Bayesian Deep Learning for Probabilistic Virtual Load Monitoring of Offshore Wind Farms

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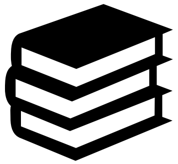
PhairywinD
Belgian Offshore PhD Expertise

Virtual load monitoring of offshore wind turbines

(1) Uncertainty quantification

Aleatory uncertainty

Inherent physical randomness



Standards and guidelines

Measurement uncertainty of sensing devices

ST2 FBG strain sensors
Embedded in composites
Strain accuracy 1%

S11 FBG strain sensors
Glued to various materials
Strain accuracy 1%

Ref: https://www.fibergratings.com/

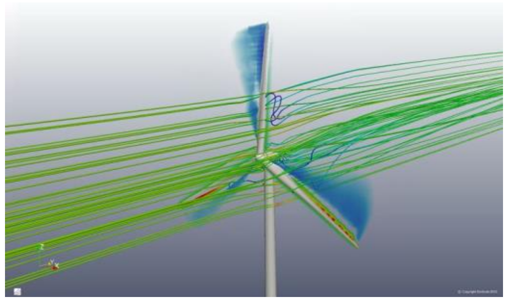
Model uncertainty

Labels ⇔ Model predictions (e.g., MAE, RMSE)

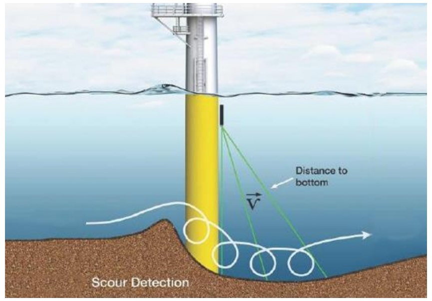
Conditions of strain gauges

time

Wind turbine dynamics changes over time…



Ref: https://www.pinterest.com/

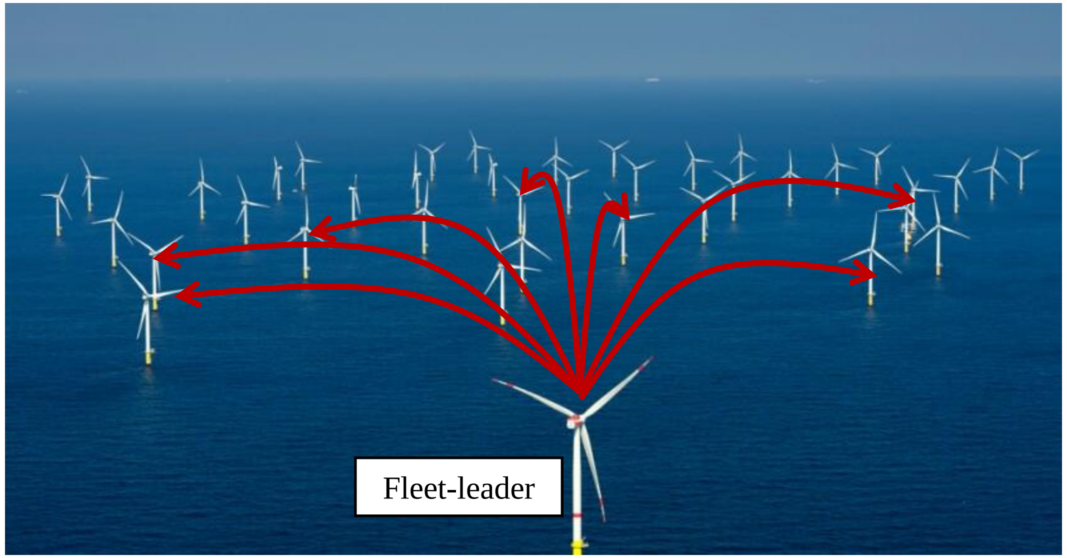


Ref: https://www.offshorewind.biz/

Virtual load monitoring of offshore wind turbines

(2) Farm-wide applicability

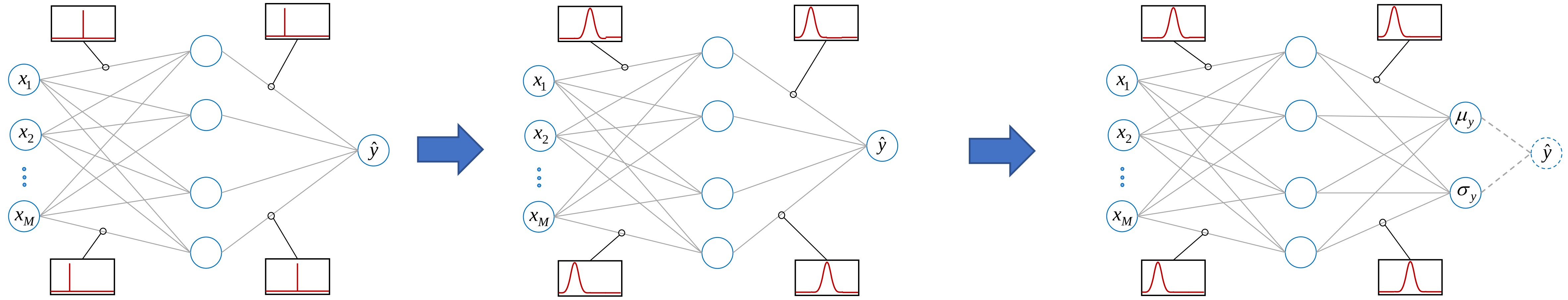
- Economic constraints to fully instrument all turbines
- Absence of strain measurements, only SCADA and accelerations are available
- Variations in water depth, soil properties, structural designs
- Extrapolation of model uncertainty?



Ref: https://www.governing.com/now/wind-turbines-and-lawsuits-are-coming-to-the-jersey-shore

Farm-wide virtual load monitoring framework through BNNs

Bayesian Neural Networks



Standard deterministic neural networks

- Point weights and biases
- Point estimate output

Epistemic Bayesian neural networks

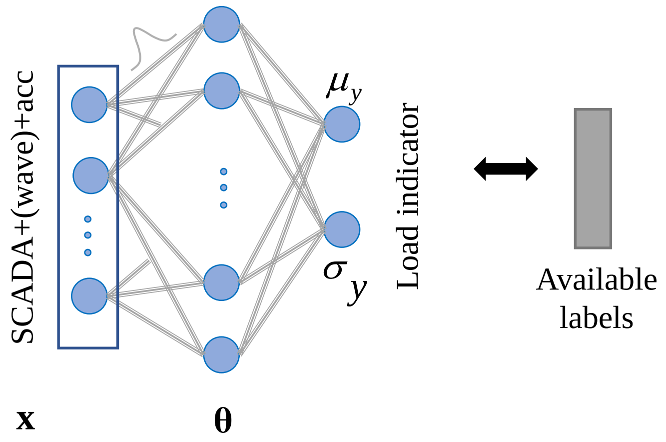
- Probability distribution weights and biases
- Point estimate output

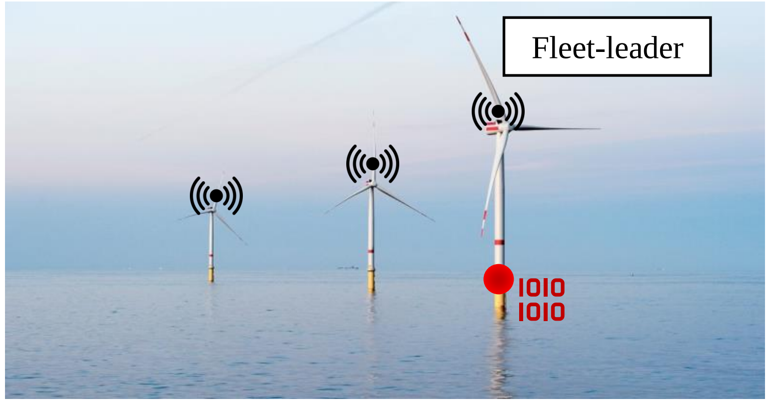
Probabilistic Bayesian neural networks

- Probability distribution weights and biases
- Probability distribution output

Farm-wide virtual load monitoring framework through BNNs

1. Training with fleet-leader data (input + labels)





Ref: Hlaing, N., Morato, P. G., de Nolasco Santos, F., Weijtjens, W., Devriendt, C. & Rigo, P. (2023). Farm-wide virtual load monitoring for offshore wind structures via Bayesian neural networks. arXiv preprint. DOI:10.48550/arXiv.2211.00642

Farm-wide virtual load monitoring framework through BNNs

Bayesian inference

Posterior distribution of weights: $$P(\theta|\, D) = \frac{P(D|\, \theta)P(\theta)}{\int P(D|\, \theta)P(\theta)d\theta}$$

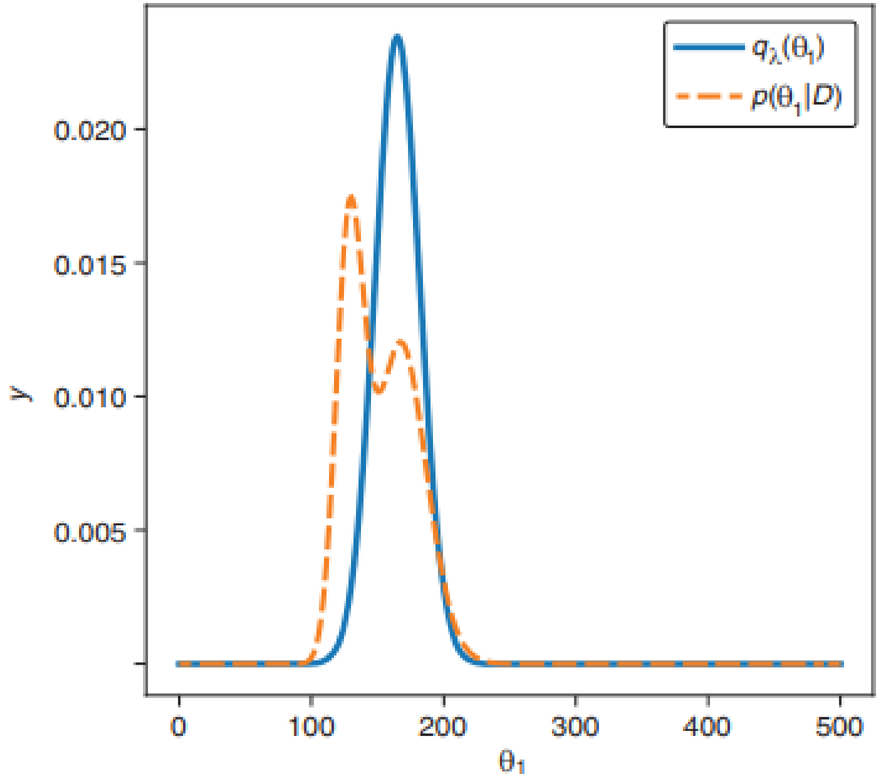
Intractable!!

Variational inference

- to estimate unknown posterior distribution by a variational distribution $q_\lambda(\theta)$

- to minimize KL divergence between variational and posterior distributions

$$\mathbb{KL}\left(q_\lambda(\theta)||\, P(\theta|\, D)\right) = \int q_\lambda(\theta)\log\frac{q_\lambda(\theta)}{P(\theta|\, D)}d\theta$$



Farm-wide virtual load monitoring framework through BNNs

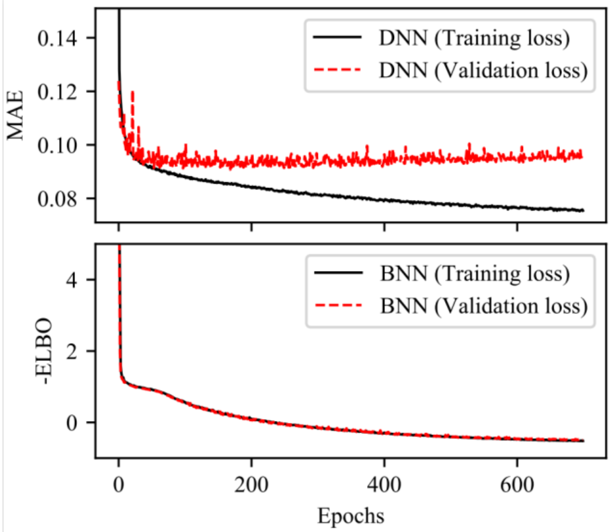
Variational inference as an approximation of Bayesian inference

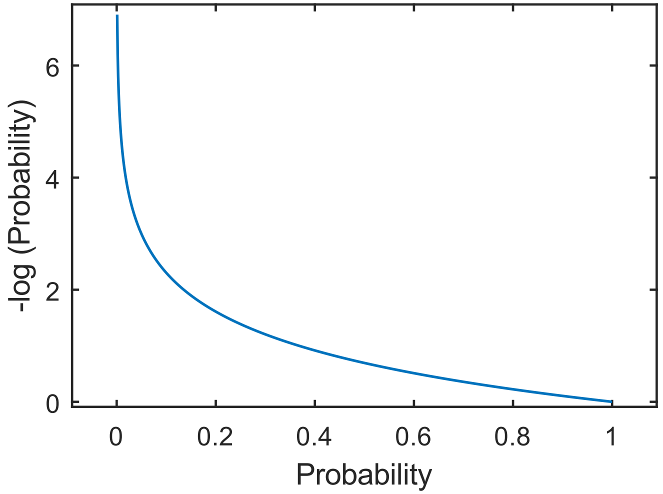
Loss function derived from Variational Inference:

$$\lambda^* = \text{argmin}\boxed{\left\{\underbrace{\mathbb{KL}\left(q_\lambda(\theta) \| P(\theta)\right)}_{\text{Regularizer}} - \underbrace{\mathbb{E}_{\theta \sim q_\lambda}\left[\log(P(D|\theta))\right]}_{\text{Expected negative log-likelihood}}\right\}}$$

- ✓ KL between variational and prior distributions.
- ✓ Prevents overfitting.

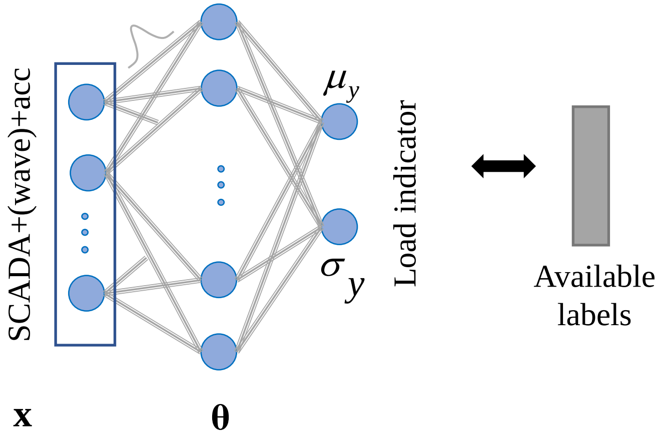
- ✓ Maximize the likelihood of the ‘labels’.

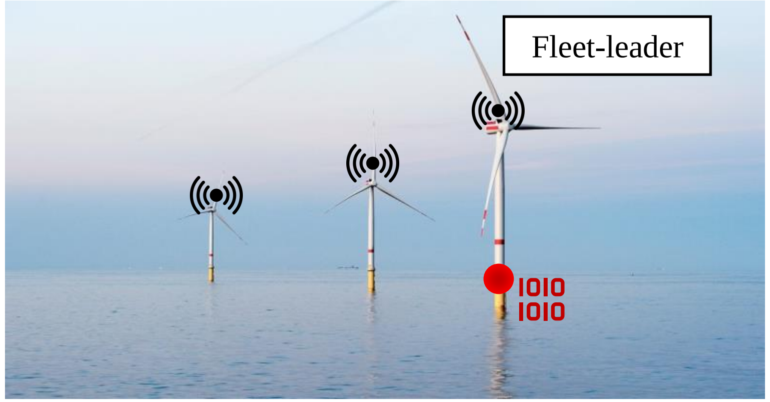




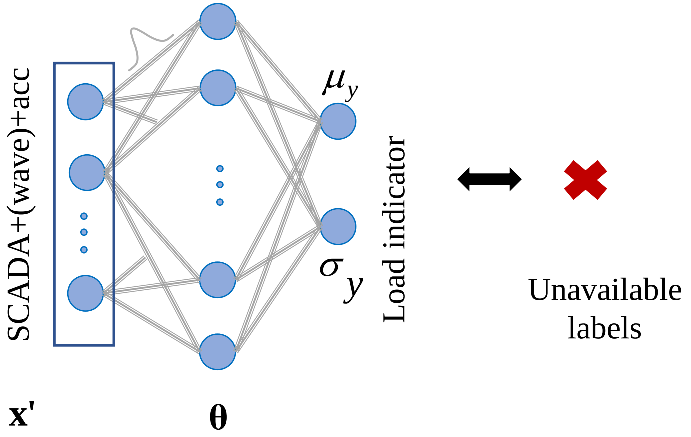
Farm-wide virtual load monitoring framework through BNNs

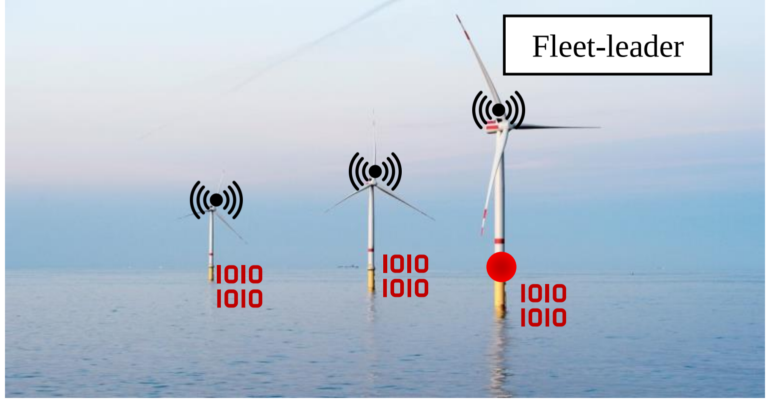
1. Training with fleet-leader data (input + labels)





2. Deployment on fleet-leader or other turbines (only inputs)





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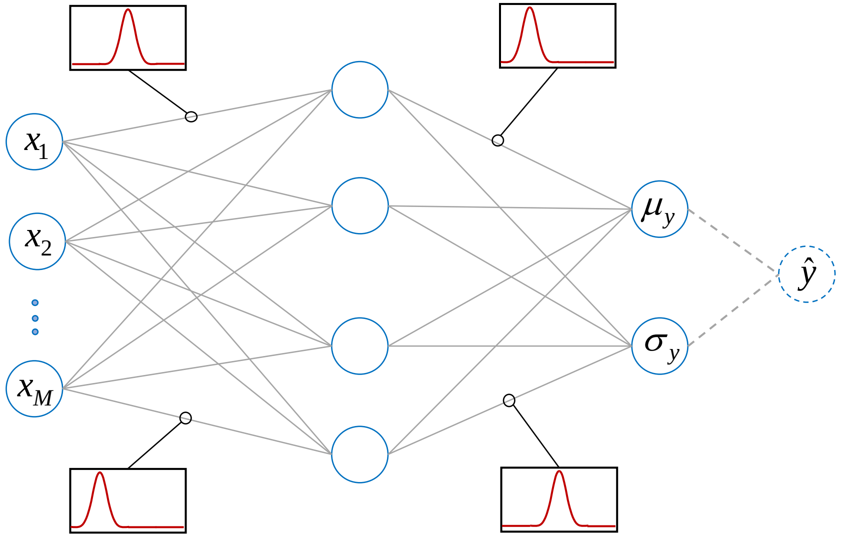
Farm-wide virtual load monitoring framework through BNNs

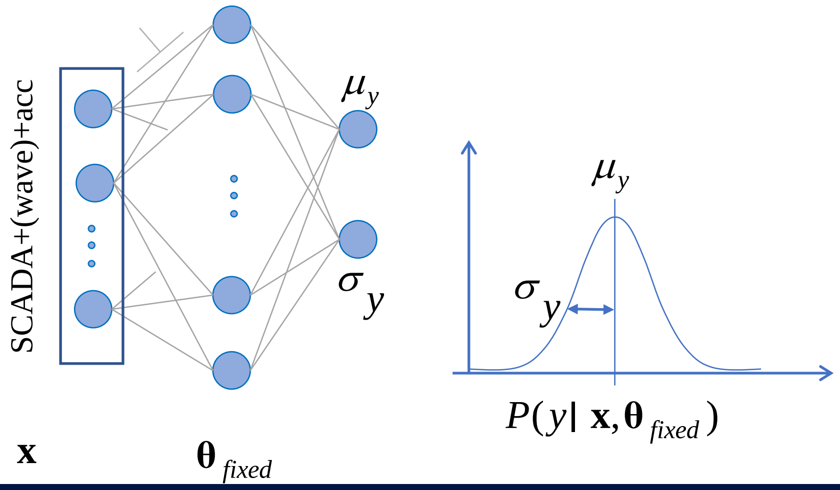
Uncertainty quantification of load predictions



- Total variance theorem:

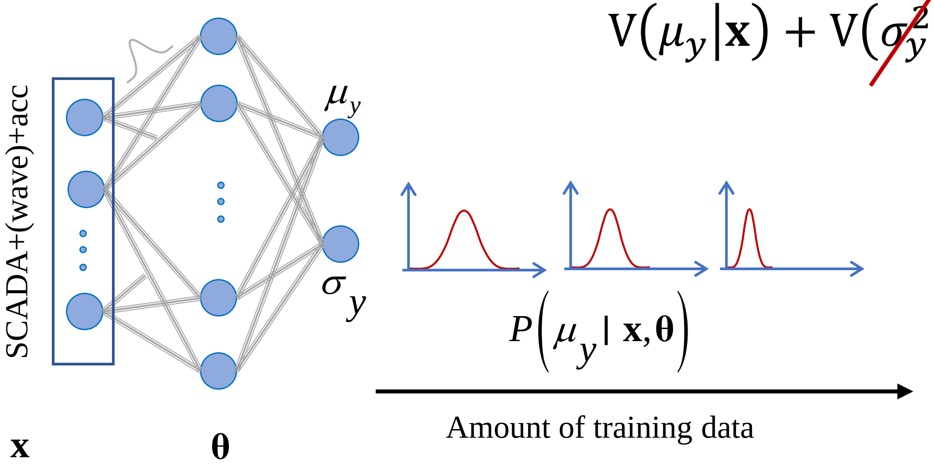
$$\mathbb{V}(\hat{y}|\, \mathbf{x}) = \mathbb{E}[\sigma_y^2|\, \mathbf{x}] + \mathbb{V}(\mu_y|\, \mathbf{x})$$

Aleatory uncertainty

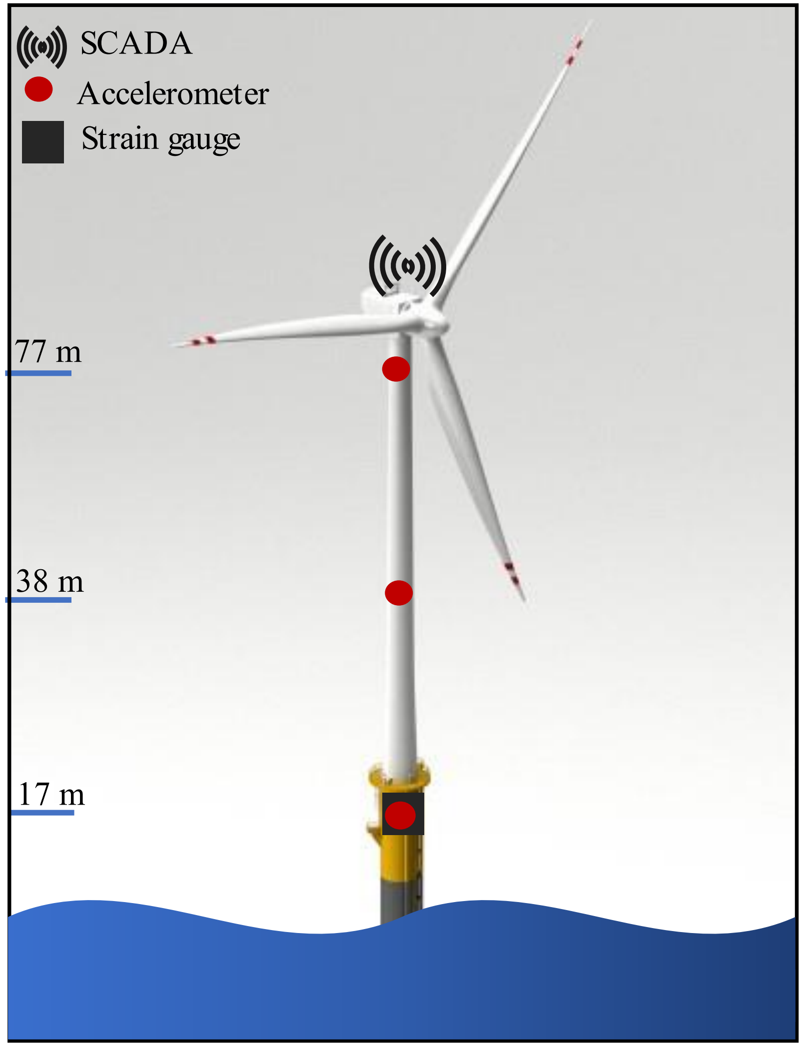


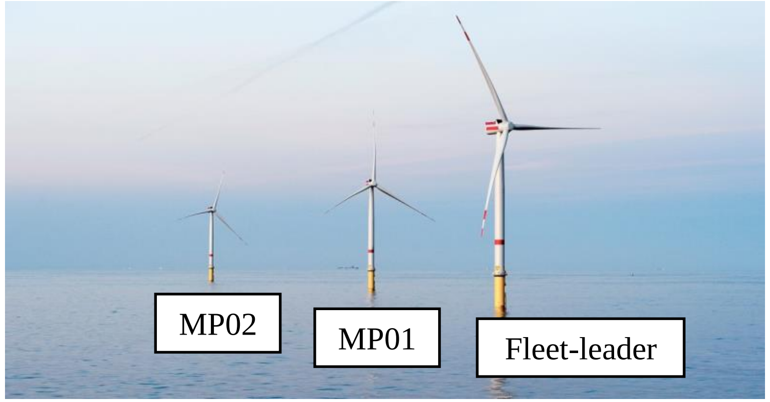
Model uncertainty

$$\mathbb{V}(\mu_y|\mathbf{x}) + \mathbb{V}(\cancel{\sigma_y^2}|\mathbf{x})$$



Case study: Belgian offshore wind farm



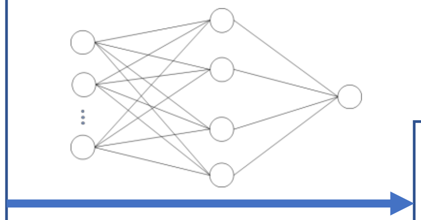


Ref: https://www.gov.uk/

SCADA
Rotational speed (mean)
Yaw angle (mean)
Pitch angle (mean)
Power (mean)
Wind speed (mean)
Wind speed (std)
Wind direction (mean)

Wave buoy
Wave height
Average wave period
Wave direction

Accelerometers
FA acceleration (max, min, rms)
SS acceleration (max)



Strain gauges at 17m LAT
DEM_{tl}
DEM_{tn}

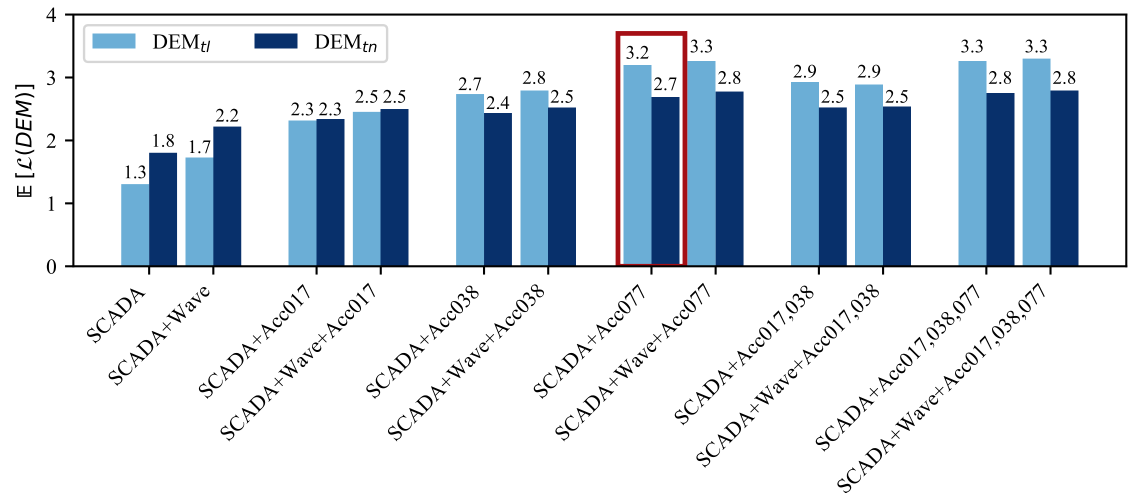
Case study: Belgian offshore wind farm

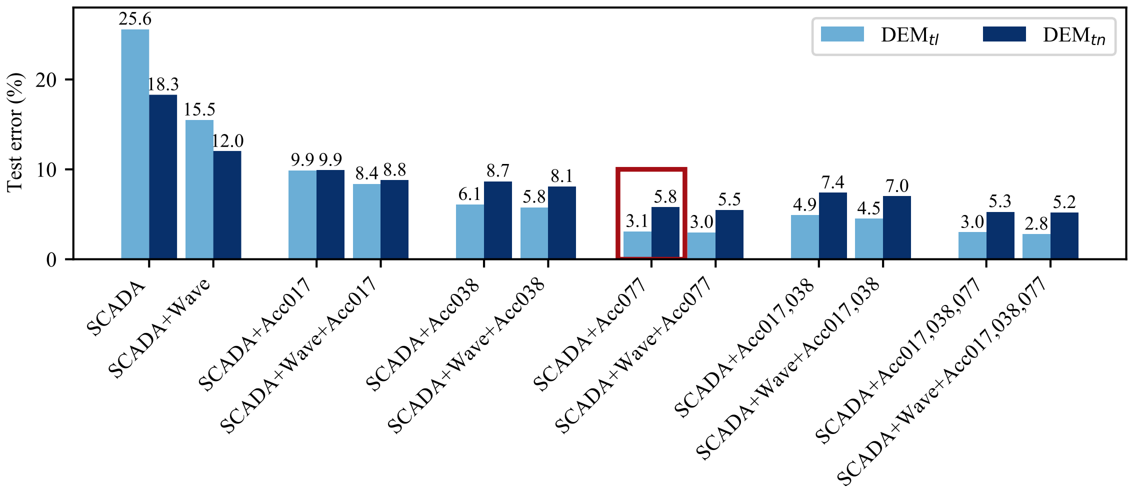
Selection of input monitoring signals

- Aimed for farm-wide application

Maximum performance

Minimum instrumentation

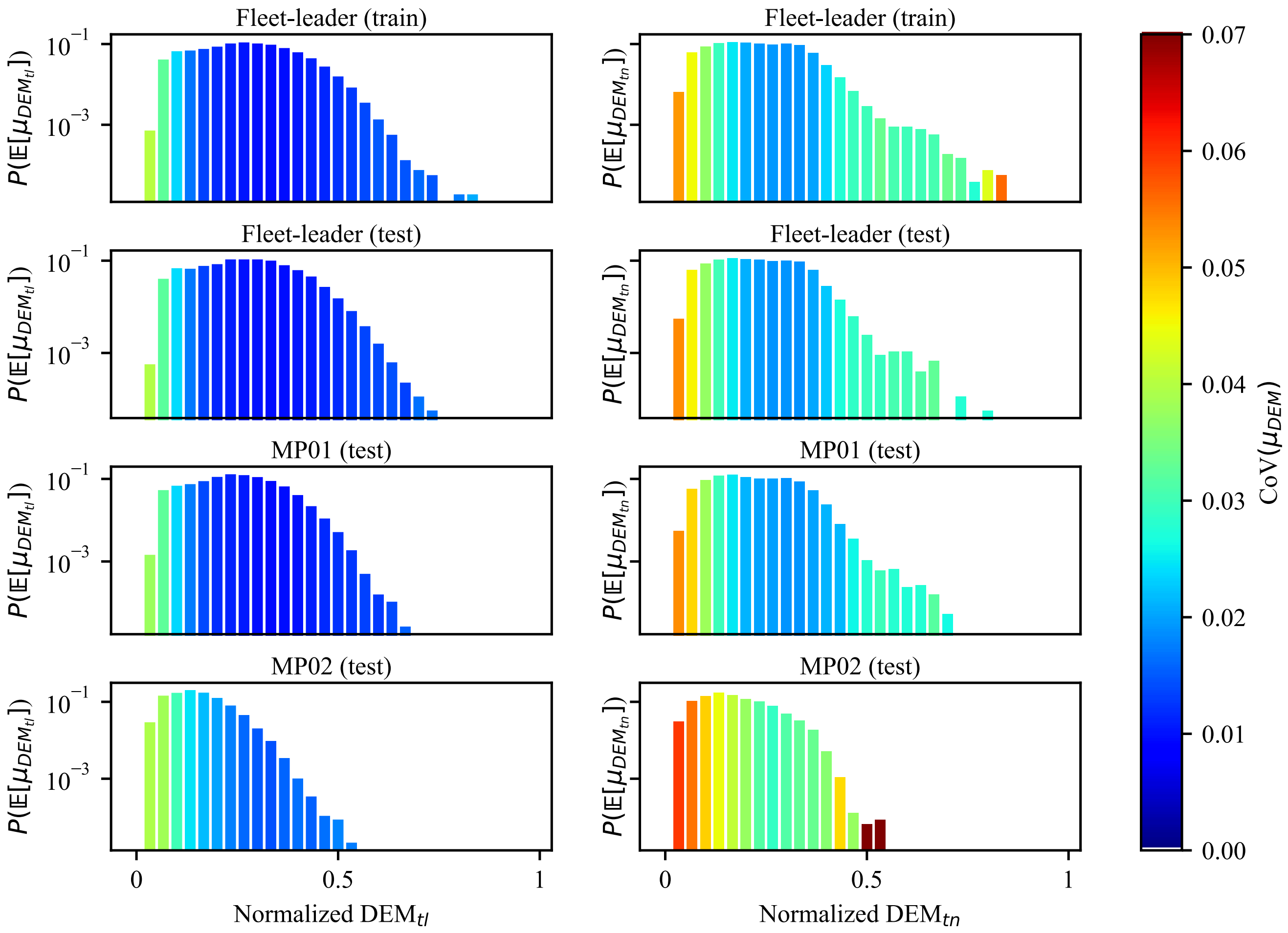




Case study: Belgian offshore wind farm

Farm-wide deployment

Distribution of DEM (side-to-side and fore-aft) and model uncertainty

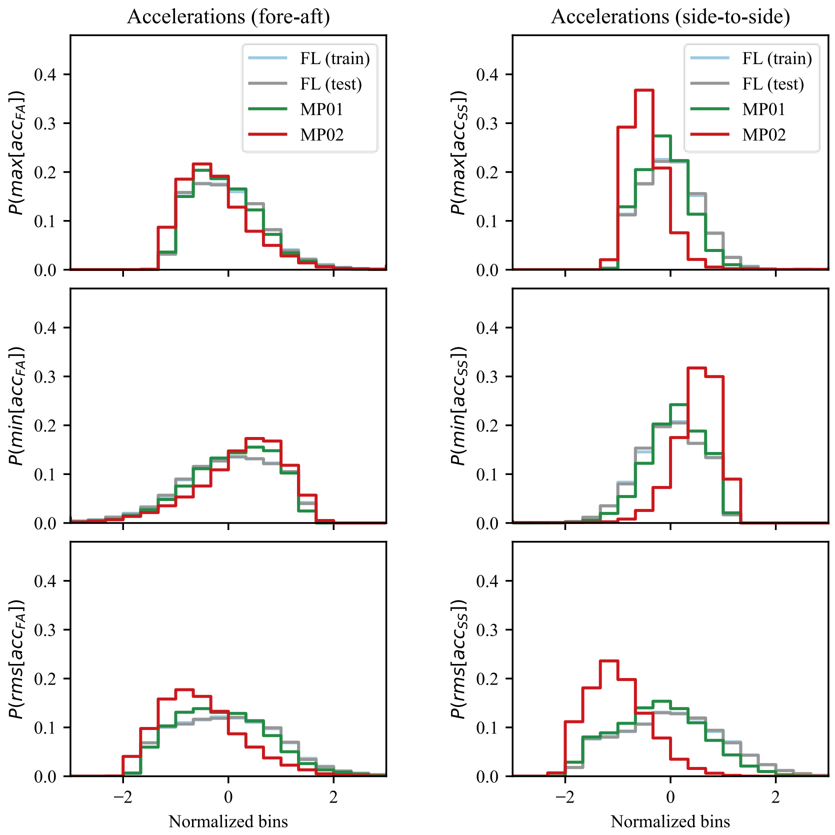


Okay

Okay

↑ $\mathrm{CoV}(\mu_y)$

Potential prediction inaccuracies

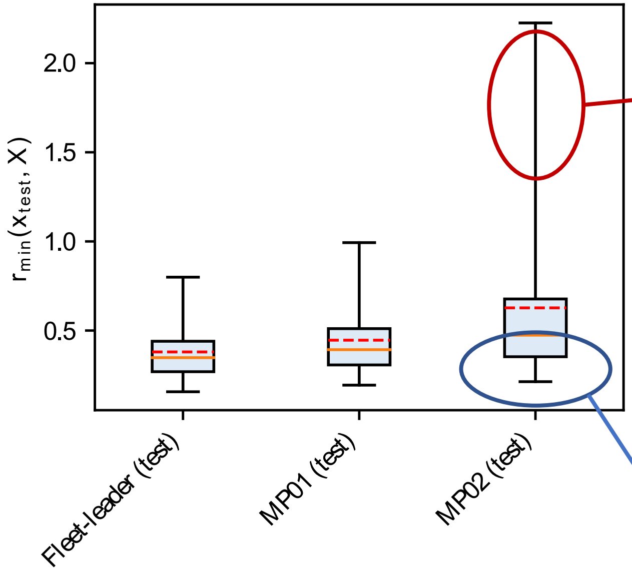


The BNN is receiving some unexplored data when deployed to MP02.

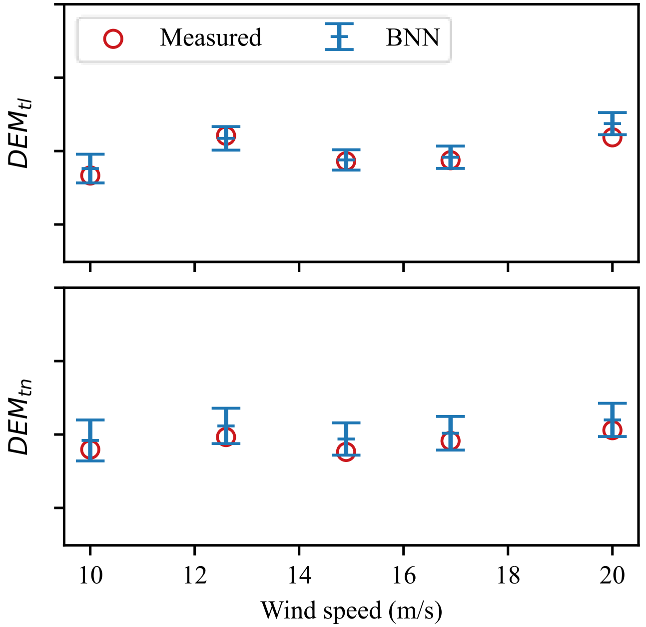
Case study: Belgian offshore wind farm

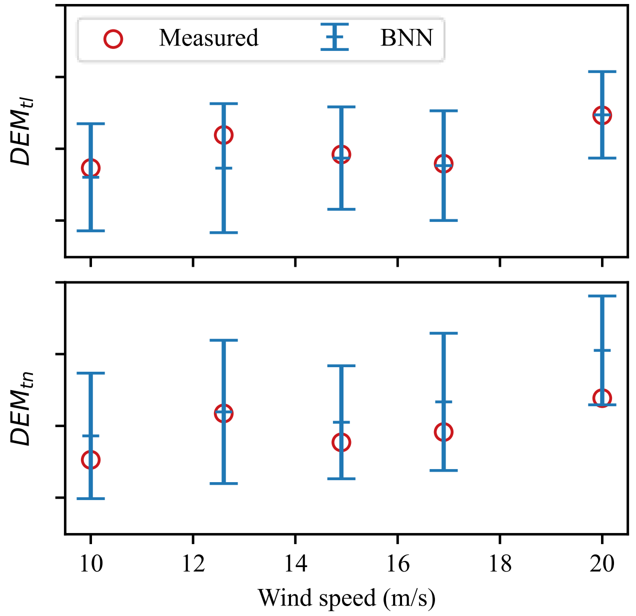
Comparison with measured labels (A subset of MP02 test data)

Minimum Eucleadian distance to the nearest training point.



In-training test samples.





Out-of-training test samples.

Future Work

- To compare with kernel-based methods, e.g., Gaussian processes.
- To quantify uncertainty for non-Gaussian output distributions.
- To implement in decision-making for life-cycle management.

For questions and comments:

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