A Deep Learning Approach for Discovering the Underlying Physics of Degradation for Data-Driven Prognostics

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Deep Learning for Prognostics and Health Management

- Advantages
  - Ability to handle high-dimensional data
  - Recognize highly nonlinear patterns in data

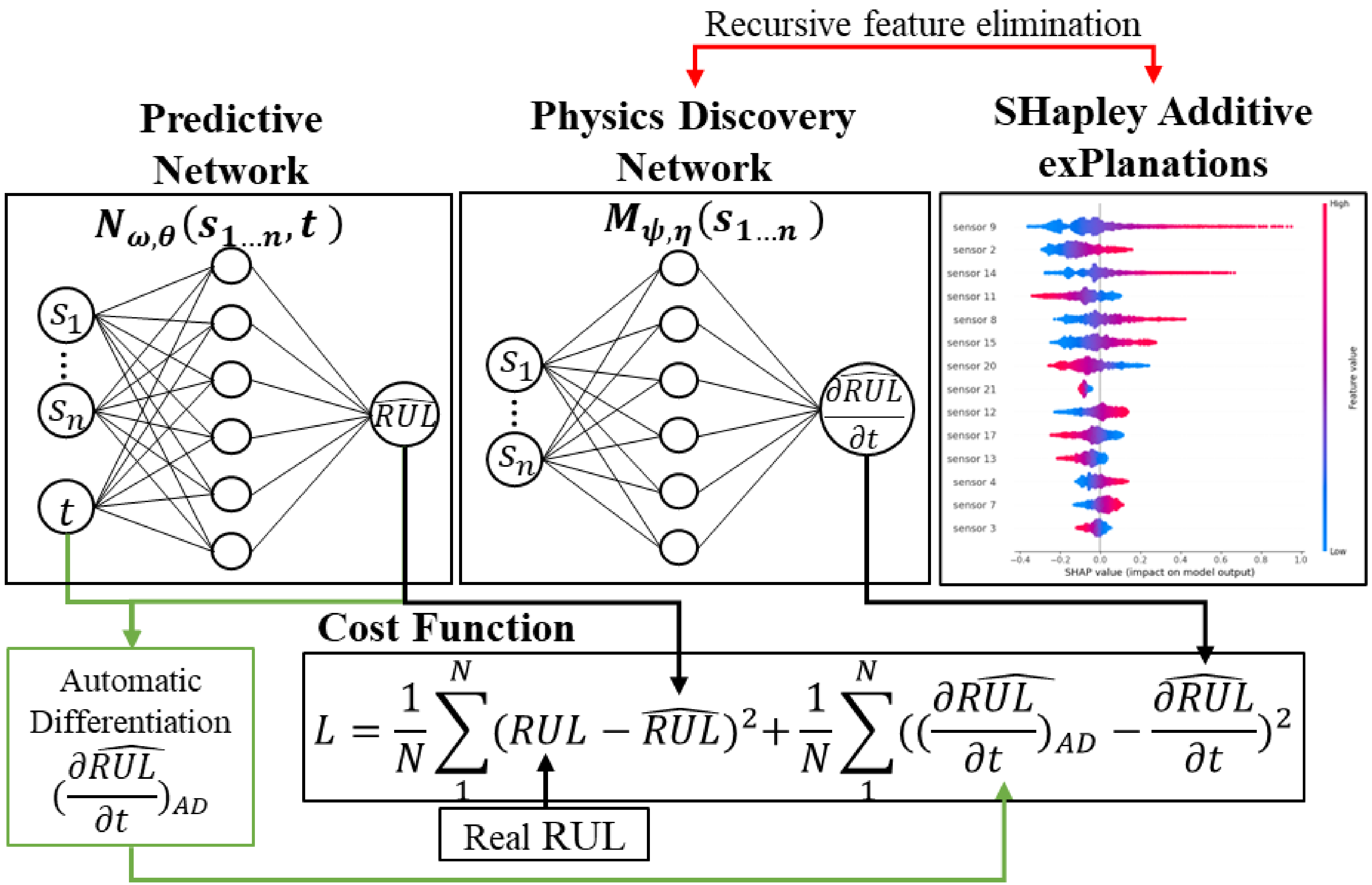
- Challenges
  - Disregarding the underlying physics of degradation
  - Requiring a substantial amount of training data
  - Lack of interpretability

Study Objectives

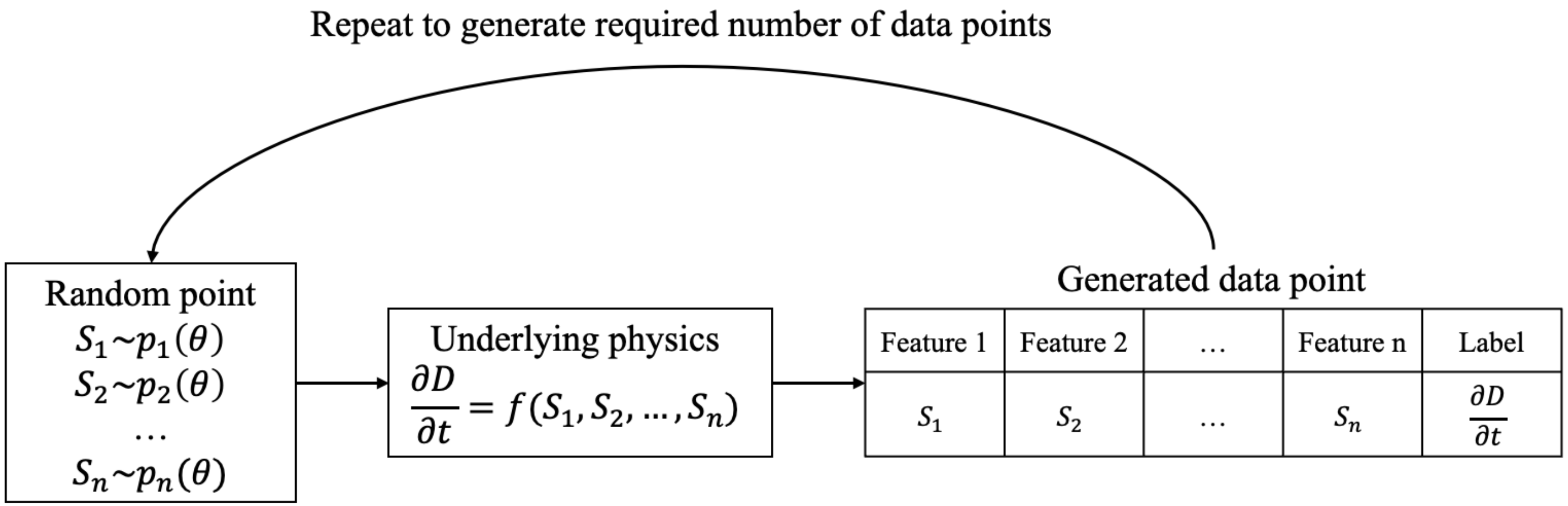
- Discovering/Incorporating Physics
  - Establishing a relationship between the suspected influential environmental factors and the degradation rate: $\frac{\partial RUL}{\partial t} = f(S_1, S_2, \dots, S_n)$

- Providing Interpretability
  - Identifying the primary environmental factors that significantly impact the degradation process

Proposed Approach



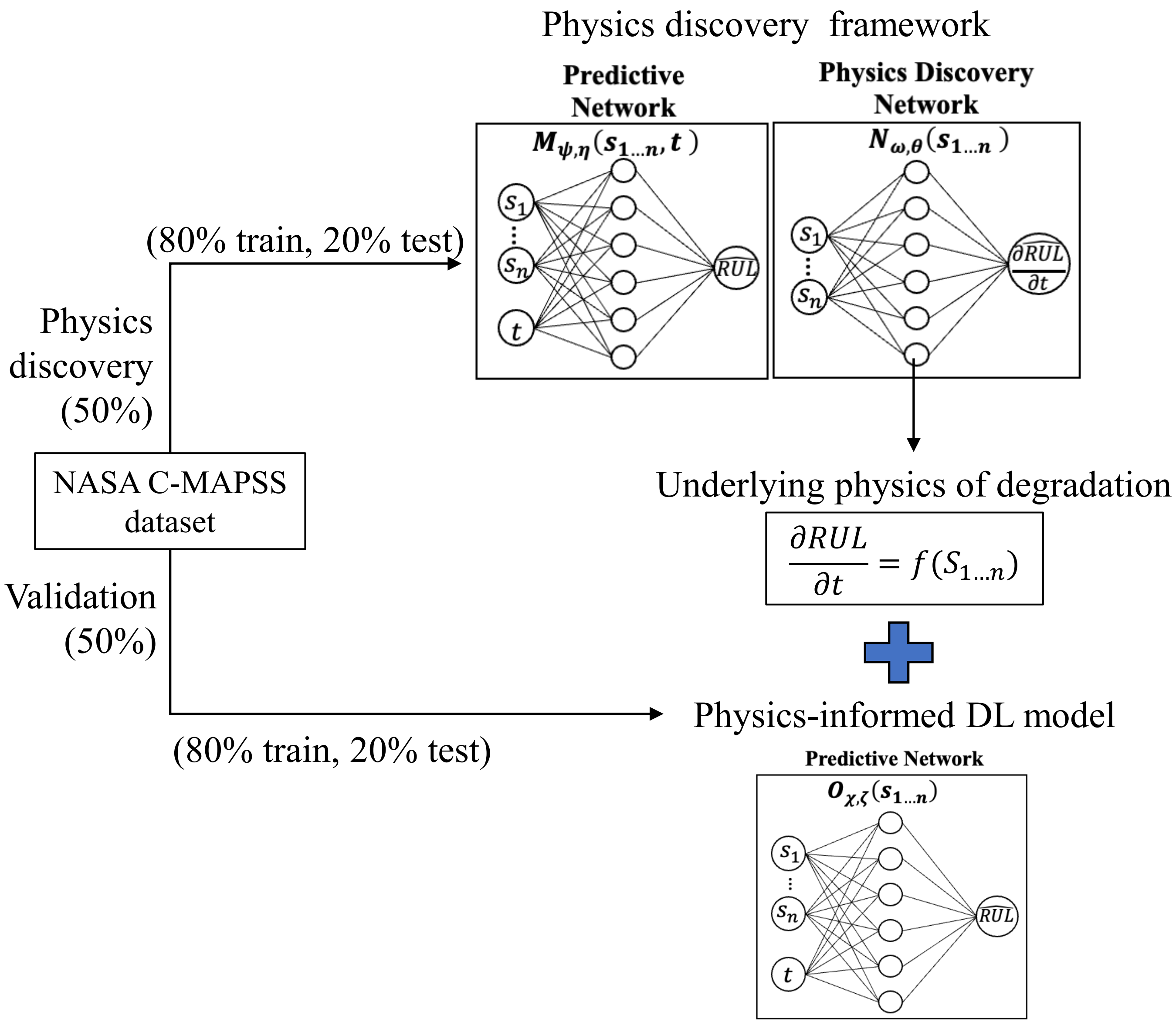
Validation Through Data Simulation



- Assumptions:
  - Seven environmental factors are collected by seven sensors (i.e., $S_1, S_2, \dots, S_7$).
  - 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

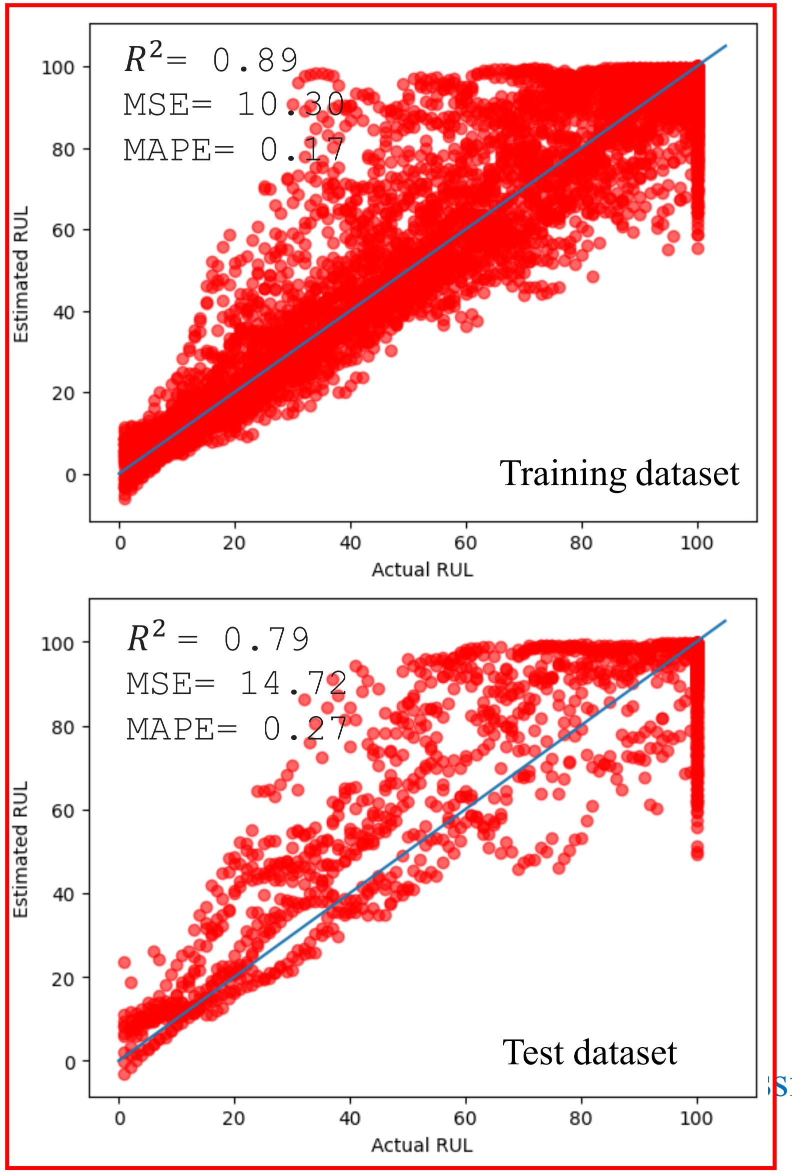
Degradation in Aircraft Engines



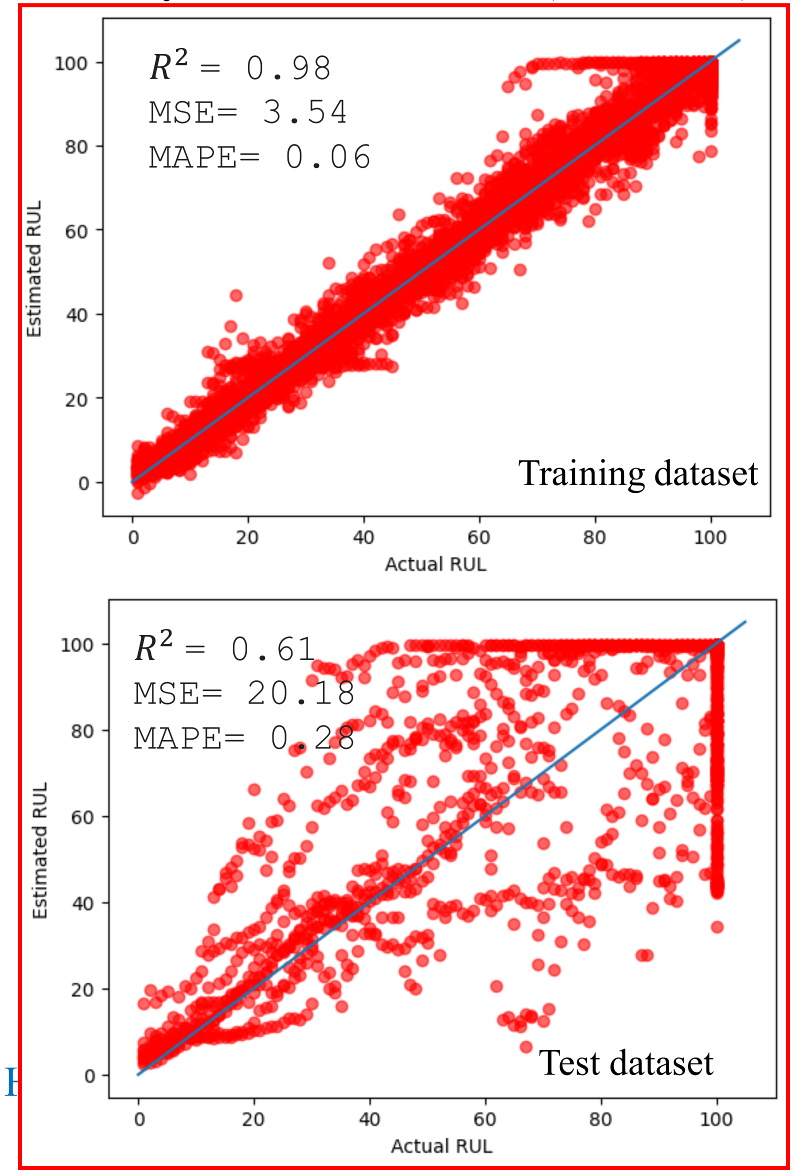
H. Habibollahi Najaf Abadi and M. Modarres, "A Deep learning approach for discovering and incorporating the underlying physics of degradation in data-driven prognostics," in 2024 Annual Reliability and Maintainability Symposium (RAMS), Albuquerque, 2024

Case Study – Effect of Adding Physics

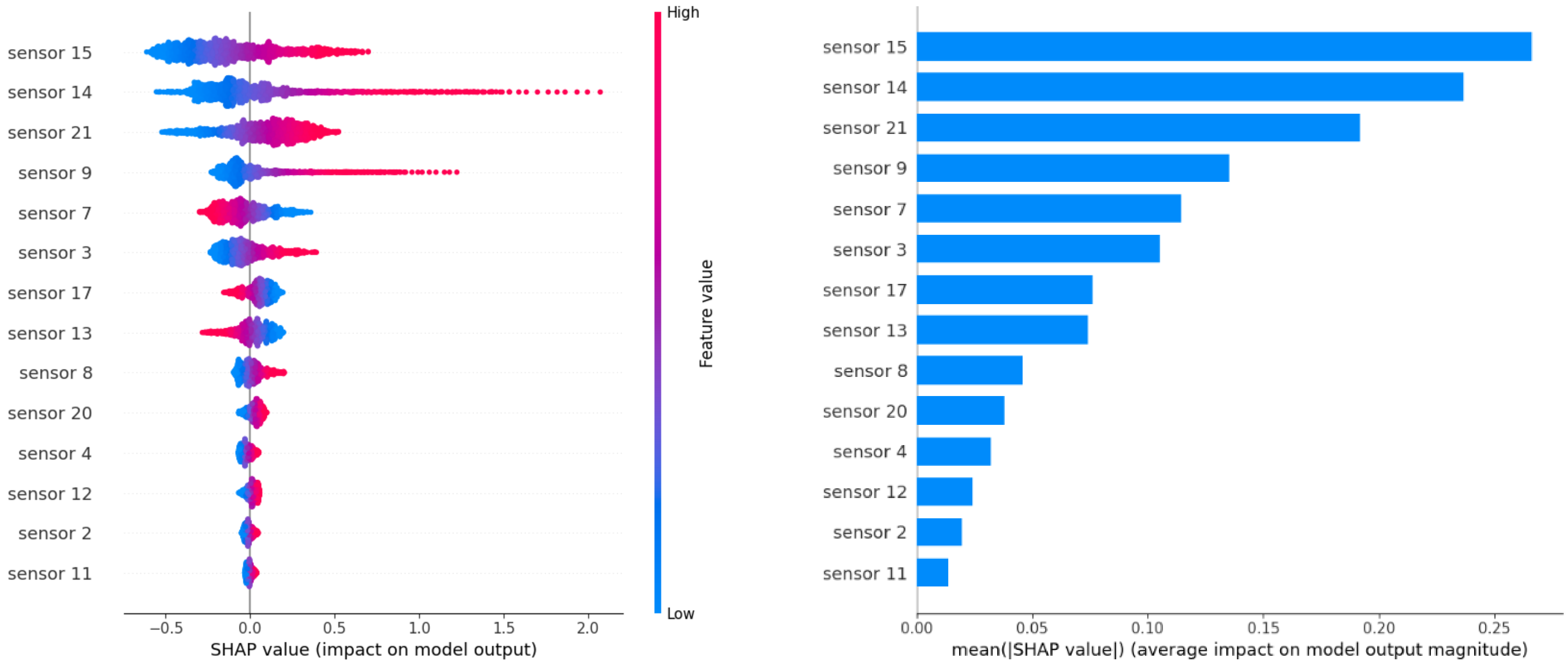
Physics-informed model (14 sensors)



Purely data-driven model (14 sensors)



Case Study – Feature Importance Measurement

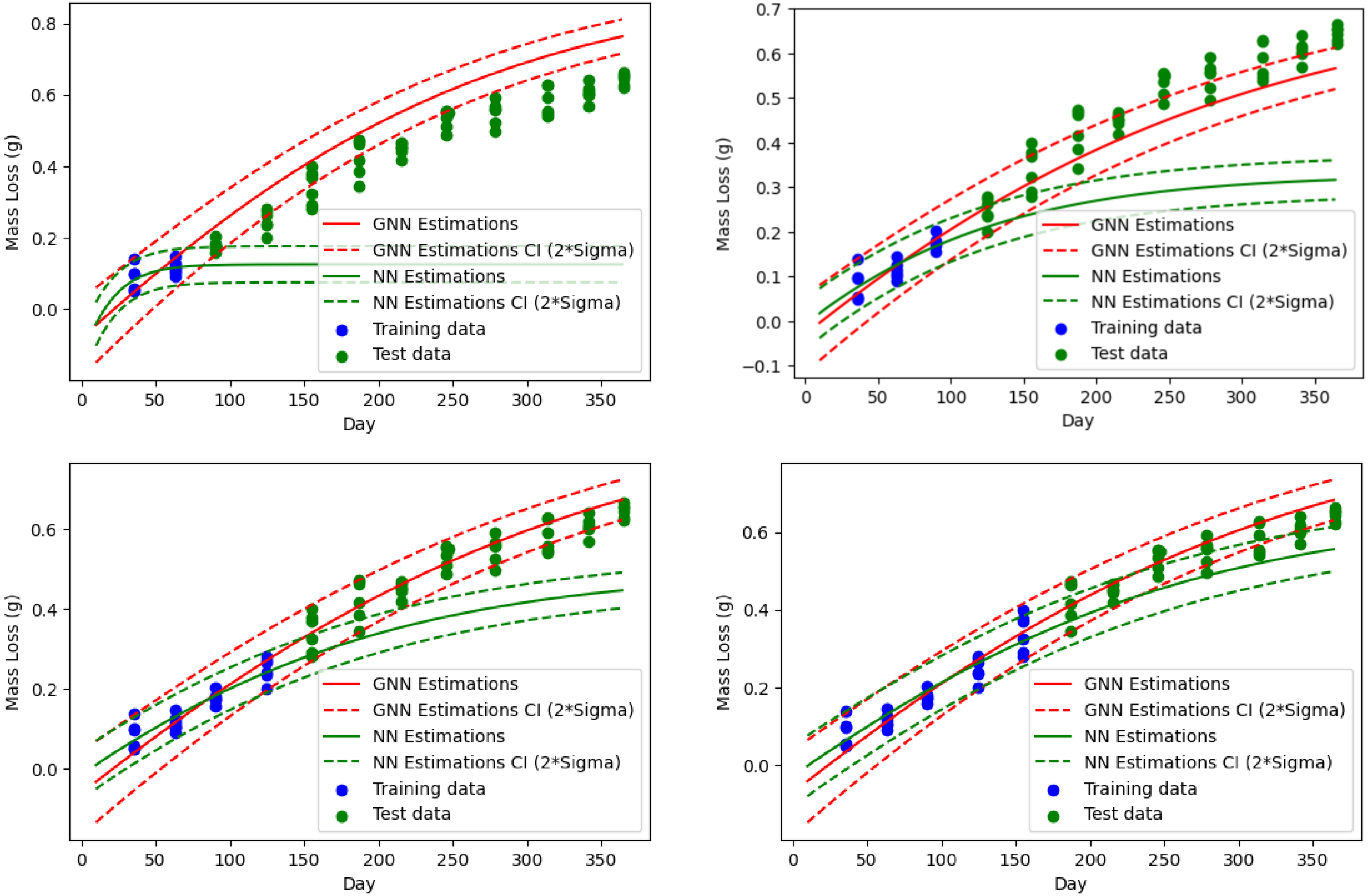


Case Study – Recursive Feature Elimination

Number of considered factors	Dataset	MSE	MAPE	R^2
14	Training	10.30	0.17	0.89
	Test	14.72	0.27	0.79
10	Training	10.67	0.17	0.88
	Test	15.07	0.26	0.78
8	Training	10.57	0.17	0.89
	Test	14.65	0.27	0.79
6	Training	11.05	0.18	0.88
	Test	14.40	0.25	0.80
5	Training	32.03	1.60	0
	Test	32.55	1.71	0

Case study 2 Results

- Comparing the physics-informed Predictive (Guided) NN with a Regular NN



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

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

Summary & Conclusions

- DL prognostic models: black-box regression model
  - Do not provide any information about the underlying physics of degradation and the dominant stresses
- Proposed approach: a dual NN framework and a feature importance measurement tool
- Integrating the discovered physics into a DL prognostic model significantly improved performance
- The proposed approach offers valuable benefits to designers and users