Probabilistic Virtual Load Monitoring of Offshore Wind Substructures: A Supervised Learning Approach

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ISOPE-2022 Shanghai Conference

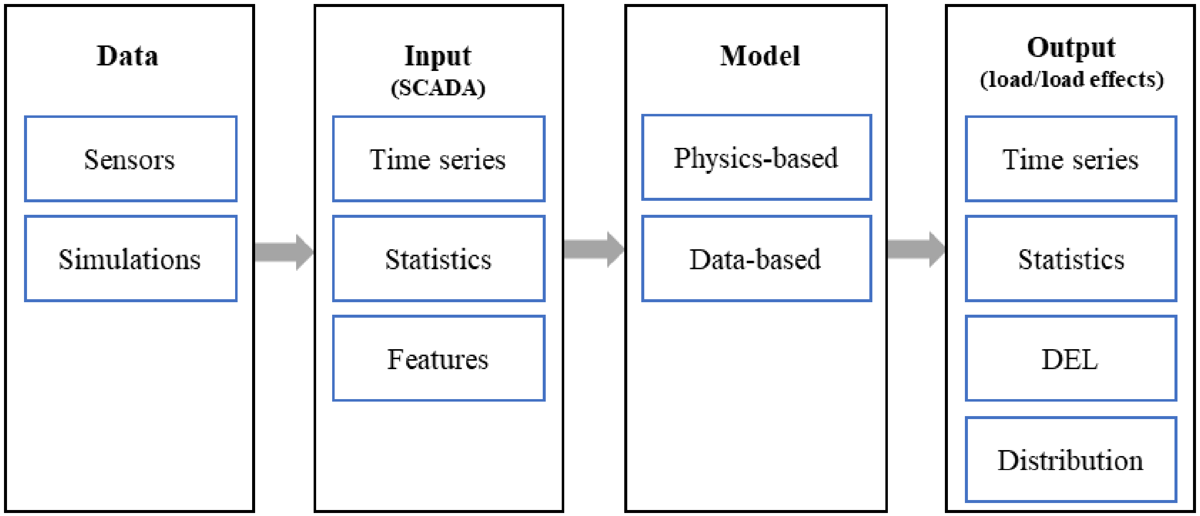
The 32nd International Ocean and Polar Engineering Conference

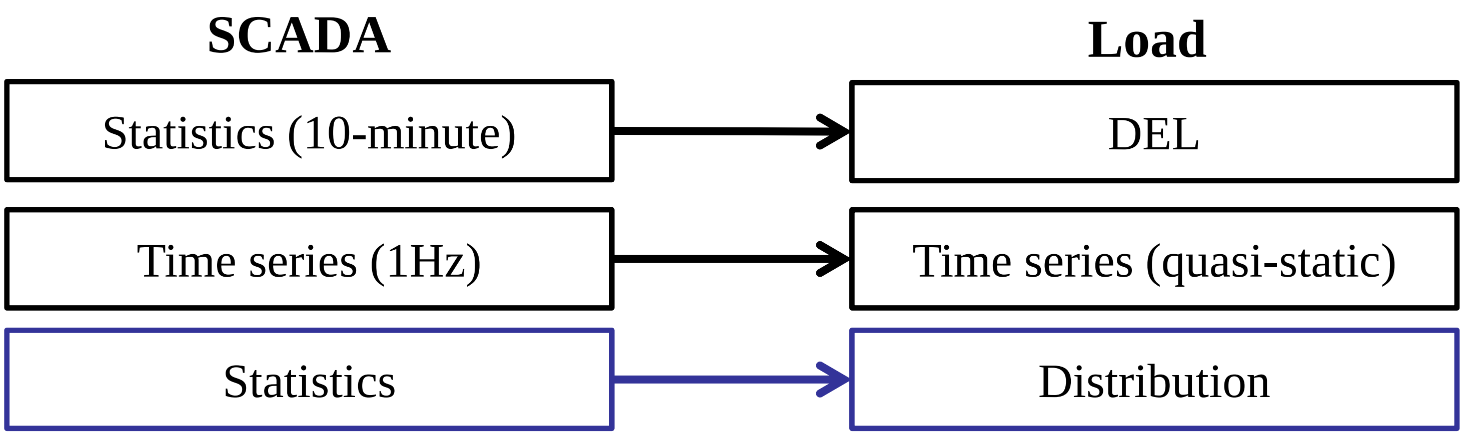
Shanghai, China, June 5-10, 2022: www.isope.org

Motivation

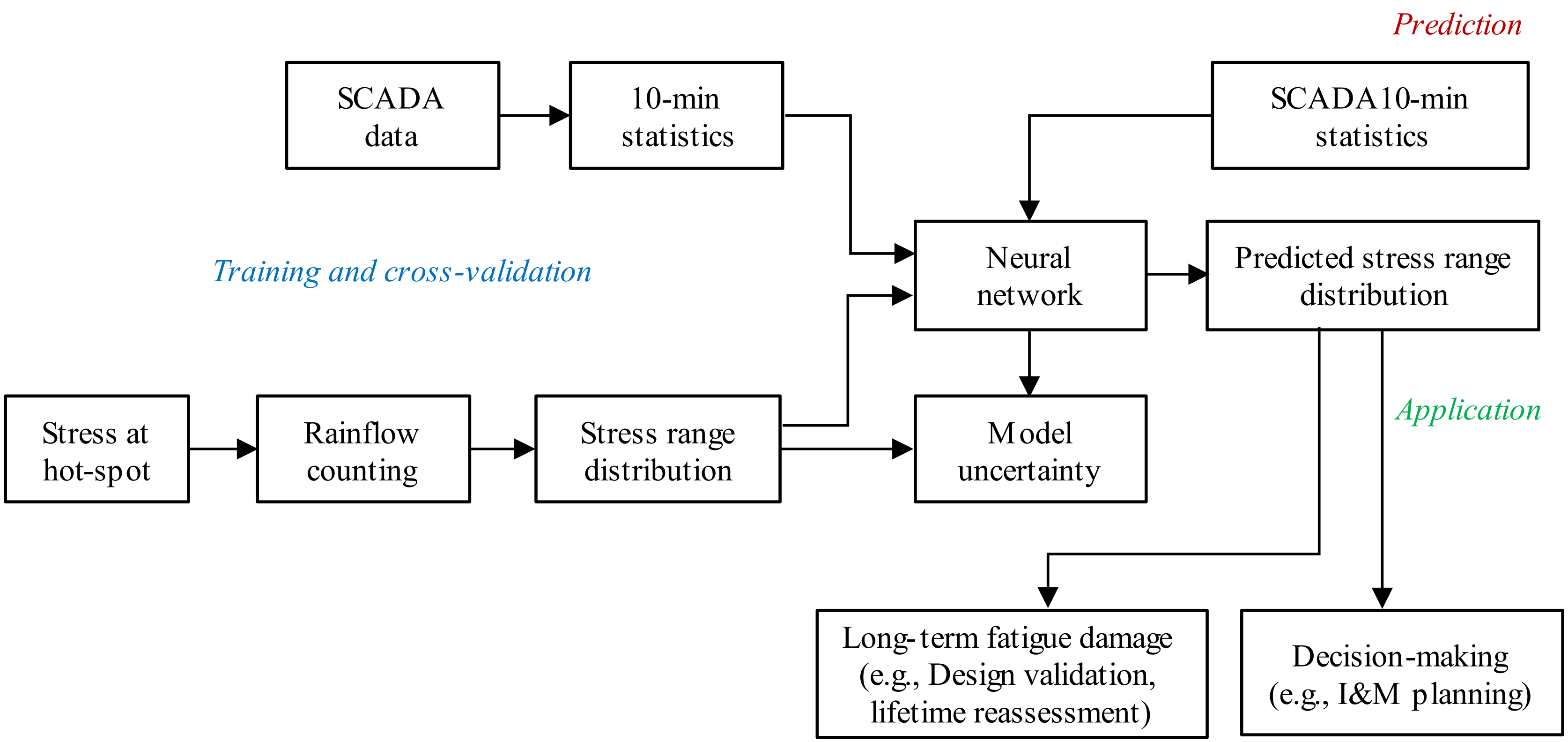
- Current trend towards larger wind turbines, deeper water depths, farther from shore.
- Accentuated structural degradations.
- Difficult and costly inspections and maintenance.
- Advancement of sensor technologies and monitoring solutions.
- Sensors prone to damage in harsh marine environments.
- Limited lifetime of sensors Vs SCADA data available throughout lifetime

Virtual load monitoring





Framework for the development and deployment of a virtual load monitoring model



Uncertainty quantification

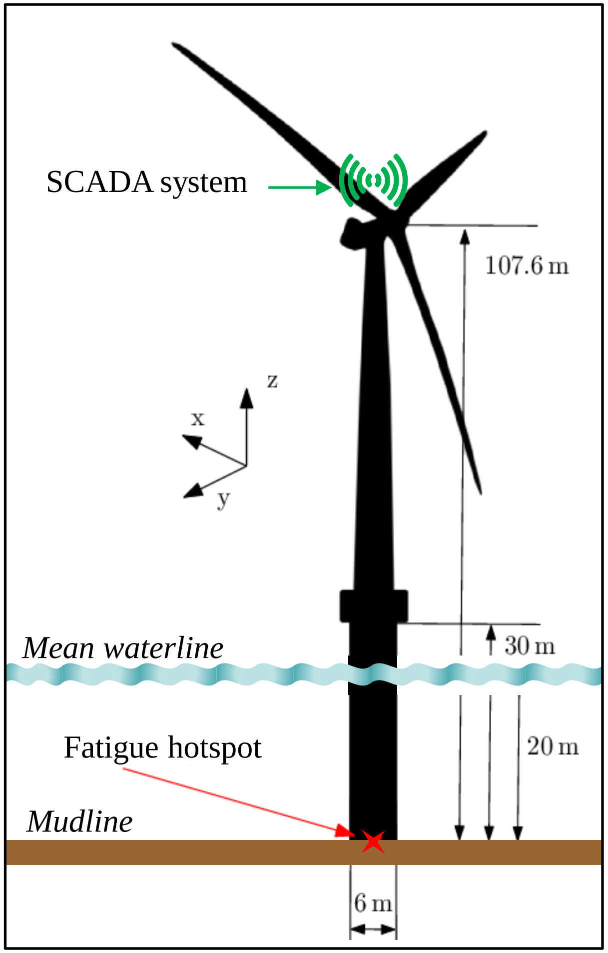
- Residual variability
- Observation error
- Parametric variability
  - *minimize overfitting*
  - *Sensor re-installation/ re-calibration of network weights*
- Model inadequacy

$$\boldsymbol{z} = \delta + \eta(\mathbf{x}, \boldsymbol{\theta})$$

  - z = sensor data
  - x = SCADA data
  - $\boldsymbol{\theta}$ = trained weights and bias
  - δ = model inadequacy

Ref: Kennedy, M.C. and O'Hagan, A. (2001), Bayesian calibration of computer models. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 63: 425-464. https://doi.org/10.1111/1467-9868.00294

Virtual load monitoring of an offshore structural connection



Wind turbine: **Monopile-supported NREL 5MW**
Location: **Ijmuiden site (Dutch North Sea)**

Variable	Description
Wind speed (V_w)	$V_w \sim$ Weibull ($scale = 10.49,\ shape = 2.08$)
Wind direction (θ_{wind})	$P(\theta_{wind}, \theta_{wave} \mid V_w)$
Turbulence intensity (I)	IEC-3 ($I_{15\ \mathrm{m/s}} = 0.14$)
Significant wave height (H_s)	$P(H_s, T_p \mid V_w)$
Peak period (T_p)	$P(H_s, T_p \mid V_w)$
Wave direction (θ_{wave})	$P(\theta_{wind}, \theta_{wave} \mid V_w)$
Rotational speed (ω)	$f(V_w)$
Yaw error (θ_{yaw})	$\theta_{yaw} \in [-10, 10]$

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Numerical simulations and data processing

Input environmental and operational parameters (Pseudo-SCADA) — Ancestral sampling

↓

Coupled aero-hydro-servo-elastic simulations — OpenFAST

↓

Computation of hot-spot stress — $\sigma_{hs} = SCF \cdot \left(-\frac{F_{Zss}}{A_{sub}} + \frac{M_{Xss} \cdot R_{sub}}{I_{sub}} \right)$

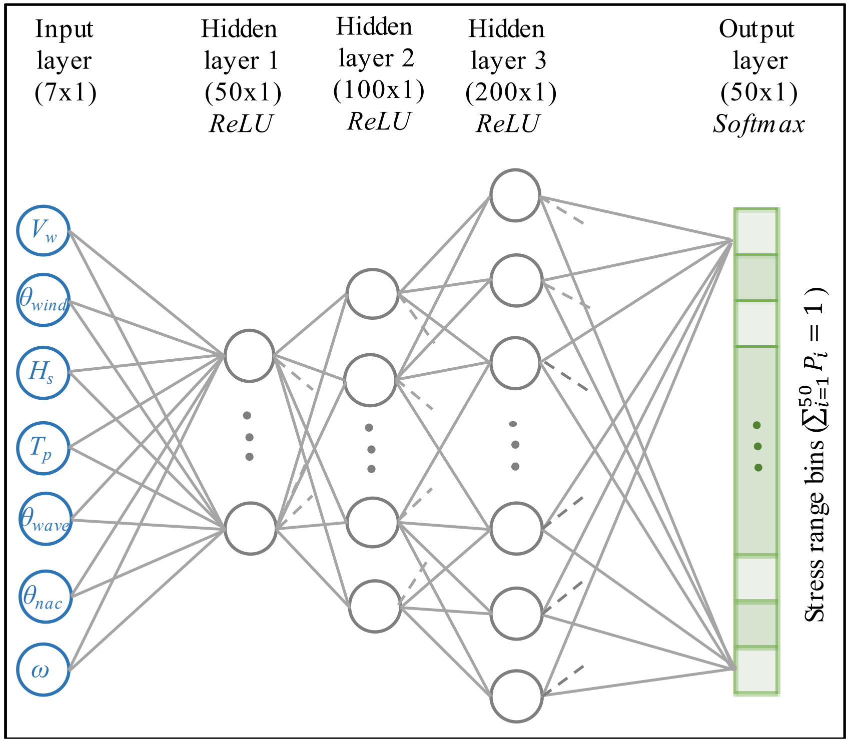
↓

Probability distribution of stress ranges — Rainflow counting

Network architecture

- Data normalization
- Input layer (7 neurons)
- 3 hidden layers (50, 100, 200 neurons) with ReLU activation function
- Output layer (50 neurons)

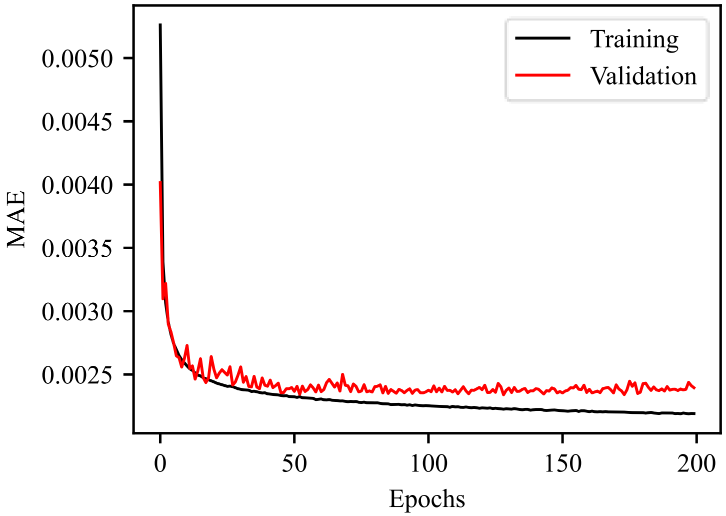
$$\text{Softmax: } P(s_i) = \frac{e^{x_i}}{\sum_{j=1}^{S_n} e^{x_j}}, i = 1, 2, \ldots S_n$$



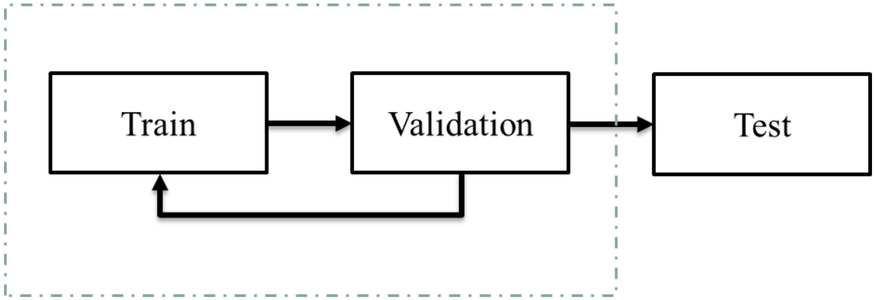
Training the neural network

- Optimizer – RMSProp (Lr = 0.001)
- Mean absolute error (MAE):

$$MAE = \frac{1}{N}\frac{1}{S_n}\sum_{j=1}^{N}\sum_{i=1}^{S_n}\left| P_{pred,j}(s_i) - P_{data,j}(s_i)\right|$$



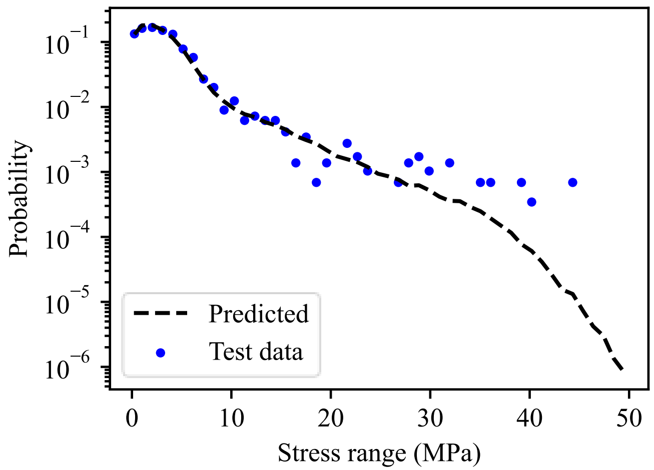
- Early stopping callback which monitors validation MAE
- 80% trainset (training + validation), 20% testset



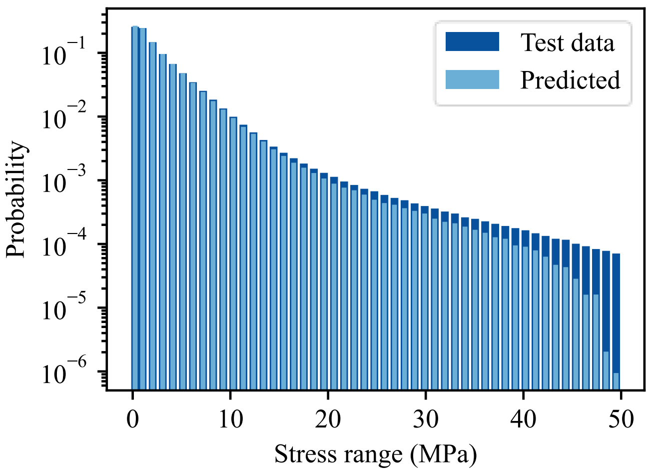
Nandar Hlaing, & Pablo G. Morato. (2022). Post-processed dataset from 50000 numerical simulations of monopile-supported NREL 5MW wind turbine in OpenFAST (Version V1) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.5957394

Training and cross-validation results

Random test sample



Testset



Random test sample

- Data → zero-probability bins
- Prediction → non-zero probability (due to softmax)

Under-estimations, e.g. bins 30-40 MPa

Test set

- Under-estimations in low probability regions
- Small stress ranges are more critical than higher stress ranges in fatigue

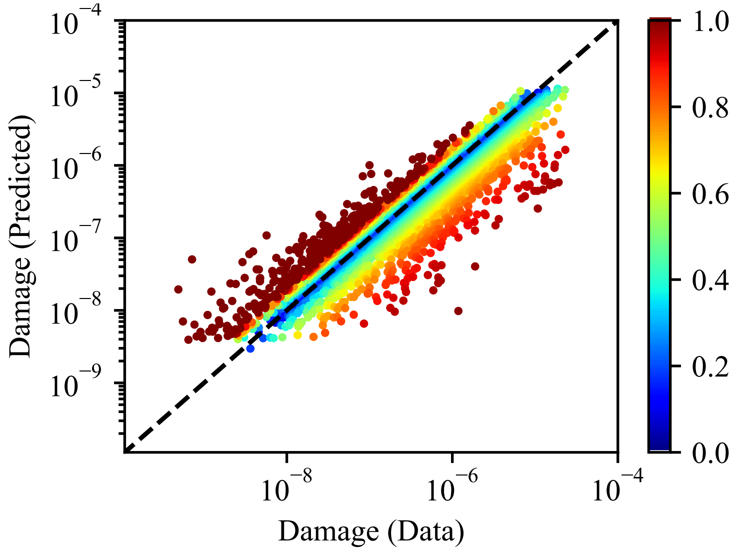
Prospective applications: Short-term/ long-term fatigue damage estimation

Example: Fatigue hotspot at the mudline

$n = 1200$ cycles/10-minute

$\log_{10} K = 11.687$

$m = 3$



- Miner's rule (linear SN curve):

$$D = n\sum_{i=1}^{S_n}\frac{P(s_i)}{N_{f_i}}, \text{ with } \log_{10} N_{f_i} = \log_{10} K - m\log_{10} s_i$$

Prospective applications: Bayesian inference of load effects

Example: Probabilistic fatigue assessment

$$D(t) = nt\left[\frac{q^m}{K}\Gamma\left(1+\frac{m}{h}\right)\right], t = 0,1,2,\ldots T_d$$

Fatigue assessment representative parameters

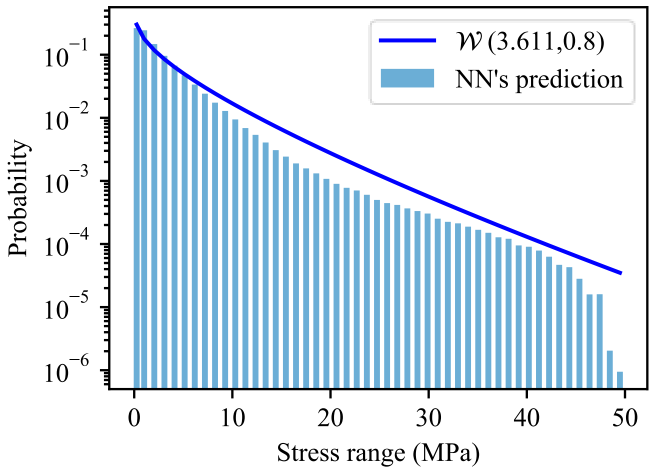
Variable	Distribution	Mean	Std (CoV)
FDF	Deterministic	3	
m	Deterministic	3	
$log_{10}K$	Normal	11.687+2Std	0.2
h	Deterministic	0.8	
q	Normal	*1.9776	(0.2)
n	Deterministic	$6.32 \cdot 10^6$	

Time-invariant Weibull-scale parameter

$$q_{t=0} = 1.97666 \; (T_d = 20, FDF = 3)$$

$$q_{t+1} = q_t + \varepsilon, \text{ where } \varepsilon \sim \mathcal{N}(0, 0.1)$$

Prospective applications: Bayesian inference of load effects

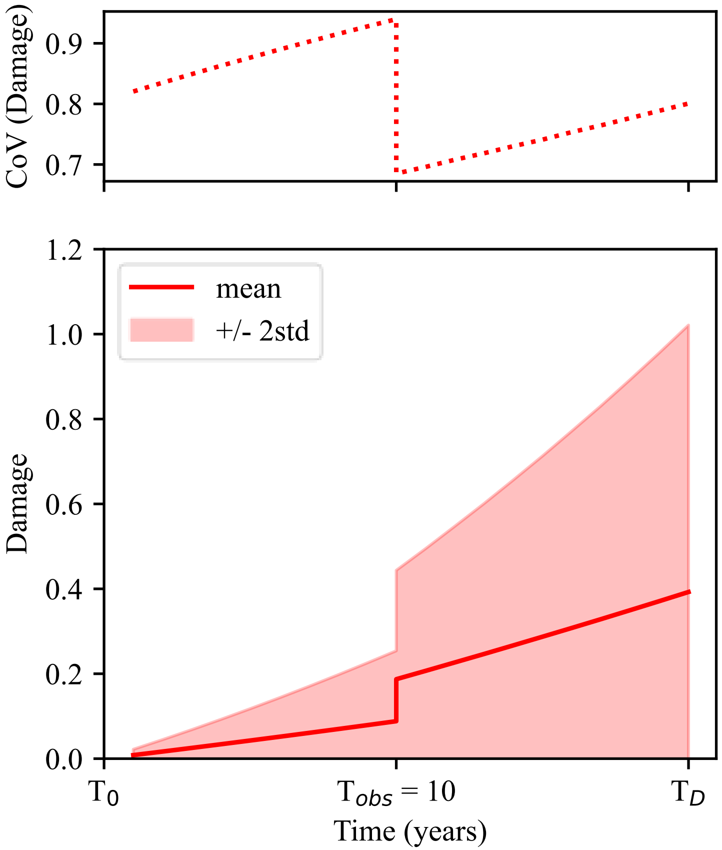


$$q_{obs} = q_{pred} + U_O + U_{PR} + U_{MI}$$

Variable	Distribution	Mean	Std (CoV)
U_O	Normal	0	0.25
U_{PR}	Normal	0	0.25
U_{MI}	Normal	0	0.5

Baye's rule: $P(q'|\, q_{obs}) \propto P(q_{obs}|\, q)P(q)$

Evolution of fatigue damage and uncertainty



Conclusions and outlook

- A data-based model can be trained while the SCADA and strain data are concurrently collected.

- The hindrance of different sampling frequencies can be circumvented by specifying the output as a probability distribution.

- The virtual load monitoring can be applied in
  - Fatigue damage evaluation, e.g., for design verification.
  - Decision making for optimal management planning, lifetime extension, etc.

Conclusions and outlook

- To explore robust feature selection methods
  - To select the most influencing input variables
  - To avoid redundant variables

- Probabilistic deep learning methods
  - Intrinsic quantification of aleatory and epistemic uncertainties
  - Reduction of model uncertainty with more training data

For questions and comments:

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