Deep Learning-Interpretive Reliability Predictive Models Using Test and Field Data

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Trajectory of my Work in AI-related Applications in Different Domain

Boolean Logic (mid-1980's) → **Fuzzy Logic** (1990's) → **Big Data Analytics / Machine Learning** (2000's-2010's) → **Deep Learning** (2018-now) → **GPT** (2024-after)

Age of *Symbolic AI*

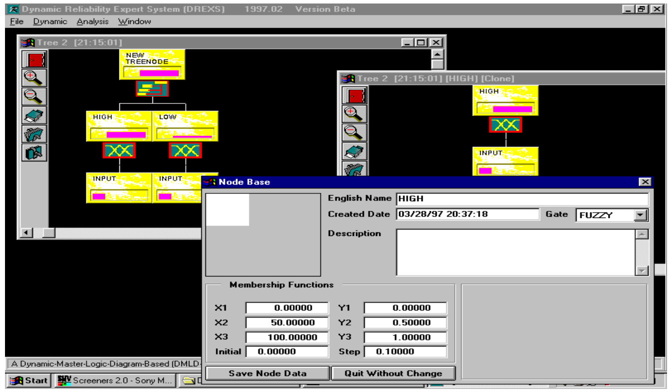
Age of connectionist AI

Age of both?

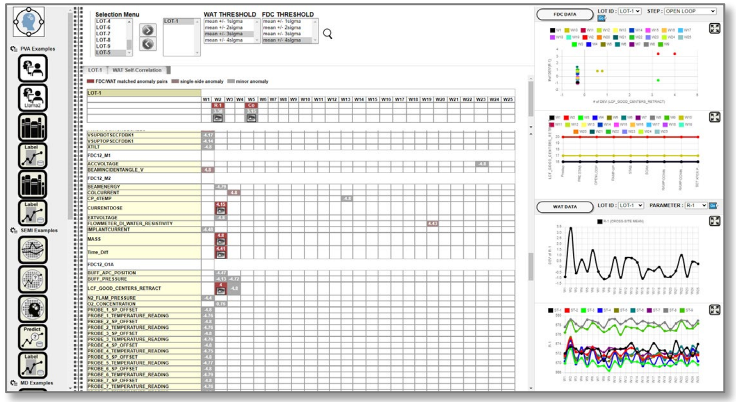
Complexity Handling

Boolean Logic (mid-1980's) → **Fuzzy Logic** (1990's) → **Big Data Analytics / Machine Learning** (2000's-2010's) → **Deep Learning** (2018-now) → **GPT** (2024-after)

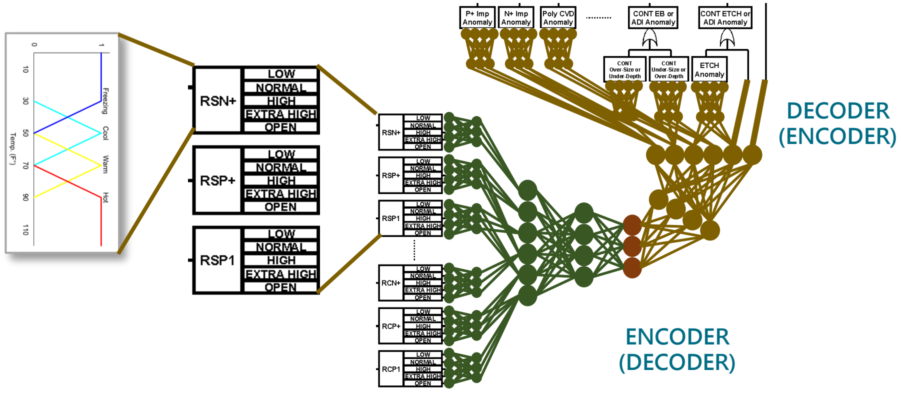
Up to100 rules



Up to 5M parameters



1B tokens



Challenge:

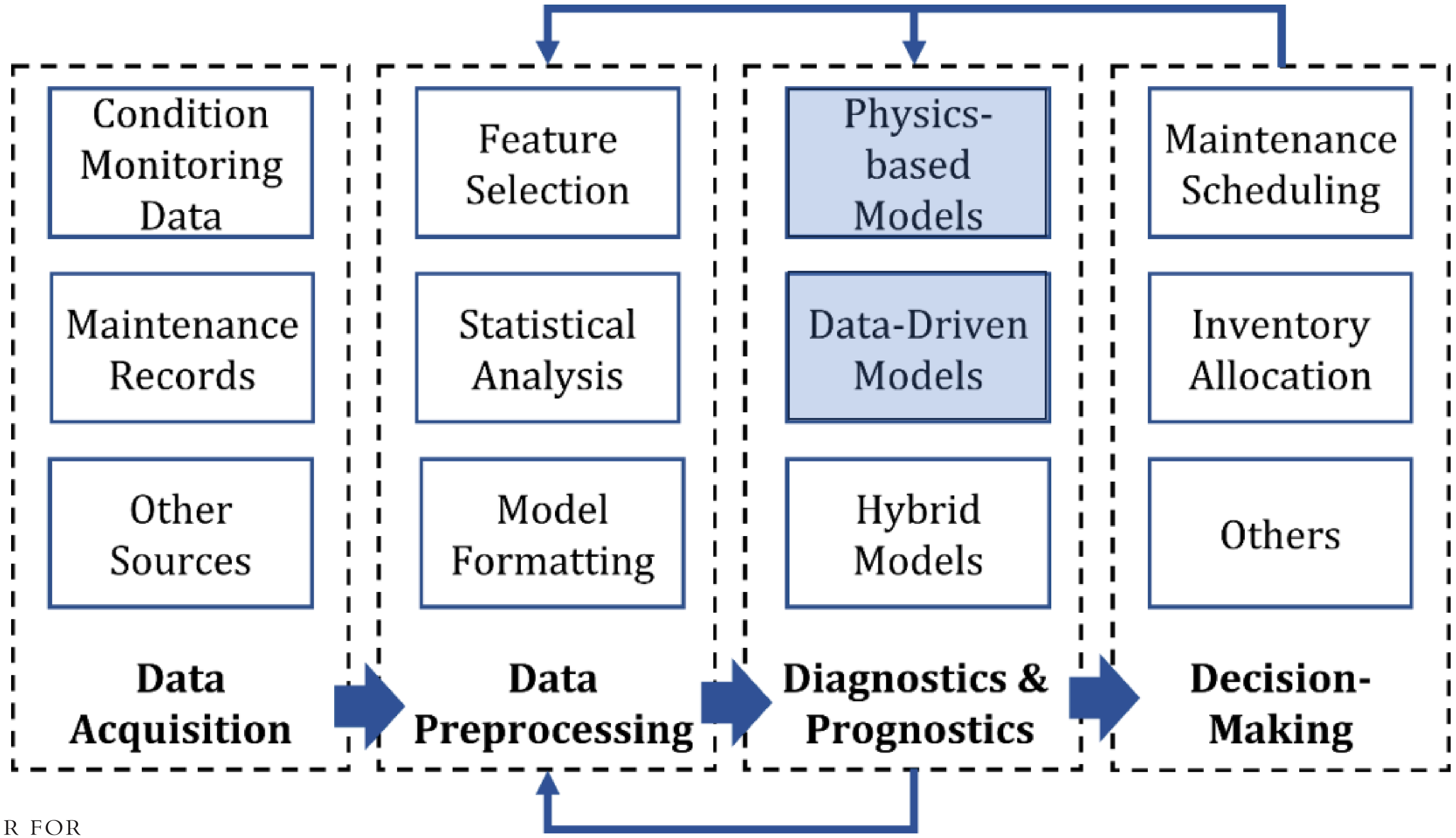
- Deep Domain Knowledge

Challenge:

- Computing Power
- Un-Structure Data Handling
- Self-Learning Algorithm

Challenge: GPT-based Causal Inference

Addressing Data Challenges: Our Work on Data Processing for ML-Based Reliability Decision Making



Physics-Based Models Using Data-Revealed Degradation Deep NN Models

Physics-Based Models

Empirical models (e.g., Paris law[1] in Fatigue Fracture)	**Data-revealed degradation models (deep learning NN models)**
Developed simple models from empirical data	Approximate multi-parameter complex functions from empirical, field and test data
Formulated explicitly mathematically	No explicit mathematical form
Do not consider environmental and user behaviors	Processes high-dimensional data including environmental and user behaviors
Hard to apply to components, products and systems	Applies to items with available (big) data

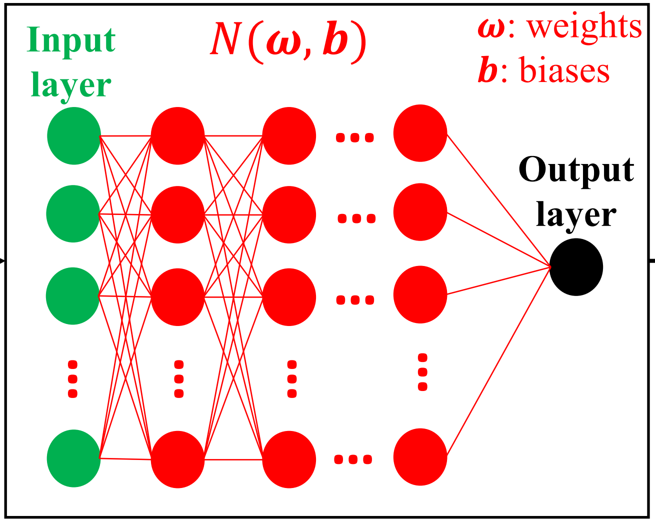
1 $\frac{da}{dN} = C\Delta K^m$, a: crack length, $\frac{da}{dN}$: crack growth rate, C & m: constants (depend on the material and environment), ΔK: stress intensity

Quick Background on Deep Learning from Labeled Data

High Dimensional Inputs

Sensor and other measurements (e.g., temperature, humidity, vibration, time)

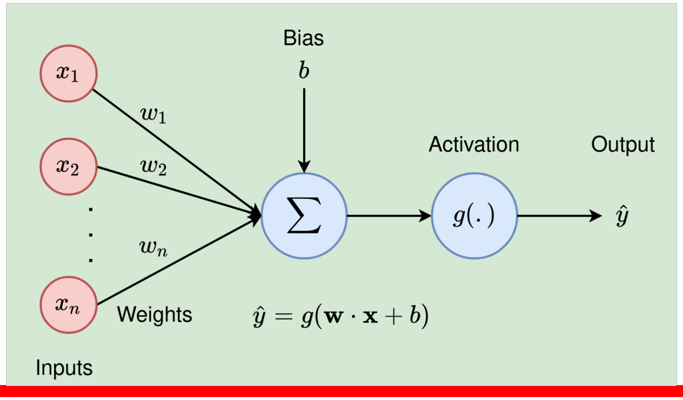
Deep learning model



Output

Degradation intensity (e.g., crack length, mass loss, remaining useful life)

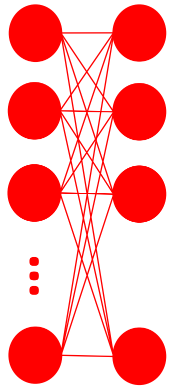
- Each layer transforms input data (output of previous layer) through weighted connections and activation functions, extracting hierarchical features.



$$\boldsymbol{h}_i = \sigma\left(\boldsymbol{W}_i^T \boldsymbol{h}_{i-1} + \boldsymbol{b}_i\right)$$

$\boldsymbol{h}_i$: output of hidden layer i
σ: activation function
$\boldsymbol{W}_i$: matrix of weights
$\boldsymbol{b}_i$: vector of biases

$\boldsymbol{h}_{i-1}$ $\boldsymbol{h}_i$

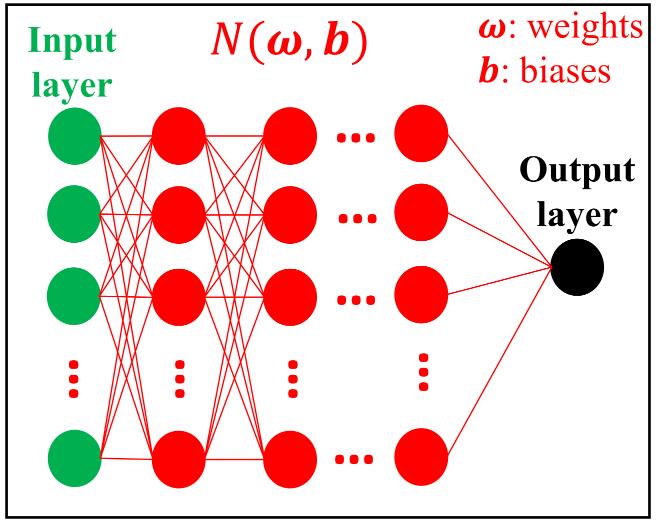


Challenges of Deep Learning-Based Degradation Modeling

1. Just fit the data: <u>Without consideration of the underlying physics of degradation</u>
2. High number of parameters: <u>Requiring a substantial amount of training data</u>
3. Numerous non-linear transformations: <u>Lack of interpretability</u>

Solution

Adding physics as a constraint



Literature on DL Degradation

DL models have been widely used for modeling degradation:

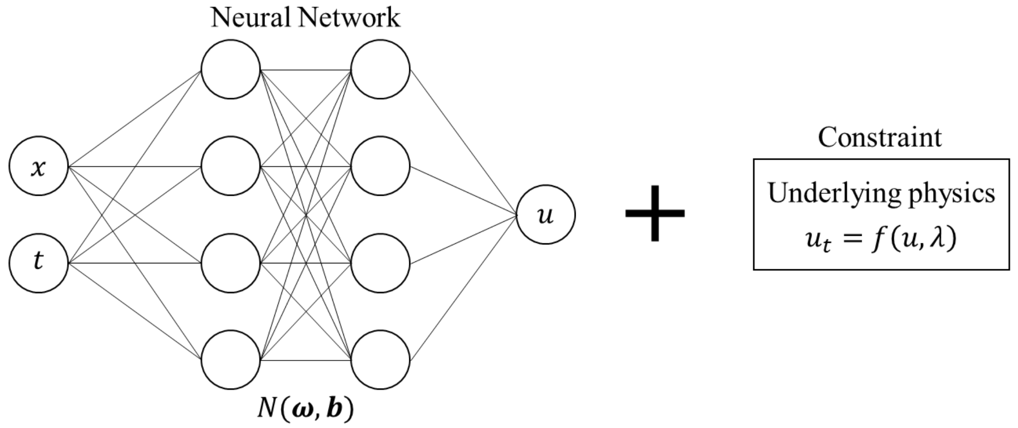
- **Algorithms:**
  - Feedforward NN [4, 5, 6, 7]
  - Convolutional NN [8, 9, 3, 10]
  - Recurrent NN [11, 12, 13]
  - Autoencoders [14, 15, 16]
  - …
- **Applications:**
  - Batteries [2]
  - Rotating machinery [1]
  - Machining tools [3]
  - …

DL: Deep Learning, NN: Neural Network

[1] M. Hamadache, J. H. Jung, J. Park and B. D. Youn, "A comprehensive review of artificial intelligence-based approaches for rolling element bearing PHM: shallow and deep learning," JMST Advances, vol. 1, no. 1, pp. 125-151, 2019.
[2] H. Meng and Y.-F. Li, "A review on prognostics and health management (PHM) methods of lithium-ion batteries," Renewable and Sustainable Energy Reviews, vol. 116, p. 109405, 2019.
[3] F. Aghazadeh, A. Tahan and M. Thomas, "Tool condition monitoring using spectral subtraction algorithm and artificial intelligence methods in milling process," The International Journal of Advanced Manufacturing Technology, vol. 7, pp. 30-34, 2018.
[4] Z. Kang, C. Catal and B. Tekinerdogan, "Remaining useful life (RUL) prediction of equipment in production lines using artificial neural networks," Sensors, vol. 21, no. 3, p. 932, 2021.
[5] P. Khumprom, D. Grewell and N. Yodo, "Deep neural network feature selection approaches for data-driven prognostic model of aircraft engines," Aerospace, vol. 7, no. 9, p. 132, 2020.
[6] F. Elasha, S. Shanbr, X. Li and D. Mba, "Prognosis of a wind turbine gearbox bearing using supervised machine learning," Sensors, vol. 19, no. 14, p. 3092, 2019.
[7] A. Ismail, L. Saidi, M. Sayadi and M. Benbouzid, "A new data-driven approach for power IGBT remaining useful life estimation based on feature reduction technique and neural network," Electronics, vol. 9, no. 10, p. 1571, 2020.
[8] B. Liu, Z. Gao, B. Lu, H. Dong and Z. An, "Deep learning-based remaining useful life estimation of bearings with time-frequency information," Sensors, vol. 22, no. 19, p. 7402, 2022
[9] C. Modarres, N. Astorga, E. L. Droguett and V. Meruane, "Convolutional neural networks for automated damage recognition and damage type identification," Structural Control and Health Monitoring, vol. 25, no. 10, p. e2230, 2018.
[10] X. Li, Q. Ding and J.-Q. Sun, "Remaining useful life estimation in prognostics using deep convolution neural networks," Reliability Engineering & System Safety, vol. 172, pp. 1-11, 2018.
[11] Y. Hu, R. Wei, Y. Yang, X. Li, Z. Huang, Y. Liu, C. He and H. Lu, "Performance degradation prediction Using LSTM with optimized parameters," Sensors, vol. 22, no. 6, p. 2407, 2022.
[12] J. Zhang, Y. Zeng and B. Starly, "Recurrent neural networks with long term temporal dependencies in machine tool wear diagnosis and prognosis," SN Applied Sciences, vol. 3, pp. 1-13, 2021.
[13] L. Guo, N. Li, F. Jia, Y. Lei and J. Lin, "A recurrent neural network-based health indicator for remaining useful life prediction of bearings," Neurocomputing, vol. 240, pp. 98-109, 2017.
[14] D. Verstraete, E. Droguett and M. Modarres, "A deep adversarial approach based on multi-sensor fusion for semi-supervised remaining useful life prognostics," Sensors, vol. 20, no. 1, p. 176, 2019.
[15] Y. Ding, P. Ding and M. Jia, "A novel remaining useful life prediction method of rolling bearings based on deep transfer auto-encoder," IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-12, 2021.
[16] M. Wei, M. Ye, Q. Wang and J. P. Twajamahoro, "Remaining useful life prediction of lithium-ion batteries based on stacked autoencoder and Gaussian mixture regression," Journal of Energy Storage, vol. 47, p. 103558, 2022.

Literature on DL Degradation (cont.)

- **Physics-informed NN for solving challenging PDEs**
  - Fluids mechanics, quantum mechanics, propagation of nonlinear shallow-water waves [17]
  - Euler equations that model high-speed aerodynamic flows [18]
  - Klein-Gordon equation [19]



- **Physics-informed NN in degradation modeling**
  - Creep-fatigue life [20]
  - Fatigue life [21]
  - Bearing degradation and crack growth [22]

NN: Neural Network, PDE: Partial Differential Equation

[17] M. Raissi, P. Perdikaris and G. E. Karniadakis, "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations," Journal of Computational Physics, vol. 378, pp. 686-707, 2019.
[18] Z. Mao, A. D. Jagtap and G. E. Karniadakis, "Physics-informed neural networks for high-speed flows," Computer Methods in Applied Mechanics and Engineering, vol. 360, p. 112789, 2020.
[19] A. D. Jagtap, K. Kawaguchi and G. E. Karniadakis, "Adaptive activation functions accelerate convergence in deep and physics-informed neural networks," Journal of Computational Physics, vol. 404, p. 109136, 2020.
[20] X.-C. Zhang, J.-G. Gong and F.-Z. Xuan, "A physics-informed neural network for creep-fatigue life prediction of components at elevated temperatures," Engineering Fracture Mechanics, vol. 258, p. 108130, 2021.
[21] T. Zhou, S. Jiang, T. Han, S.-P. Zhu and Y. Cai, "A physically consistent framework for fatigue life prediction using probabilistic physics-informed neural network," International Journal of Fatigue, vol. 166, p. 107234, 2023.
[22] S. Kim, J.-H. Choi and N. H. Kim, "Data-driven prognostics with low-fidelity physical information for digital twin: physics-informed neural network," Structural and Multidisciplinary Optimization, vol. 65, no. 9, p. 255, 2022.

Objectives

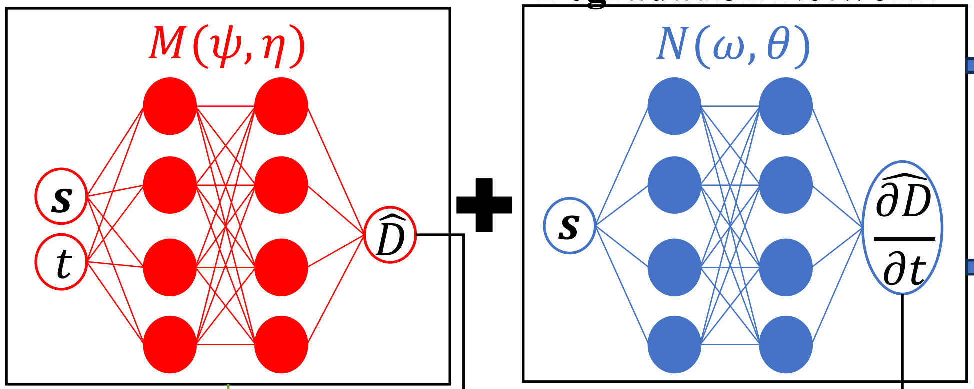
- Discovering/Incorporating Physics
  - Establishing a relationship between the suspected influential user and environmental factors and first-order degradation rate: $\frac{\partial D}{\partial t} = f(S_1, S_2, \dots, S_n)$
- Providing Interpretability
  - Identifying the primary users stresses and environmental factors that significantly impact the degradation process

The Core Approach: Dual Guided Neural Network (GNN) Framework

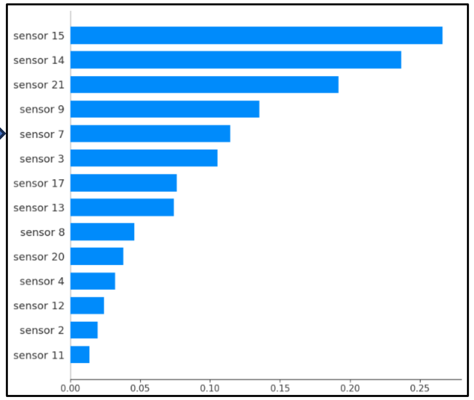
Predictive Network

Revealed Physics of Degradation Network

Underlying Physics of Degradation



$$\frac{\partial D}{\partial t} = f(\boldsymbol{s})$$



Features Importance

$\boldsymbol{s}$: Sensors and other data
$\boldsymbol{t}$: time or cycle of use

Automatic Differentiation
$$\left(\frac{\partial \hat{D}}{\partial t}\right)_{AD}$$

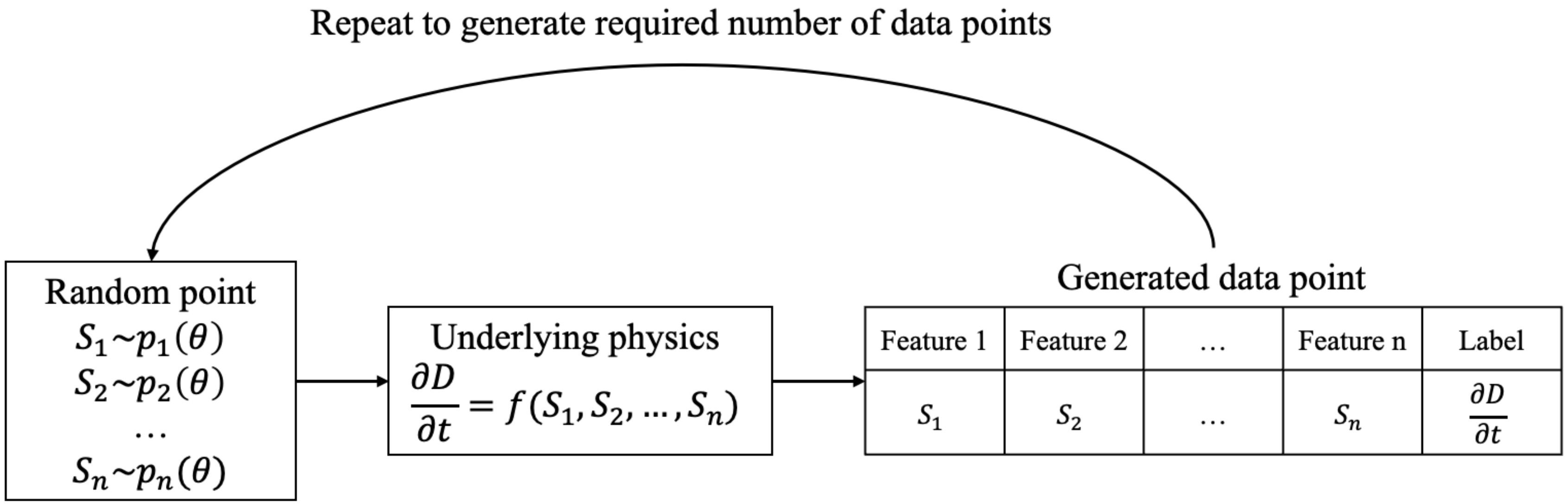
Custom designed Cost function

$$C = \underbrace{\frac{1}{N}\sum_{1}^{N}(D-\hat{D})^2}_{\text{Error}} + \underbrace{\frac{\lambda}{N}\sum_{1}^{N}\left(\left(\frac{\partial \hat{D}}{\partial t}\right)_{AD} - \frac{\widehat{\partial D}}{\partial t}\right)^2}_{\text{Constraint}}$$

D: Actual degradation intensity
$\hat{D}$: Degradation intensity estimated by the predictive network
$\left(\frac{\partial \hat{D}}{\partial t}\right)_{AD}$: Degradation rate based on predictive network estimation
$\frac{\widehat{\partial D}}{\partial t}$: Degradation rate estimated by the physics discovery network
N: Number of data points
λ: Weight coefficient

- **Scenario 1**: Trained separately (when degradation rate labels are available).
- **Scenario 2**: Trained together (when degradation rate labels are not available).

Data Simulation for Demonstration



- Assumptions:
  - Seven environmental factors are collected by seven sensors (i.e., $S_1, S_2, \ldots, S_7$).
  - Underlying physics: $\frac{\partial D}{\partial t} = \mathrm{a} \times \mathrm{Ln}(S_1^2) + b \times S_1 \times S_7 + c \times (S_2 + S_3 + S_4 + S_5 + S_6)$
  - Parameters a, b, and c are constants set to 0.5, 2, and 0.001, respectively.
  - Degradation rates were randomly drawn from a uniform distribution with a minimum value of 0 and a maximum value of 10.

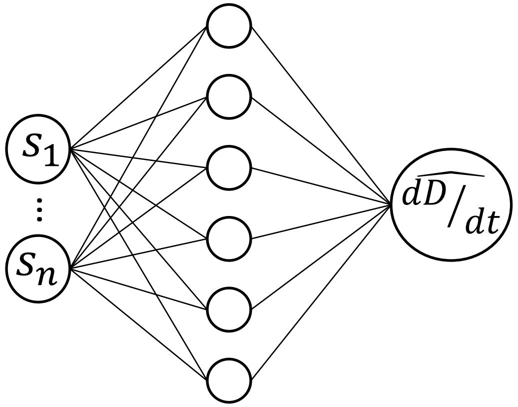
Sensor	Distribution	Inspiration factor
S_1	$\mathcal{N}(\mu = 25, \sigma = 10)$	Temperature
S_2	$\mathcal{N}(\mu = 70, \sigma = 15)$	Relative humidity
S_3	$\mathcal{N}(\mu = 7, \sigma = 2)$	pH
S_4	$\mathcal{N}(\mu = 10, \sigma = 2)$	Wind speed
S_5	$\mathcal{U}(\mu = 0, \sigma = 360)$	Wind direction
S_6	$\mathcal{N}(\mu = 100, \sigma = 10)$	Solar radiation

Verification with the Simulated Dataset

Scenario 1: Degradation rate labels are available

Physics Discovery Network

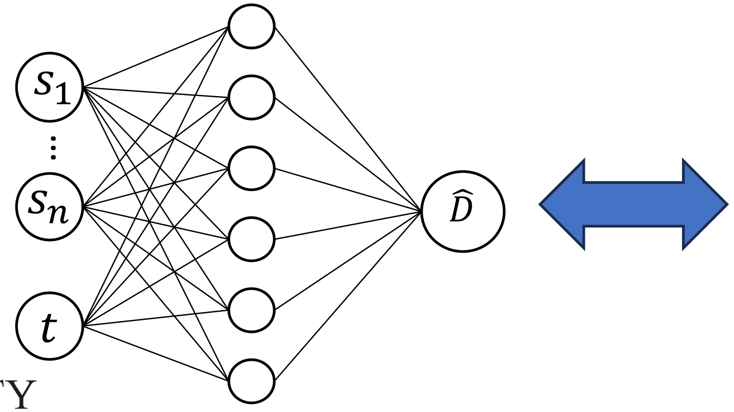
$\boldsymbol{N_{\omega,\theta}(s_{1\ldots n})}$



Scenario 2: Degradation rate labels are not available.

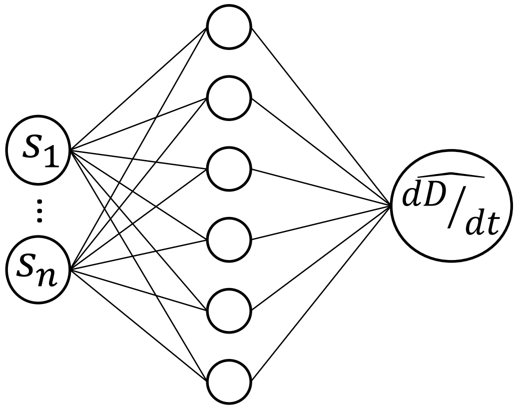
Predictive Network

$\boldsymbol{M_{\psi,\eta}(s_{1\ldots n}, t)}$



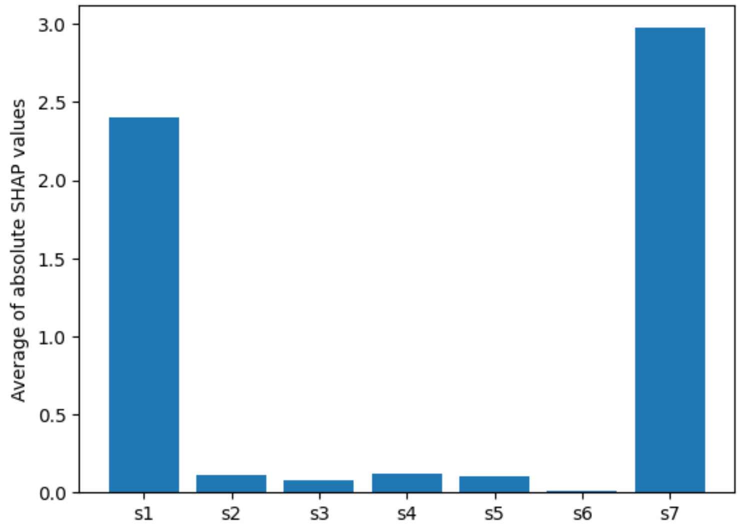
Physics Discovery Network

$\boldsymbol{N_{\omega,\theta}(s_{1\ldots n})}$

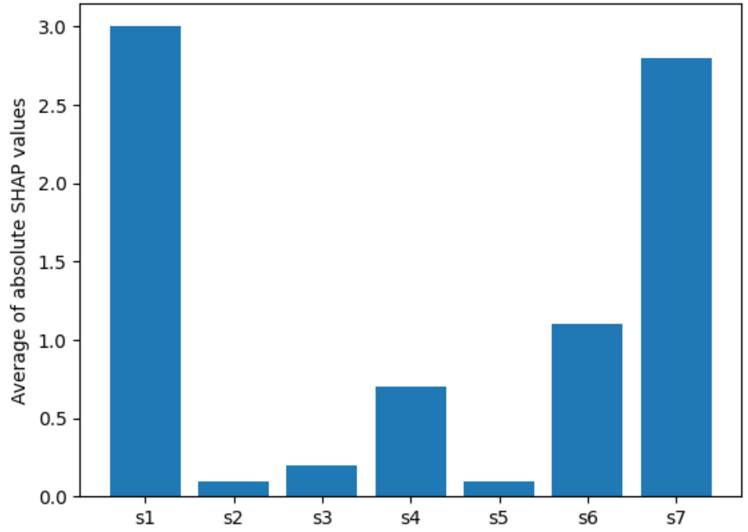


Verification with the Simulated Dataset (cont.)

Scenario 1: Degradation rate labels are available

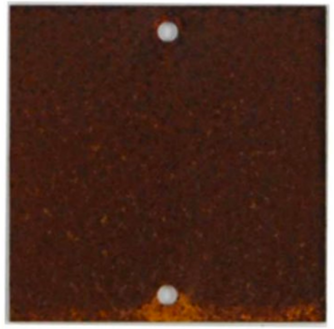


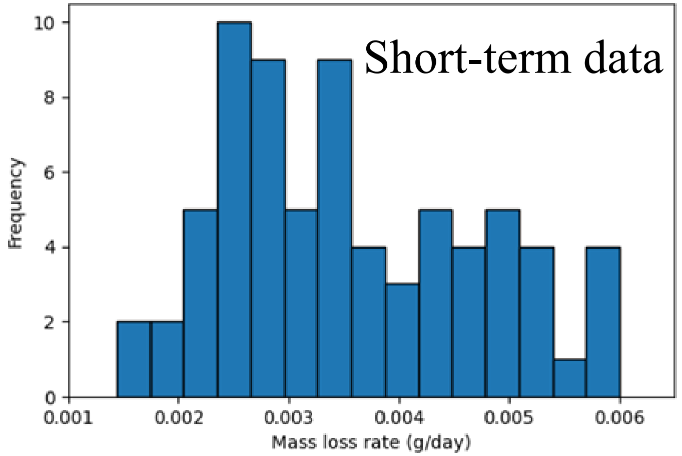
Scenario 2: Degradation rate labels are not available.

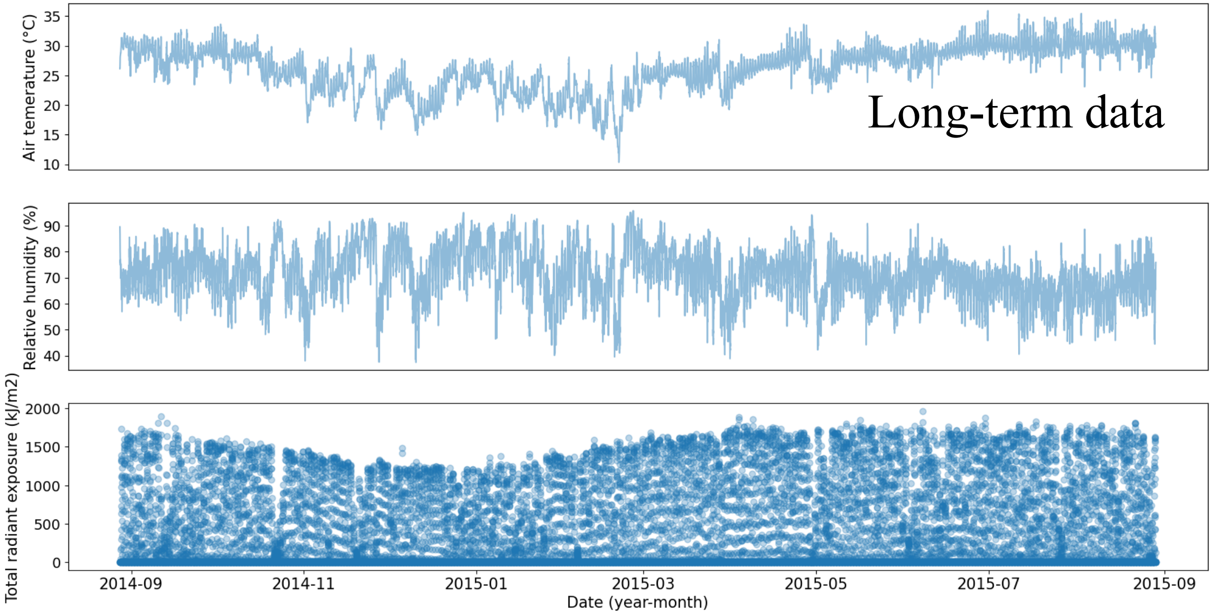


Case study for Scenario 1: Corrosion in Marine Environment

- Objective: Prediction of long-term corrosion degradation in C1010 steel coupons in marine environment
- Environmental factors
  - Exposure time
  - Temperature
  - Humidity
  - Solar radiation
  - Gradient of temperature with respect to time
  - Gradient of humidity with respect to time
  - Gradient of solar radiation with respect to time

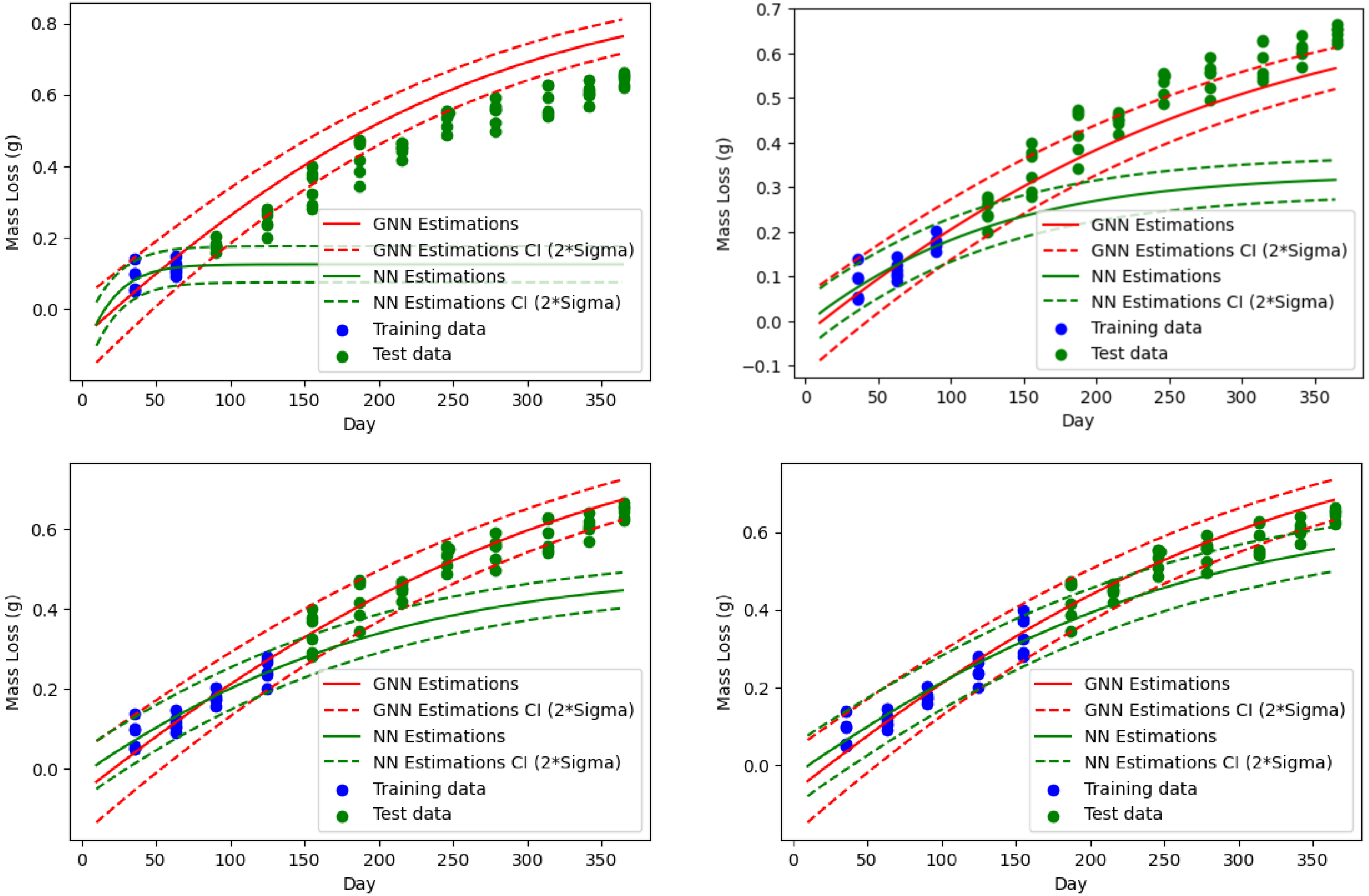






Case study for Scenario 1: Results

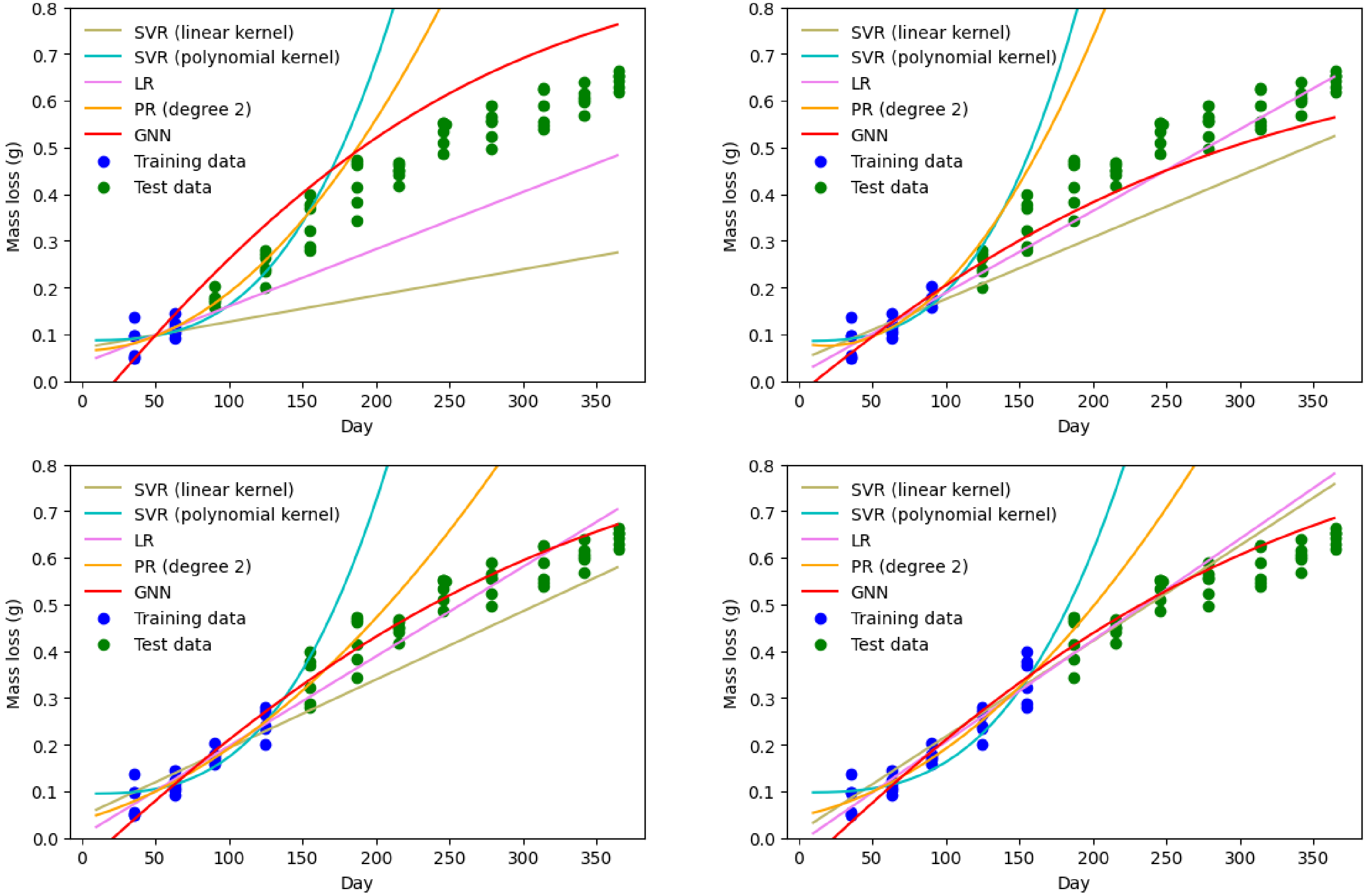
- Comparing the physics-informed (guided) NN (GNN) with a regular NN



GNN: Guided neural network, NN: Neural network, CI: confidence interval

Case study for Scenario 1: Results (cont.)

- Comparing the physics-informed (guided) NN with other machine learning techniques



SVR: Support vector regression, LR: Linear regression, PR: Polynomial regression, GNN: Guided neural network

[77] H. Habibollahi Najaf Abadi and M. Modarres, "Predicting system degradation with a guided neural network approach," Sensors, vol. 23, no. 14, p. 6346, 2023

Case study for Scenario 1: Results (cont.)

- Comparing the physics-informed (guided) NN with other machine learning techniques (**training** data)

Training data	Model	MAE	ME	MAPE
2 months	SVR (linear)	**0.022**	**0.047**	0.291
	SVR (poly)	**0.022**	**0.047**	0.291
	LR	**0.022**	0.057	0.270
	PR	**0.022**	0.057	0.270
	Regular NN	**0.022**	0.057	**0.269**
	GNN	0.0307	0.089	0.289
3 months	SVR (linear)	0.022	**0.047**	0.252
	SVR (poly)	0.020	**0.047**	0.233
	LR	0.020	0.061	0.213
	PR	**0.018**	0.057	0.210
	Regular NN	0.020	0.062	0.220
	GNN	0.021	0.076	**0.195**
4 months	SVR (linear)	0.025	**0.050**	0.244
	SVR (poly)	0.023	**0.050**	0.221
	LR	0.021	0.064	**0.181**
	PR	**0.020**	0.059	0.183
	Regular NN	0.021	0.067	0.185
	GNN	0.024	0.098	0.191
5 months	SVR (linear)	0.029	0.070	0.219
	SVR (poly)	0.030	**0.061**	0.219
	LR	**0.025**	0.074	**0.166**
	PR	**0.025**	**0.061**	0.172
	Regular NN	0.027	0.081	0.172
	GNN	0.029	0.103	0.195

MAE: Mean absolute error, ME: Maximum error, MAPE: Mean absolute percentage error
SVR: Support vector regression, LR: Linear regression, PR: Polynomial regression, GNN: Guided neural network

$$MAE(D,\widehat{D}) = \frac{1}{N}\sum_{i=1}^{N}\left|D_i - \widehat{D}_i\right|$$

$$ME(D,\widehat{D}) = max(\left|D_i - \widehat{D}_i\right|)$$

$$MAPE(D,\widehat{D}) = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|D_i - \widehat{D}_i\right|}{max(\nu, |D_i|)}$$

D: Actual degradation intensity
$\widehat{D}$: Degradation intensity estimated by the predictive network

[77] H. Habibollahi Najaf Abadi and M. Modarres, "Predicting system degradation with a guided neural network approach," Sensors, vol. 23, no. 14, p. 6346, 2023

Case study for Scenario 1: Results (cont.)

- Comparing the physics-informed (guided) NN with other machine learning techniques (**test** data)

Training data	Model	MAE	ME	MAPE
2 months	SVR (linear)	0.257	0.387	0.535
	SVR (poly)	0.995	3.100	1.725
	LR	0.135	0.215	0.285
	PR	0.383	1.094	0.681
	Regular NN	0.335	0.539	0.683
	GNN	**0.095**	**0.170**	**0.227**
3 months	SVR (linear)	0.115	0.185	0.236
	SVR (poly)	1.667	4.553	2.902
	LR	**0.047**	0.130	**0.102**
	PR	0.767	1.871	1.372
	Regular NN	0.206	0.347	0.394
	GNN	0.059	**0.109**	0.119
4 months	SVR (linear)	`0.084	0.152	0.166
	SVR (poly)	1.303	3.287	2.242
	LR	0.048	0.108	0.095
	PR	0.238	0.589	0.417
	Regular NN	0.134	0.217	0.249
	GNN	**0.032**	**0.075**	**0.068**
5 months	SVR (linear)	0.060	0.142	0.107
	SVR (poly)	1.149	2.626	1.958
	LR	0.069	0.162	0.123
	PR	0.335	0.726	0.578
	Regular NN	0.064	0.108	0.116
	GNN	**0.036**	**0.088**	**0.068**

MAE: Mean absolute error, ME: Maximum error, MAPE: Mean absolute percentage error
SVR: Support vector regression, LR: Linear regression, PR: Polynomial regression, GNN: Guided neural network

$$MAE\left(D,\widehat{D}\right) = \frac{1}{N}\sum_{i=1}^{N}\left|D_i - \widehat{D}_i\right|$$

$$ME\left(D,\widehat{D}\right) = max\left(\left|D_i - \widehat{D}_i\right|\right)$$

$$MAPE\left(D,\widehat{D}\right) = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|D_i - \widehat{D}_i\right|}{max(\nu,|D_i|)}$$

D: Actual degradation intensity
$\widehat{D}$: Degradation intensity estimated by the predictive network

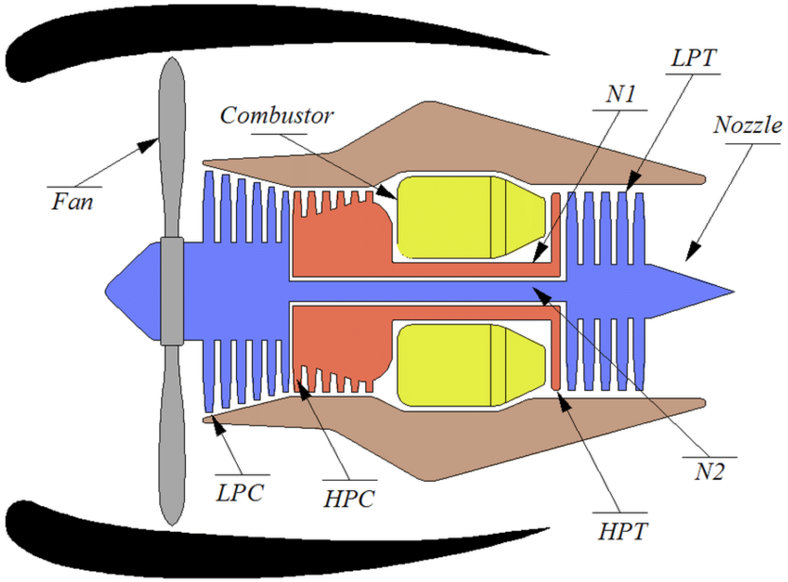
[77] H. Habibollahi Najaf Abadi and M. Modarres, "Predicting system degradation with a guided neural network approach," Sensors, vol. 23, no. 14, p. 6346, 2023

Case study for Scenario 2: Degradation in Aircraft Engines

- Objective: Prediction of degradation intensity in form of remaining useful life for aircraft engines

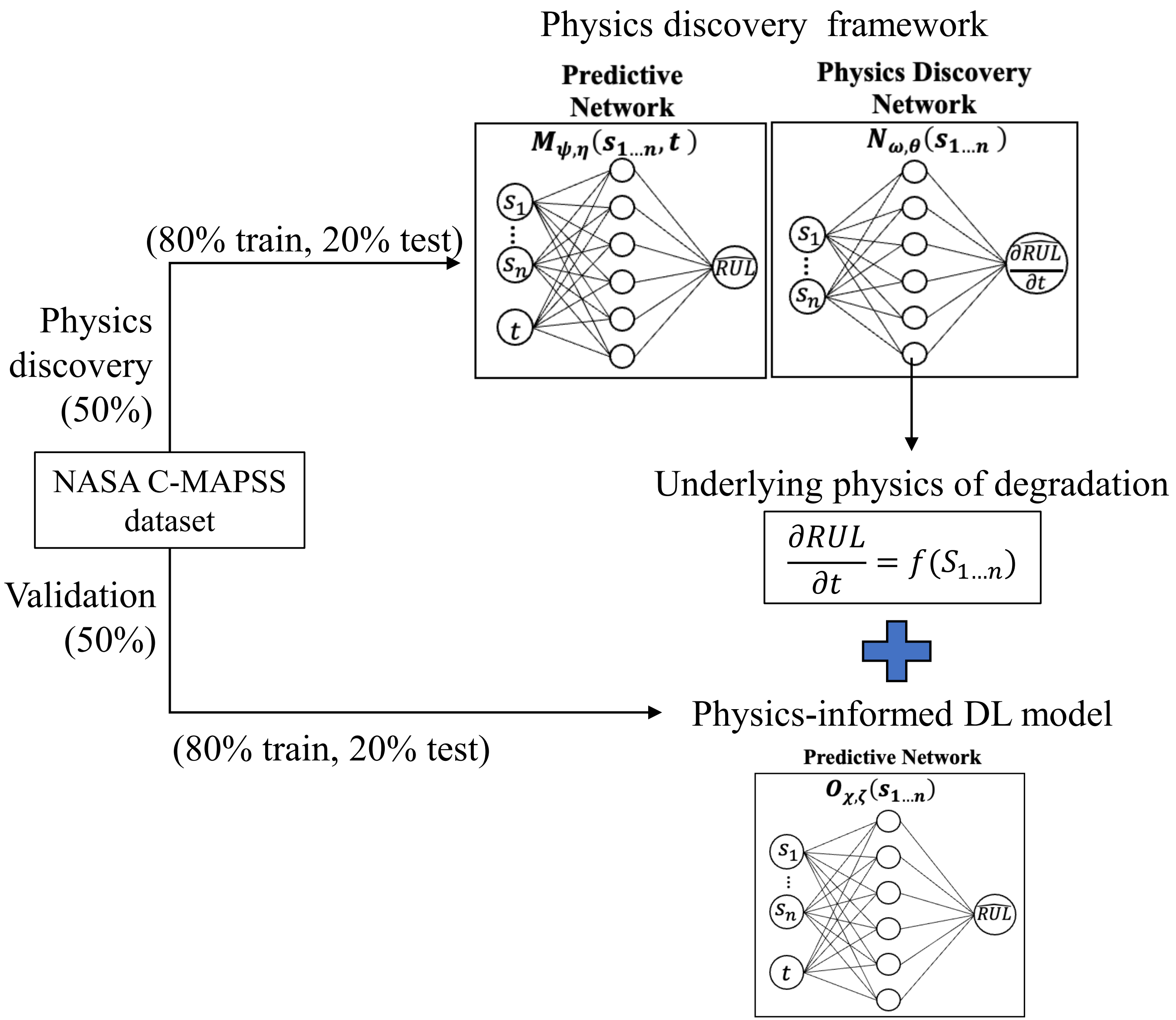
- Data: Environmental factors (21 sensors) and RUL [23]
  - 14 sensors yield statistically significant measurements [24]

Symbol	Description	Units
Parameters available to participants as sensor data		
T2	Total temperature at fan inlet	°R
T24	Total temperature at LPC outlet	°R
T30	Total temperature at HPC outlet	°R
T50	Total temperature at LPT outlet	°R
P2	Pressure at fan inlet	psia
P15	Total pressure in bypass-duct	psia
P30	Total pressure at HPC outlet	psia
Nf	Physical fan speed	rpm
Nc	Physical core speed	rpm
epr	Engine pressure ratio (P50/P2)	--
Ps30	Static pressure at HPC outlet	psia
phi	Ratio of fuel flow to Ps30	pps/psi
NRf	Corrected fan speed	rpm
NRc	Corrected core speed	rpm
BPR	Bypass Ratio	--
farB	Burner fuel-air ratio	--
htBleed	Bleed Enthalpy	--
Nf_dmd	Demanded fan speed	rpm
PCNfR_dmd	Demanded corrected fan speed	rpm
W31	HPT coolant bleed	lbm/s
W32	LPT coolant bleed	lbm/s



[23] A. Saxena, K. Goebel, D. Simon and N. Eklund, "Damage propagation modeling for aircraft engine run-to-failure simulation," in International conference on prognostics and health management, Denver, CO, USA, 2008.
[24] W. Zhang, G. Peng, C. Li, Y. Chen and Z. Zhang, "A new deep learning model for fault diagnosis with good anti-noise and domain adaptation ability on raw vibration signals," Sensors, vol. 17, no. 2, p. 425, 2017.

Case study for Scenario 2: Degradation in Aircraft Engines (cont.)

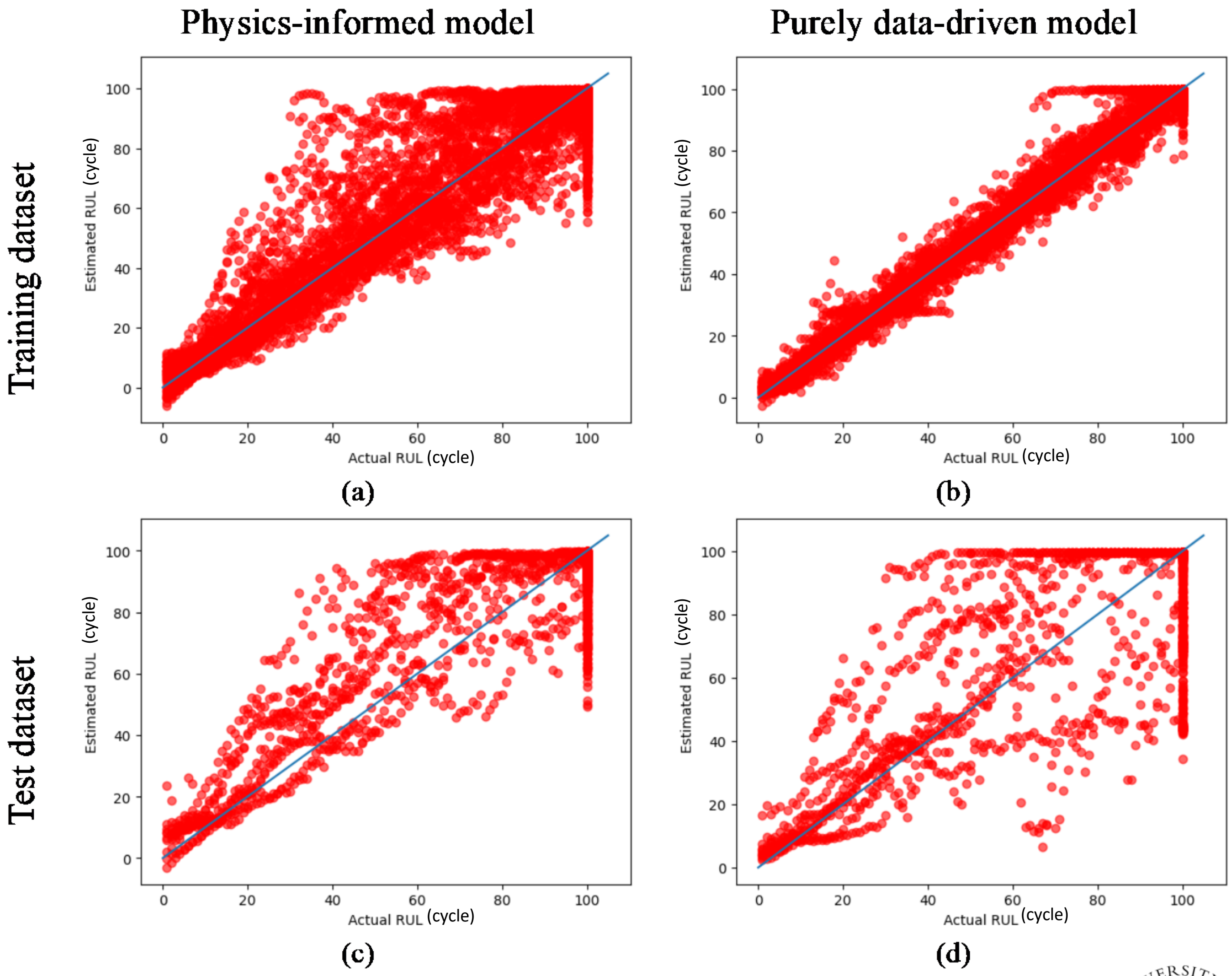


H. Habibollahi Najaf Abadi and M. Modarres, "A Deep learning approach for discovering and incorporating the underlying physics of degradation in data-driven prognostics," in 2024 Annual Reliability and Maintainability Symposium (RAMS), Albuquerque, 2024

Case study for Scenario 2: Results

- Comparing actual RUL with estimated RUL by physics-informed and purely data-driven model for training and test datasets

Model	Dataset	MSE	MAPE	R^2
Physics-informed model	Training	10.30	0.17	0.89
	Test	14.72	0.27	0.79
Purely data-driven model	Training	3.54	0.06	0.98
	Test	20.18	0.28	0.61



RUL: Remaining useful life, MSE: Mean squared error, MAPE: Mean absolute percentage error

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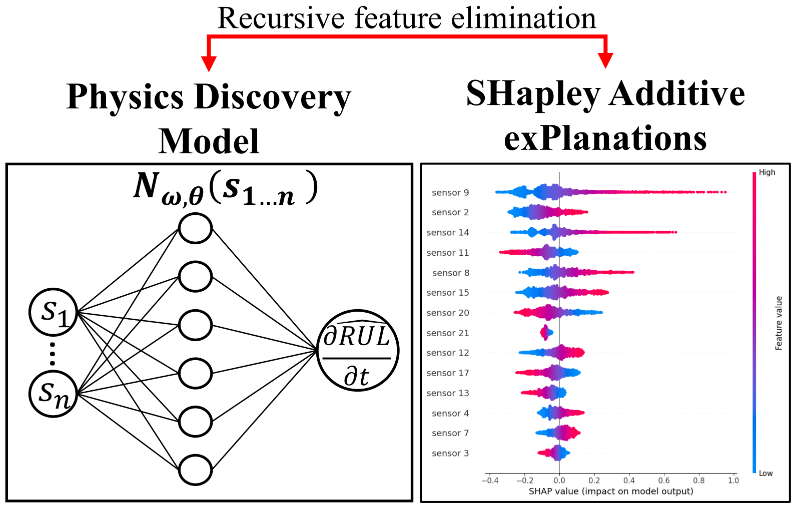
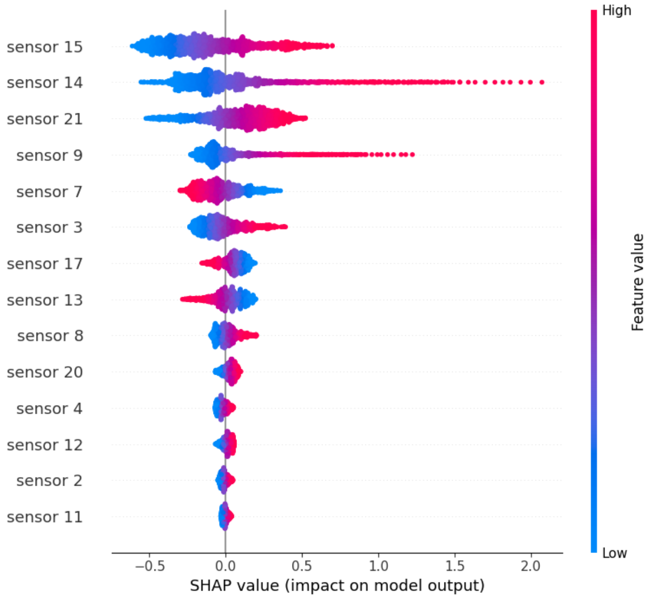
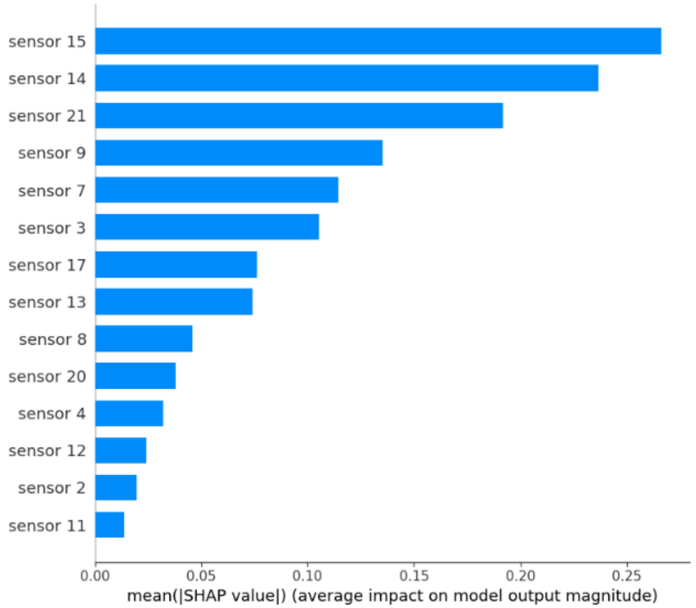
Case Study for Scenario 2: Results (cont.)

- Feature importance measurement identifies dominant environmental and user stresses variables with measurable effects on degradation.
  - SHAP applies a recursive feature elimination to remove irrelevant environmental factors—it is a game theoretic approach







  - SHAP [25] values: which sensor measurements push the RUL prediction higher (positive SHAP values) and which pull it down (negative SHAP values)
  - Magnitude of the SHAP value indicates the strength of the measured environmental factor's impact on the prediction.

[25] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *31st Conference on Neural Information Processing Systems*, Long Beach, CA, USA, 2017.
H. Habibollahi Najaf Abadi and M. Modarres, "A Deep learning approach for discovering and incorporating the underlying physics of degradation in data-driven prognostics," in 2024 Annual Reliability and Maintainability Symposium (RAMS), Albuquerque, 2024

Summary and Conclusions

- DL reliability models are black-box regression model
  - They show nothing about the underlying physics of degradation and the dominant stresses
- Proposed approach is a dual guided NN framework including input stress importance assessment and interpretability
- Integrating the discovered physics into a DL prognostic model significantly improved prediction of degradation or life
- The proposed approach offers valuable benefits to designers and users

Current and Future Works

- Consider effects of environmental and user stresses on spatial, acceleration and higher partials of degradation
  - ➢ That is, discovering an item's degradation function, $D(x, t)$, from the field, test, and survey degradation data to build the PDE:

$$F\left(x, t, D_t, D_x, D_{tt}, D_{xx}, D_{xt}\right) = 0$$

- Sensitivity and optimization of the NN structure
- Case studies: energy and process systems, composite structures, and IC manufacturing
- Applications to predictive maintenance policy and decision making