
Emission Probability
0
0.2
0.4
0.6
0.8
1
0
1
2
3
4
5
6
7
8
9
10
Discrete SHM values

NHHSMM – Γ



$$\lambda_{i,j}(s,t) = \begin{cases} \dfrac{\beta_{i,j}}{a_{i,j}}\left(\dfrac{t}{a_{i,j}}\right)^{\beta_{i,j}-1} & if\ 1 \le i \le N-1,\ \ j = i+1 \quad (soft\ failures) \\ \dfrac{\beta_{i,j}}{a_{i,j}}\left(\dfrac{s+t}{a_{i,j}}\right)^{\beta_{i,j}-1} & if\ 1 \le i \le N-2, \qquad j = N \quad (hard\ failures) \end{cases}$$

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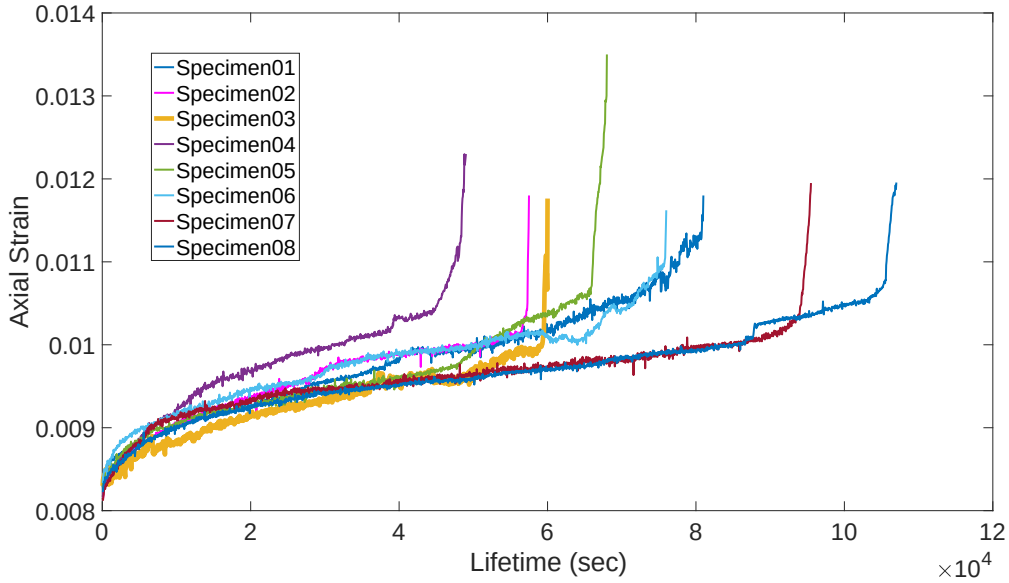
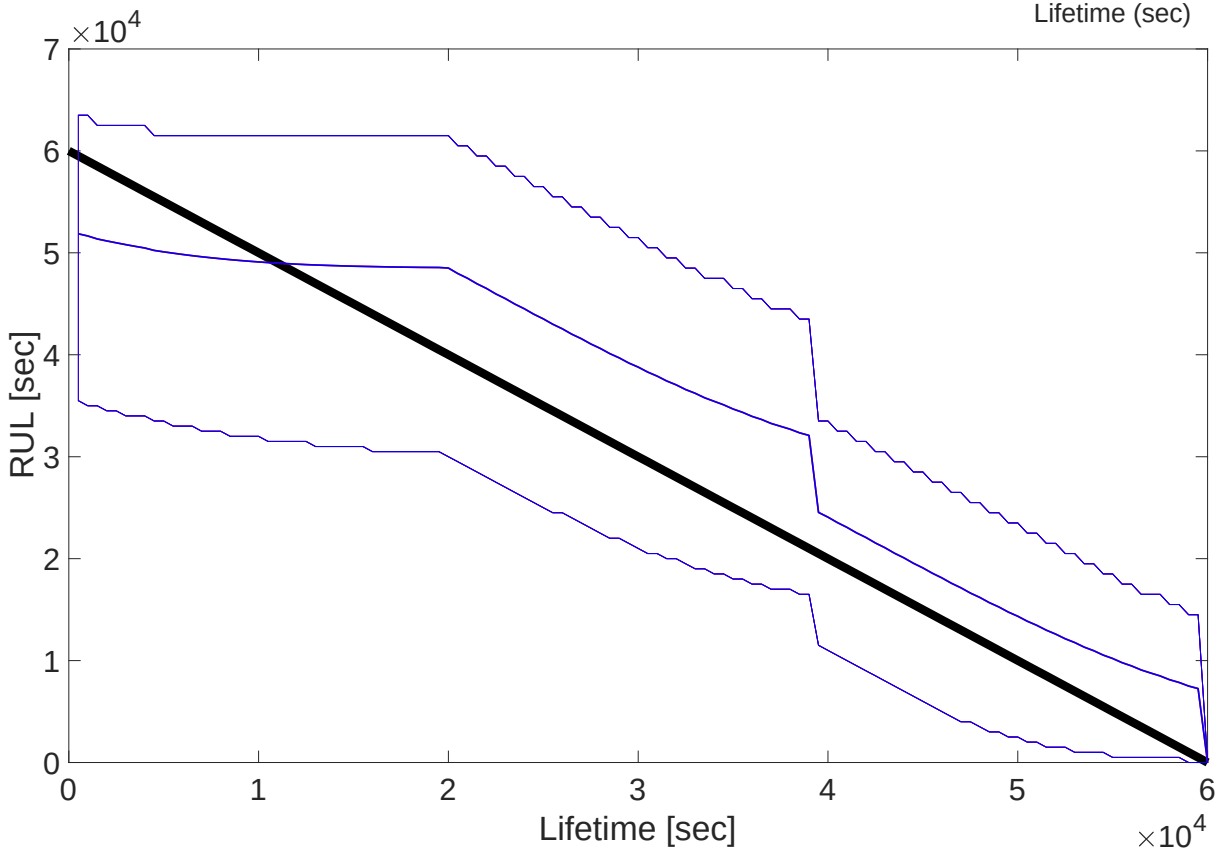
Specimen03 Prognosis





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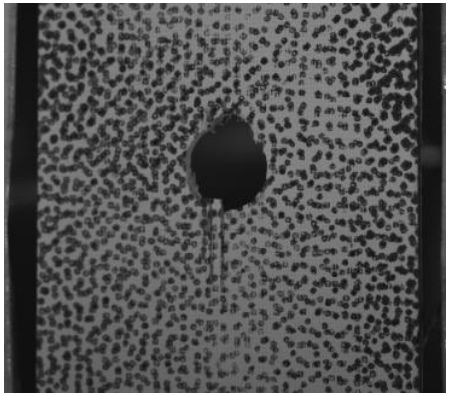
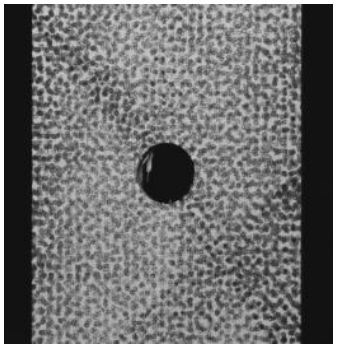
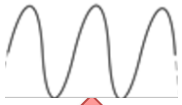
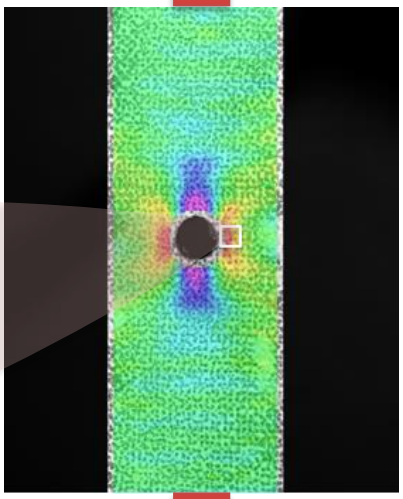
Unexpected phenomena





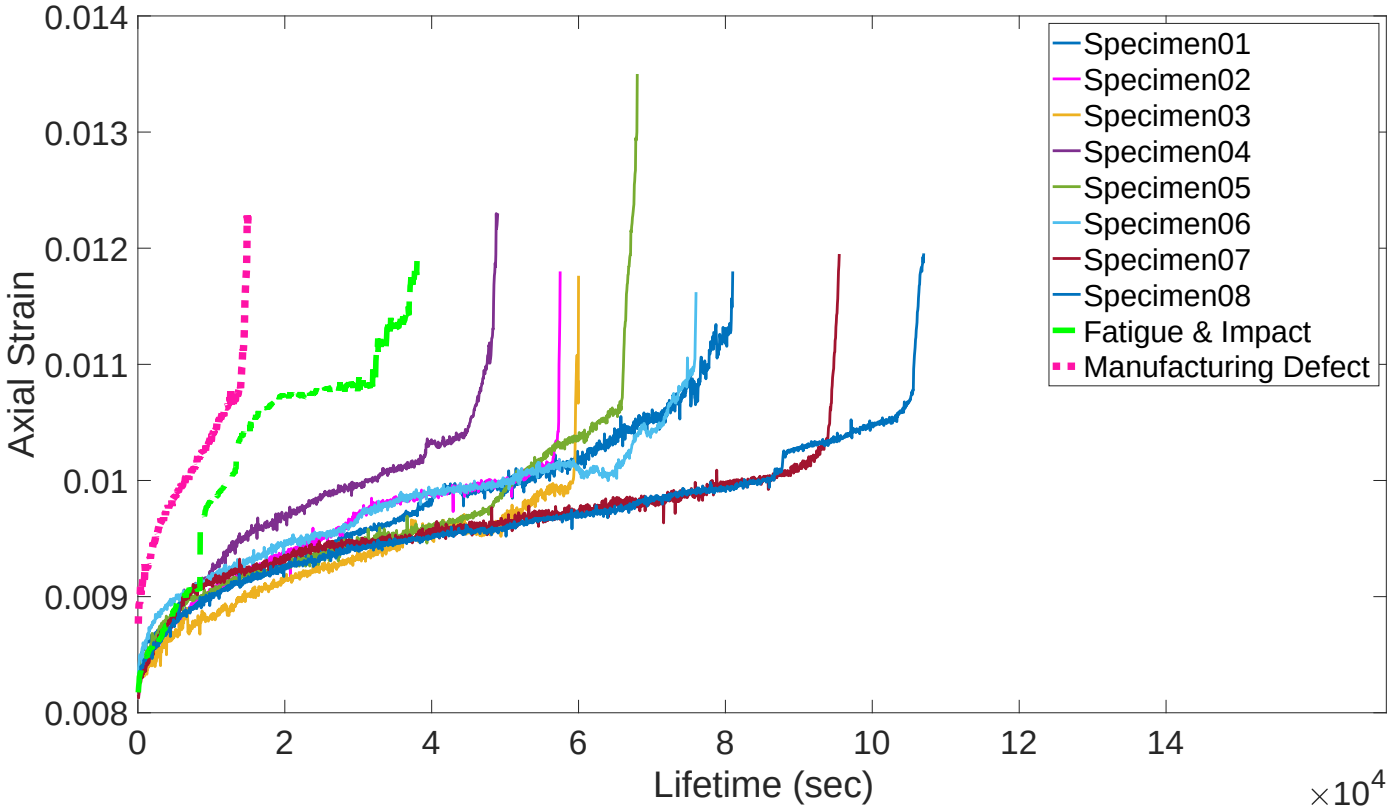




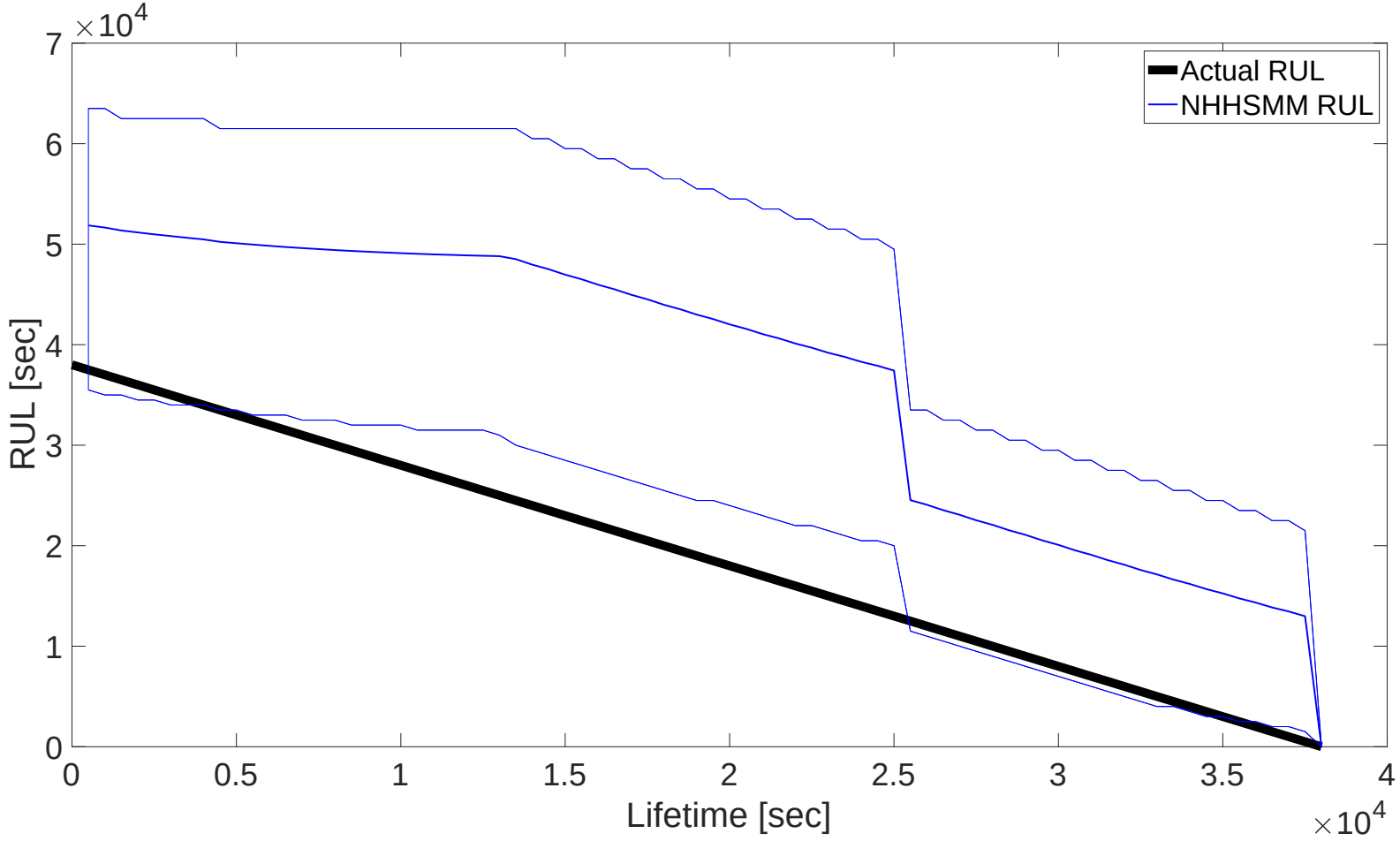
E=6 J
u=20m/sec
T=8300 sec

Unexpected phenomena

Specimen	Experimental Conditions	Lifetime (hours)
1	R=0.1 f=10 Hz A=36 x 90% kN [0/45/90/-45]2s Prepreg tape Hexply® F6376C-HTS(12K)-5-35%	22.5
2		16.1
3		16.6
4		13.6
5		18.9
6		21.1
7		26.5
8		29.7
Testing	Fatigue + Impact	**10.5**
Testing	Manufacturing Defect	**4.2**



Specimen Fatigue & Impact



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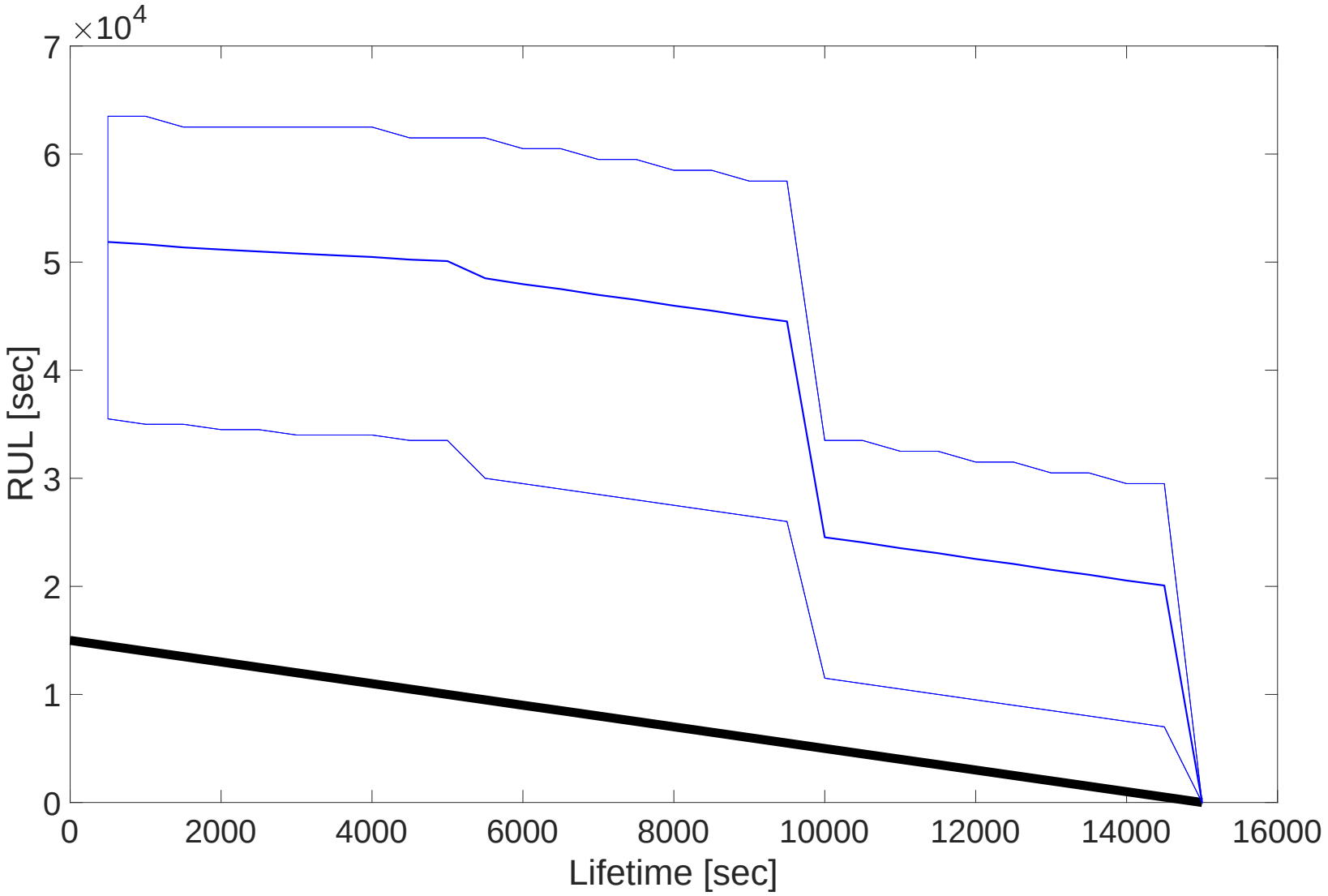
Specimen Manufacturing Defect



Sources of Uncertainty

Lifetime uncertainties

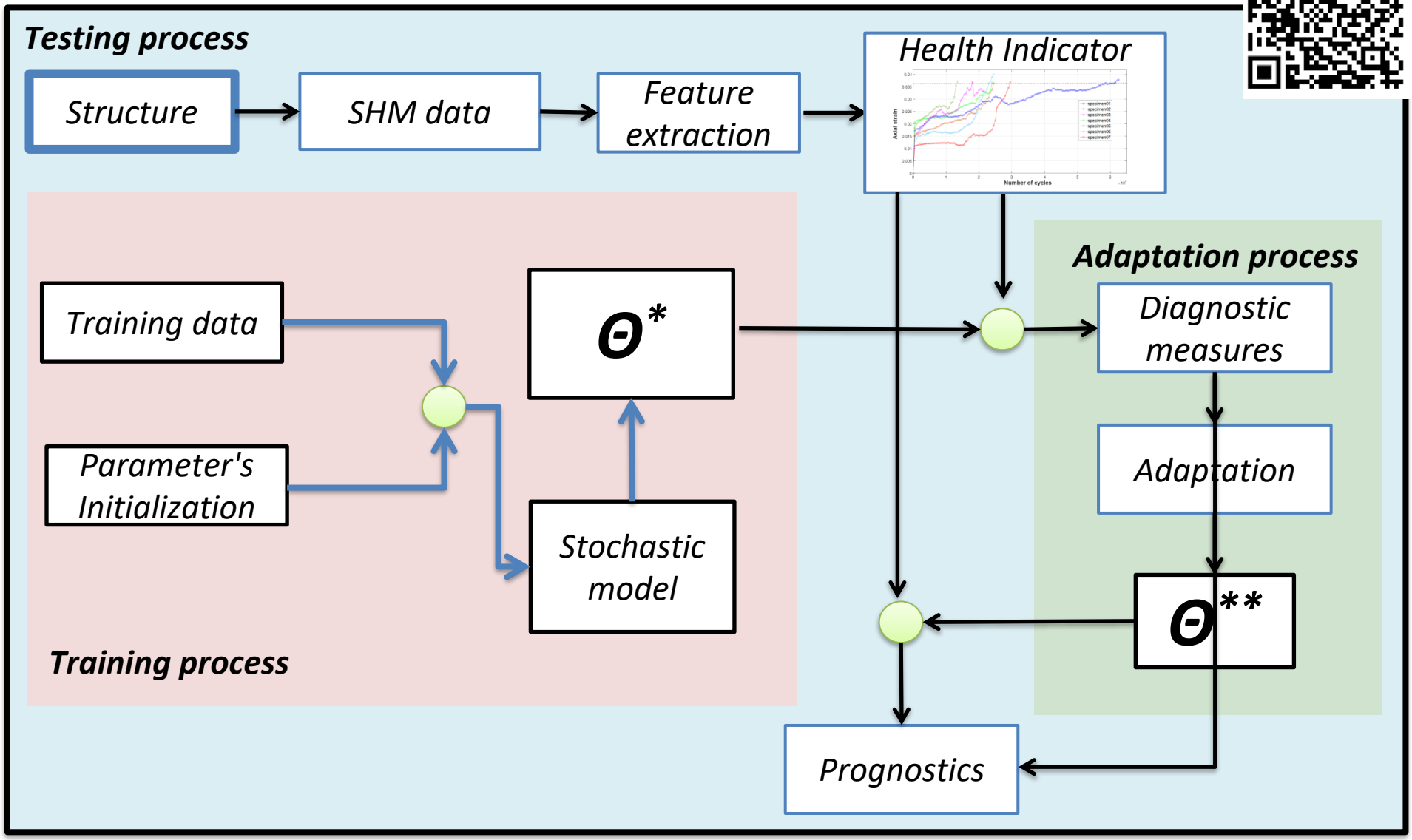
- **Past state uncertainty**
- **Present state uncertainty**
- **Future state uncertainty**

User's uncertainties

- **Modeling uncertainty**
- **Prediction uncertainty**

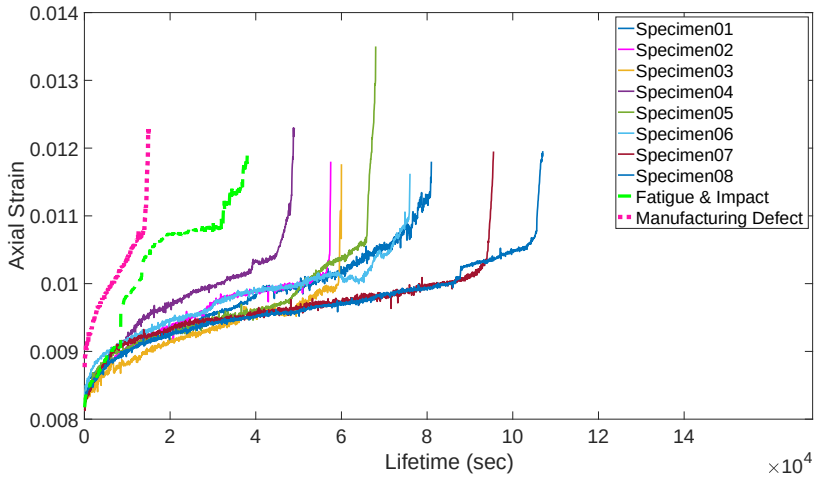
The carbon footprint of training a single big language model is equal to around 300,000 kg of CO_2 emissions.

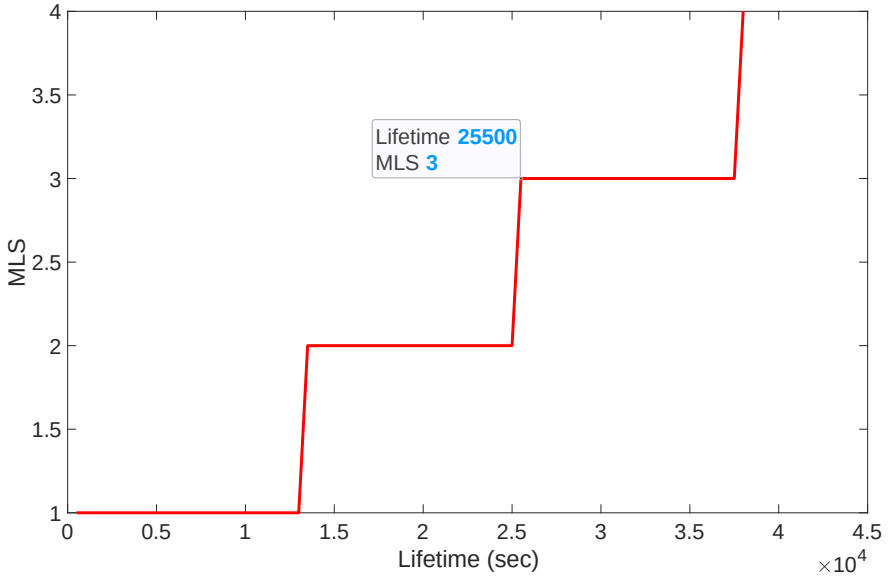
Adaptive Methodology

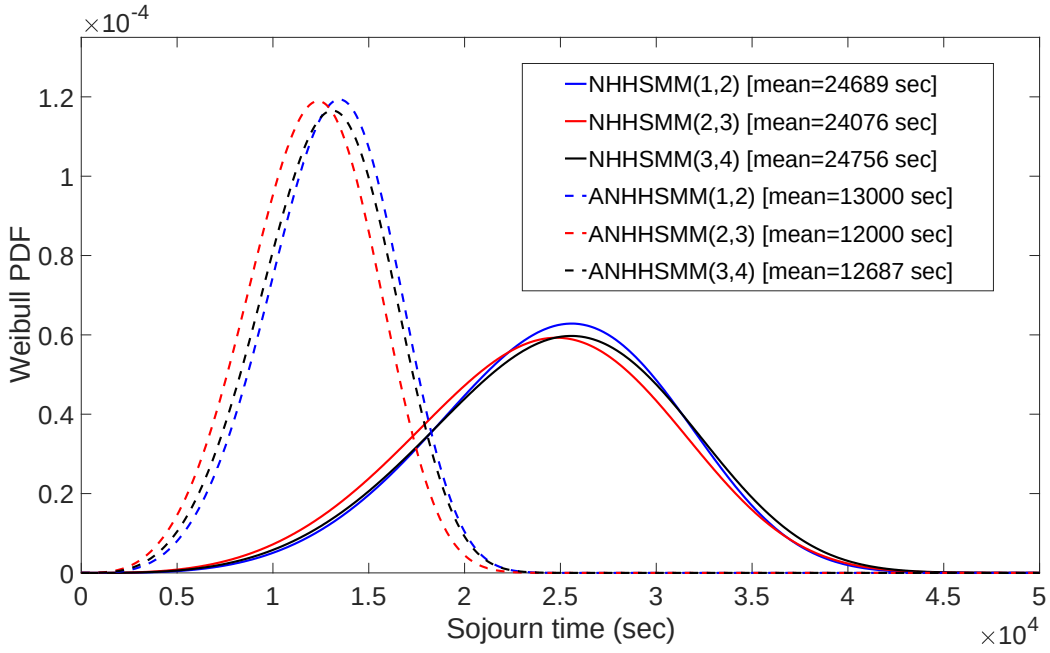


Eleftheroglou, N., Zarouchas, D. & Benedictus, R. ***An adaptive probabilistic data-driven methodology for prognosis of the fatigue life of composite structures***. Composite Structures, 245 (2020) 112386.

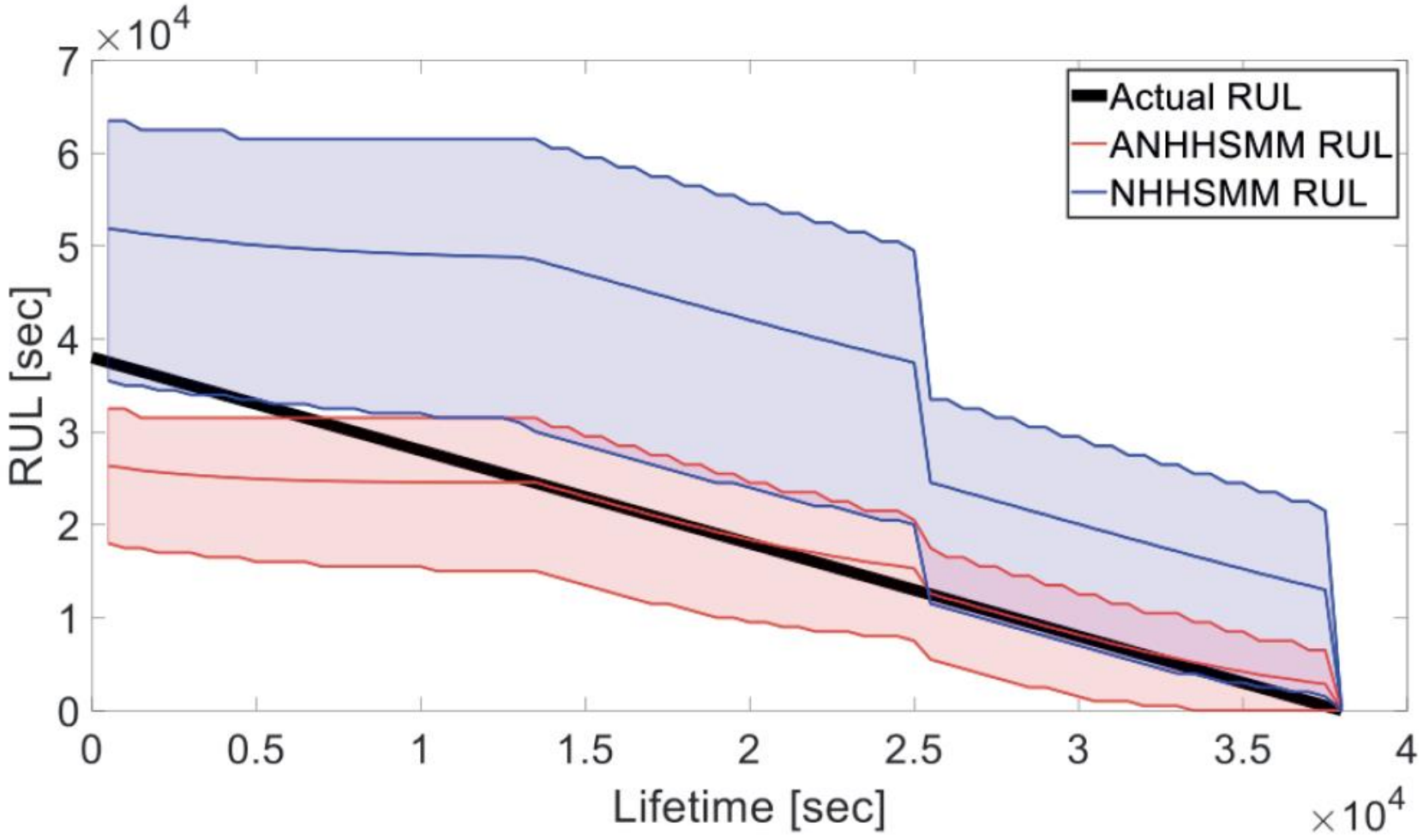
Specimen Fatigue & Impact - Adaptive Prognosis



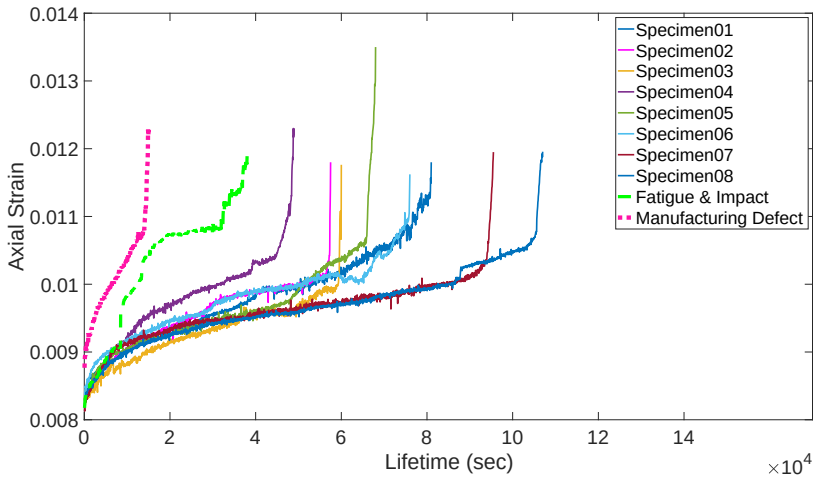


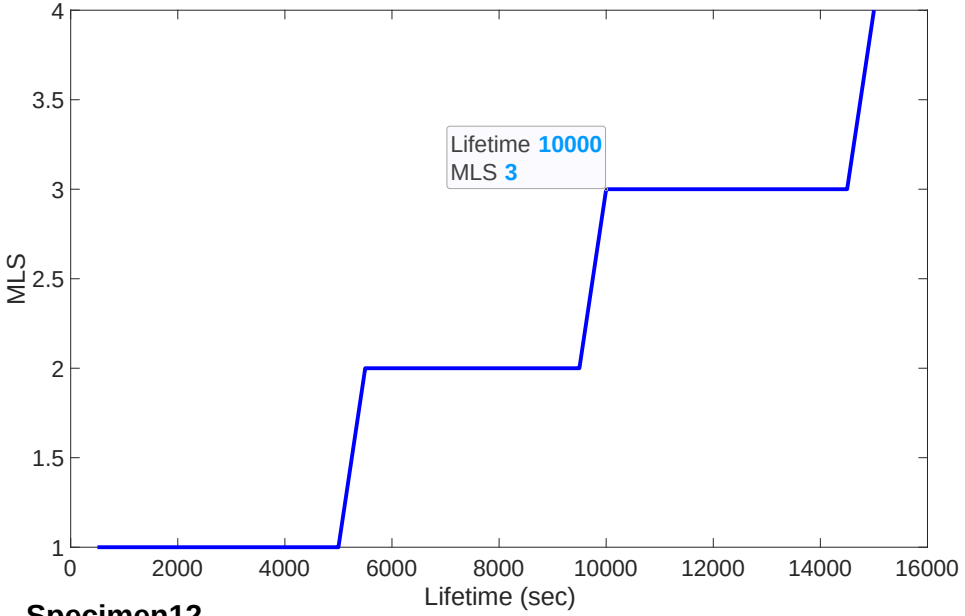


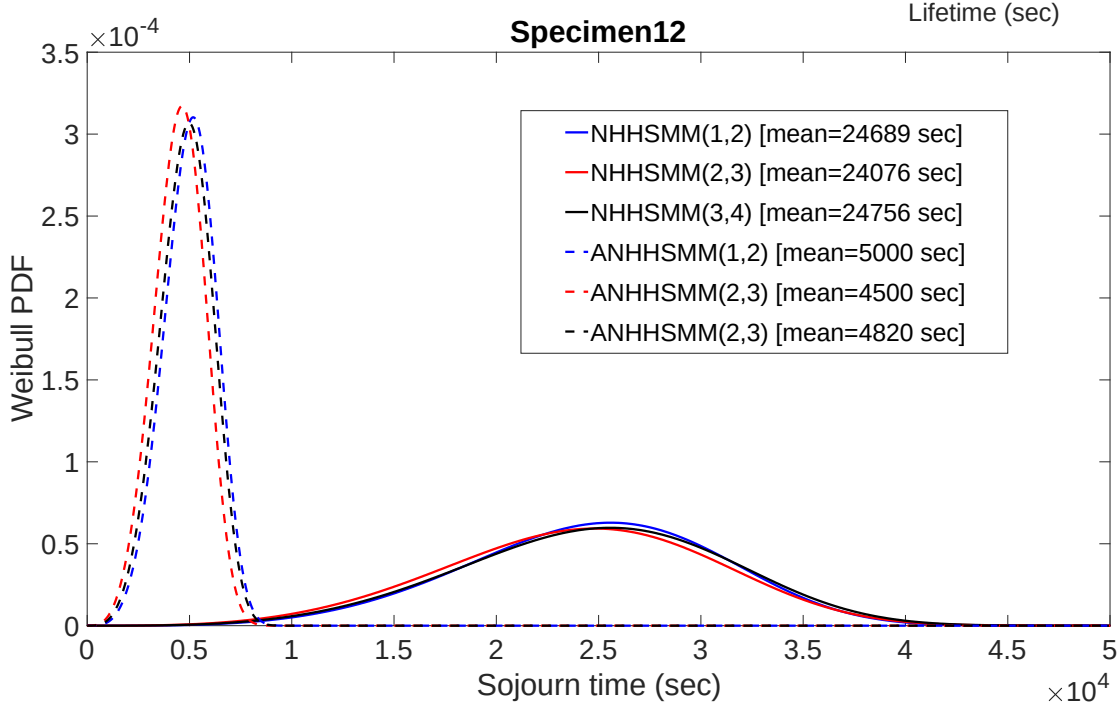
Specimen Fatigue & Impact - Prognostics



Specimen Manufacturing Defect - Prognosis







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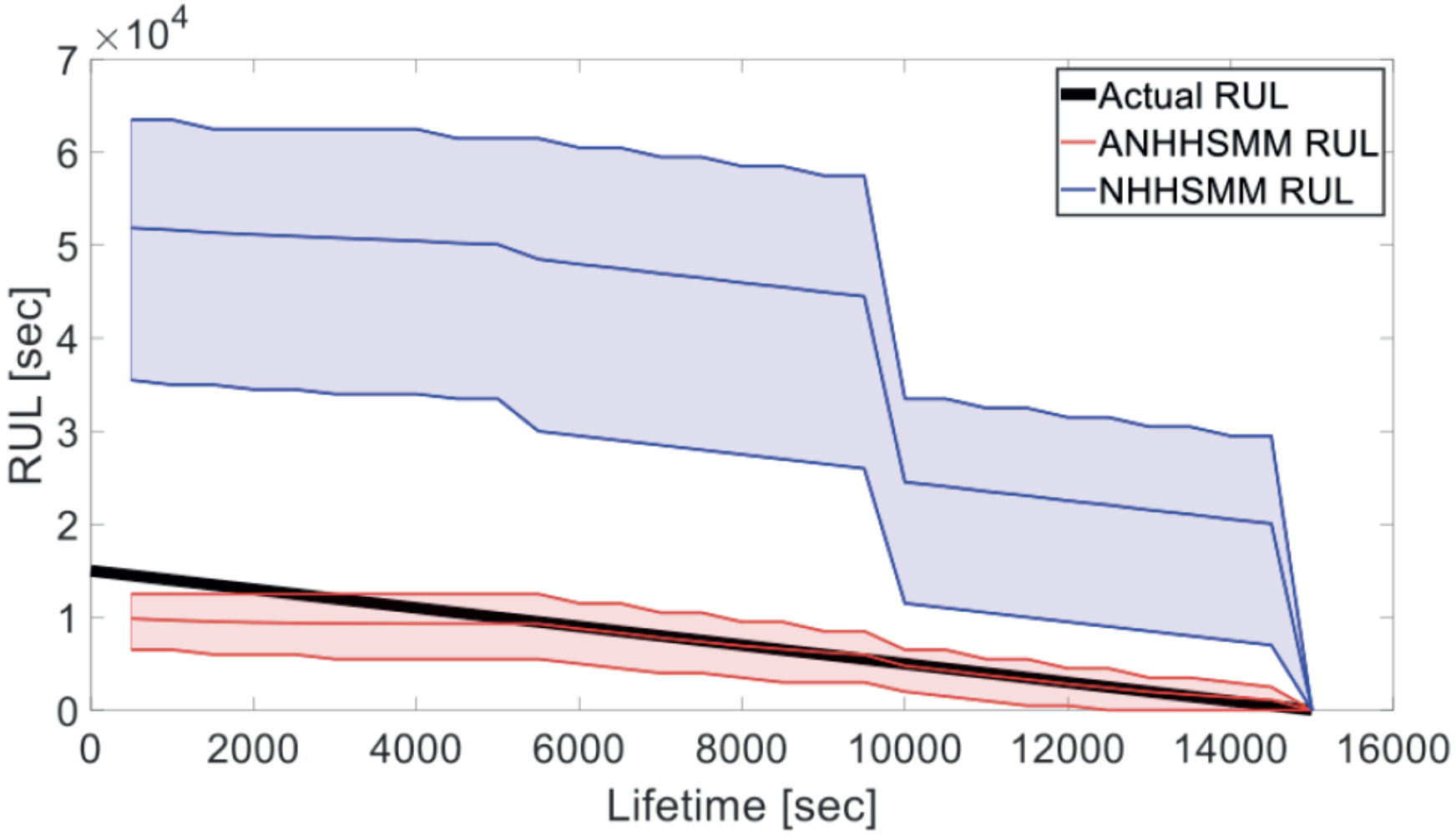
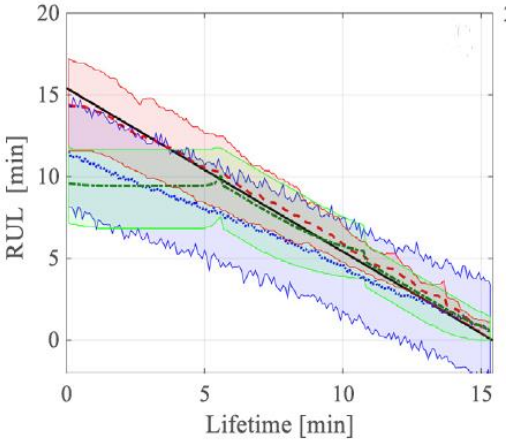
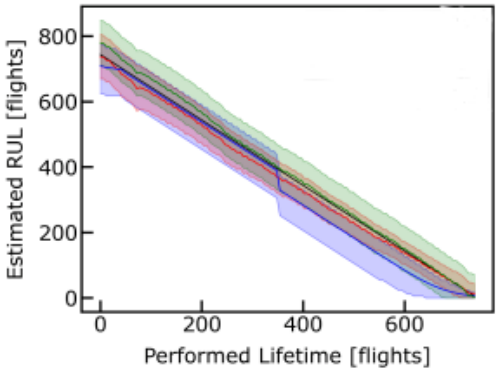
Specimen Manufacturing Defect - Prognosis



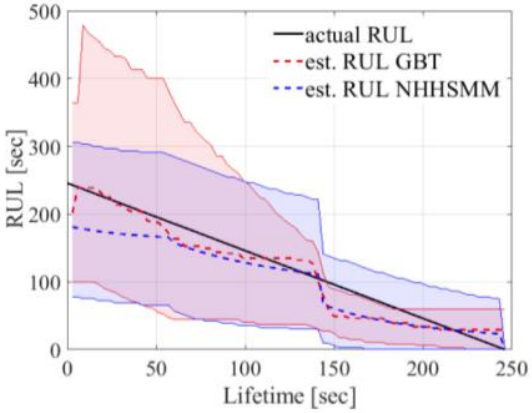
Prognostics Case-Studies

[1] Intelligent data-driven prognostic methodologies for the real-time remaining useful life until the end-of-discharge estimation of the **Lithium-Polymer batteries of unmanned aerial vehicles** with uncertainty quantification.



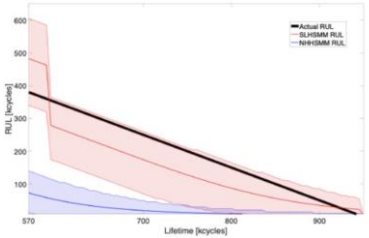


[2] Remaining useful life prognosis of **aircraft brakes**. International Journal of Prognostics and Health Management.



[3] Valve Failure Prognostics In Reciprocating **Compressors** Utilizing Temperature Measurements, PCA-based Data Fusion And Probabilistic Algorithms. Transactions of Industrial Electronics.

[4] **Similarity Learning Hidden Semi-Markov Model** for Adaptive Prognostics of Composite Structures. Reliability Engineering & System Safety.



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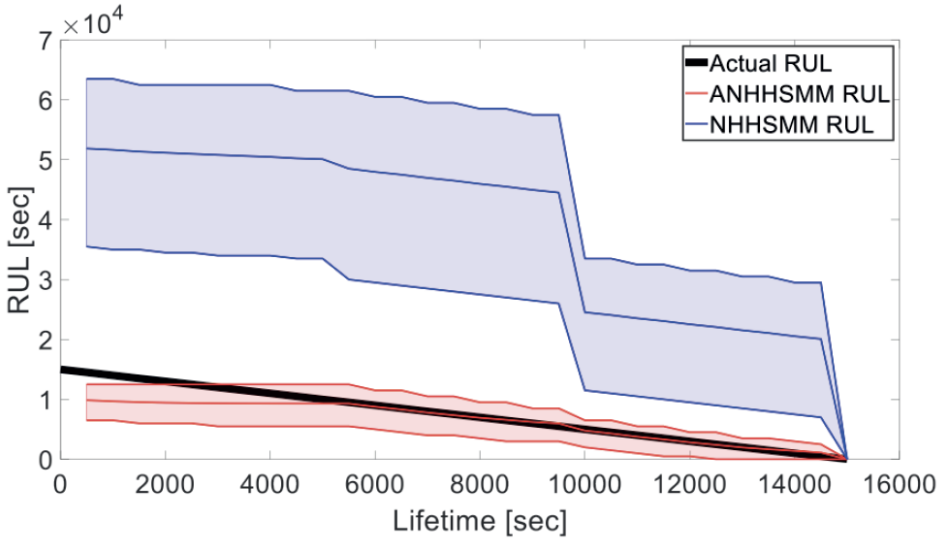
Conclusions

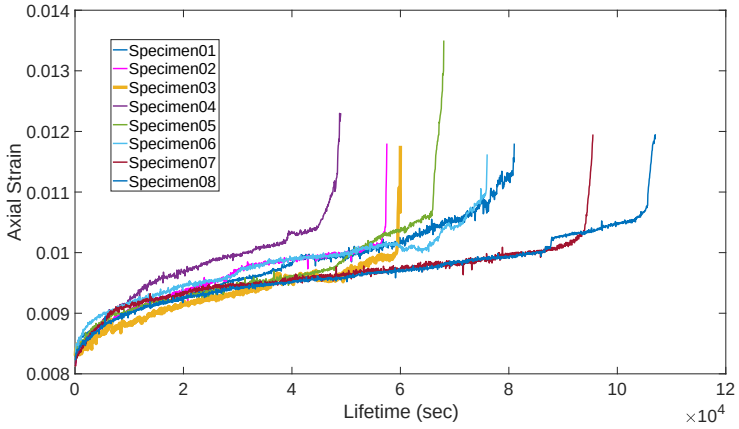
Exploring the Power of Markov Models for Comprehensive Prognostics

Comprehensive? **Robust**

Reliable

Applicable





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Thank you!

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