

Uncertainty quantification of virtual monitoring information through probabilistic Bayesian neural networks

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(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

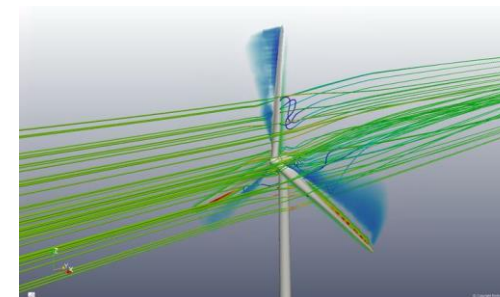
Labels \Leftrightarrow Model predictions (e.g., MAE, RMSE)

Conditions of strain gauges

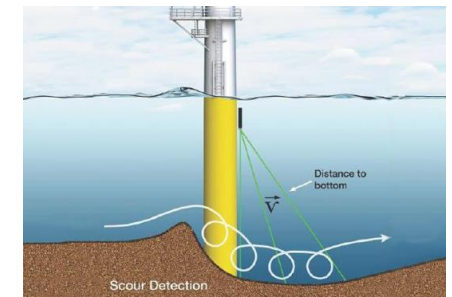


time

Wind turbine dynamics changes over time...



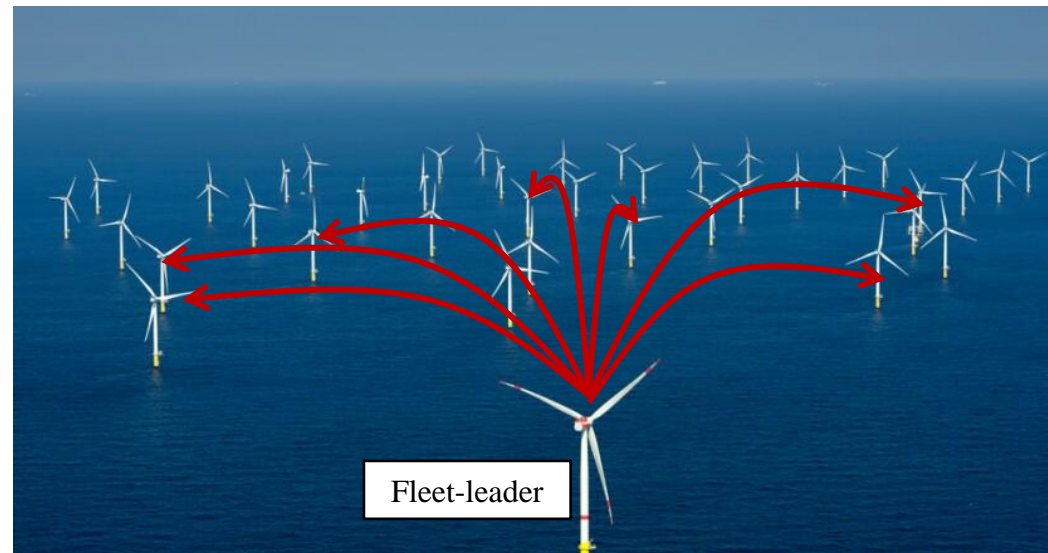
Ref: <https://www.pinterest.com/>



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

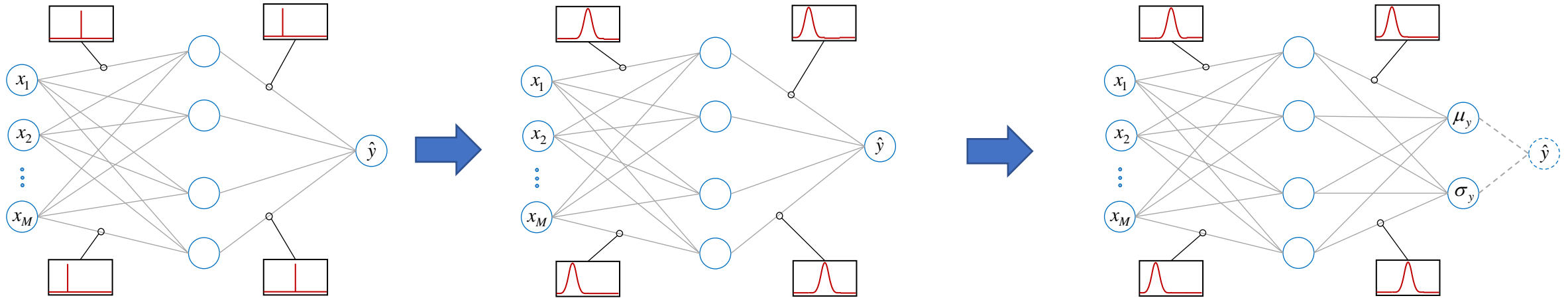
(2) Farm-wide applicability

- 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>

Bayesian Neural Networks



Standard deterministic neural networks

- Point weights and biases
- Point estimate output

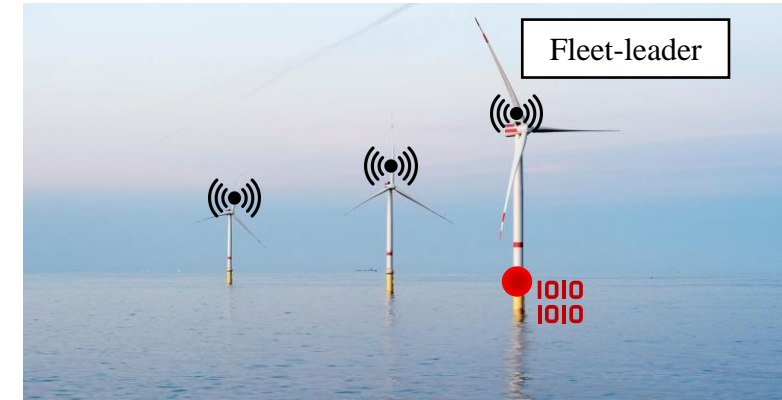
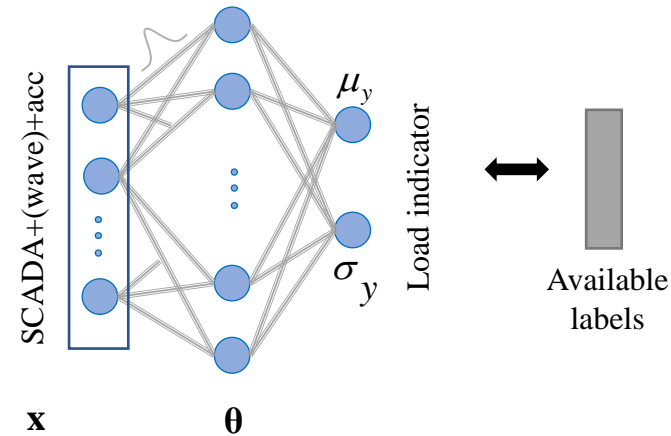
Epistemic Bayesian neural networks

- Probability distribution weights and biases
- Point estimate output

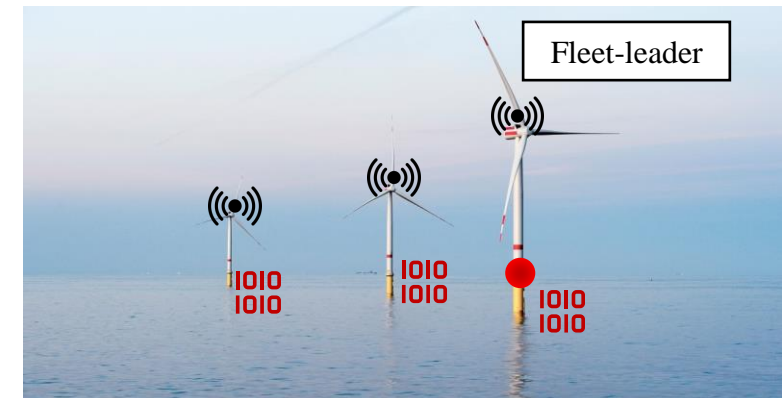
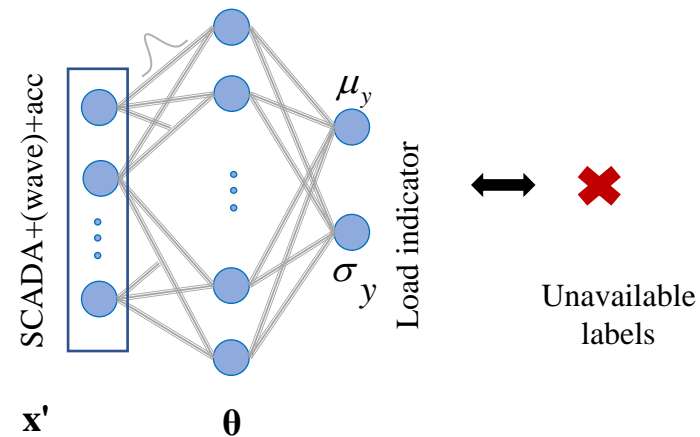
Probabilistic Bayesian neural networks

- Probability distribution weights and biases
- Probability distribution output

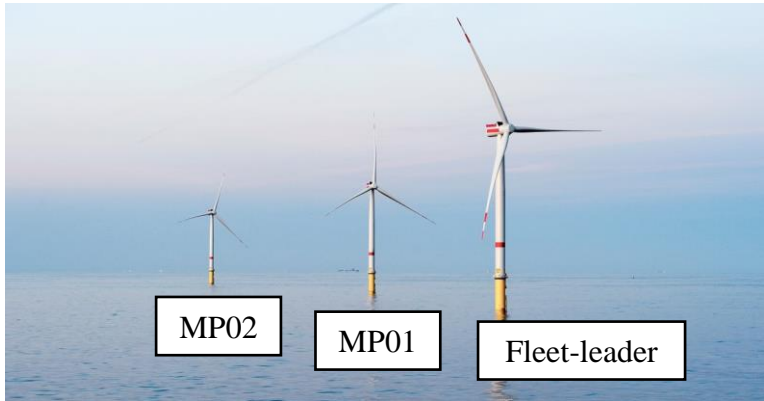
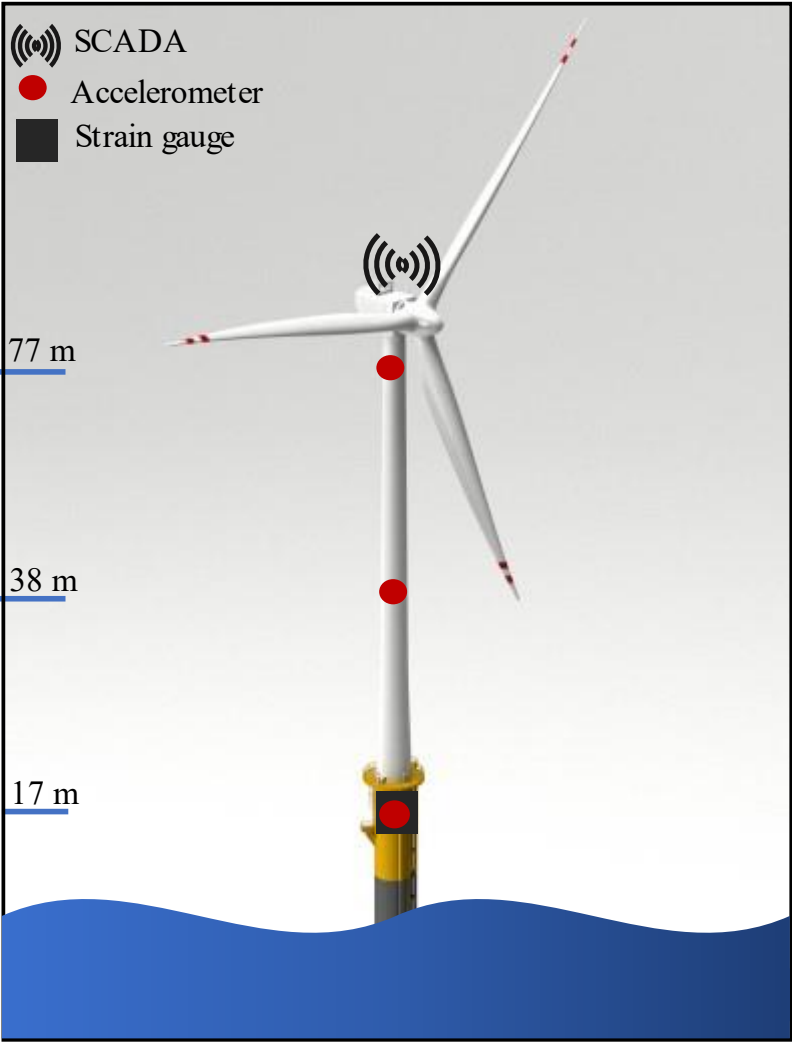
1. Training with fleet-leader data (input + labels)



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



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](https://doi.org/10.48550/arXiv.2211.00642)



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

SCADA

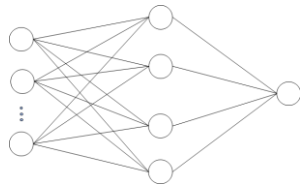
Rotational speed (mean)
Yaw angle (mean)
Pitch angle (mean)
Power (mean)
Wind speed (mean)
Wind speed (std)
Wind direction (mean)

Wave buoy

Wave height
Average wave period
Wave direction

Accelerometers

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

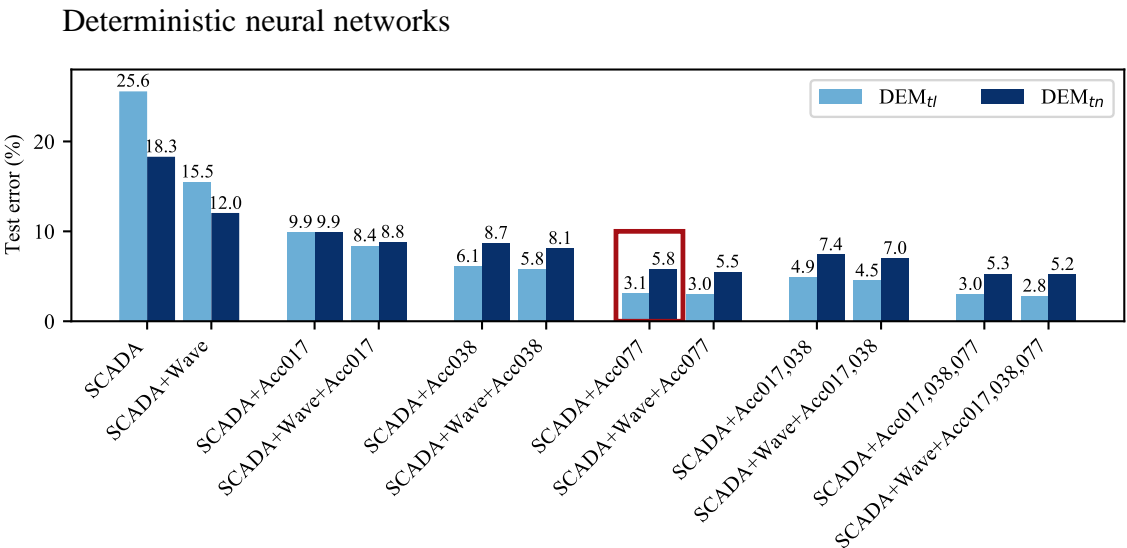
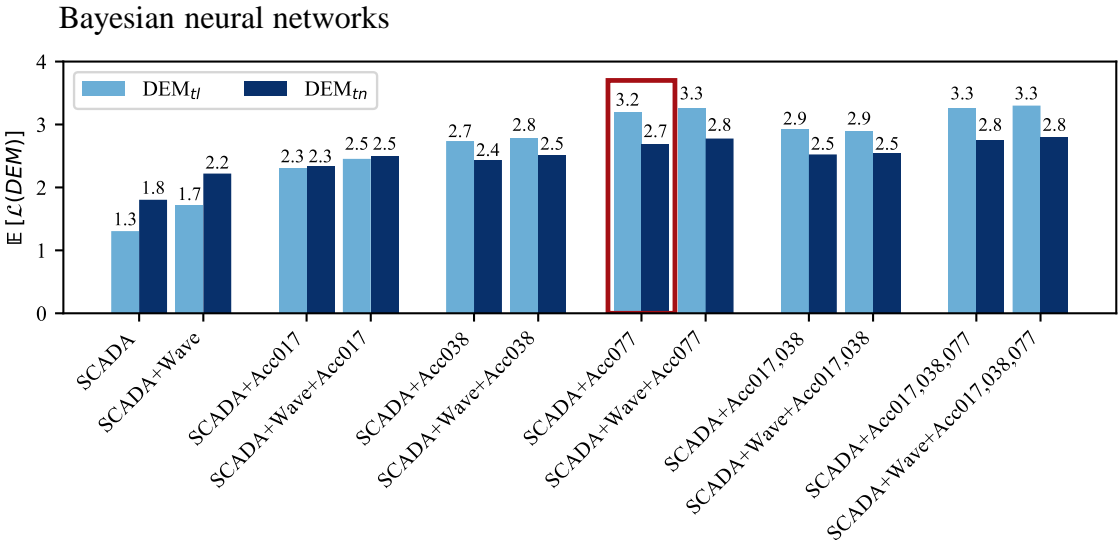
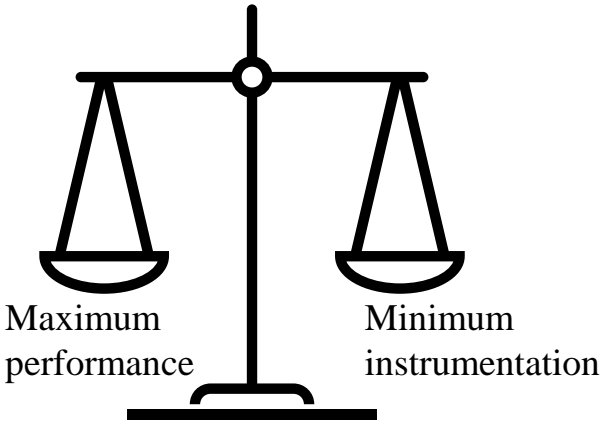


Strain gauges at 17m LAT

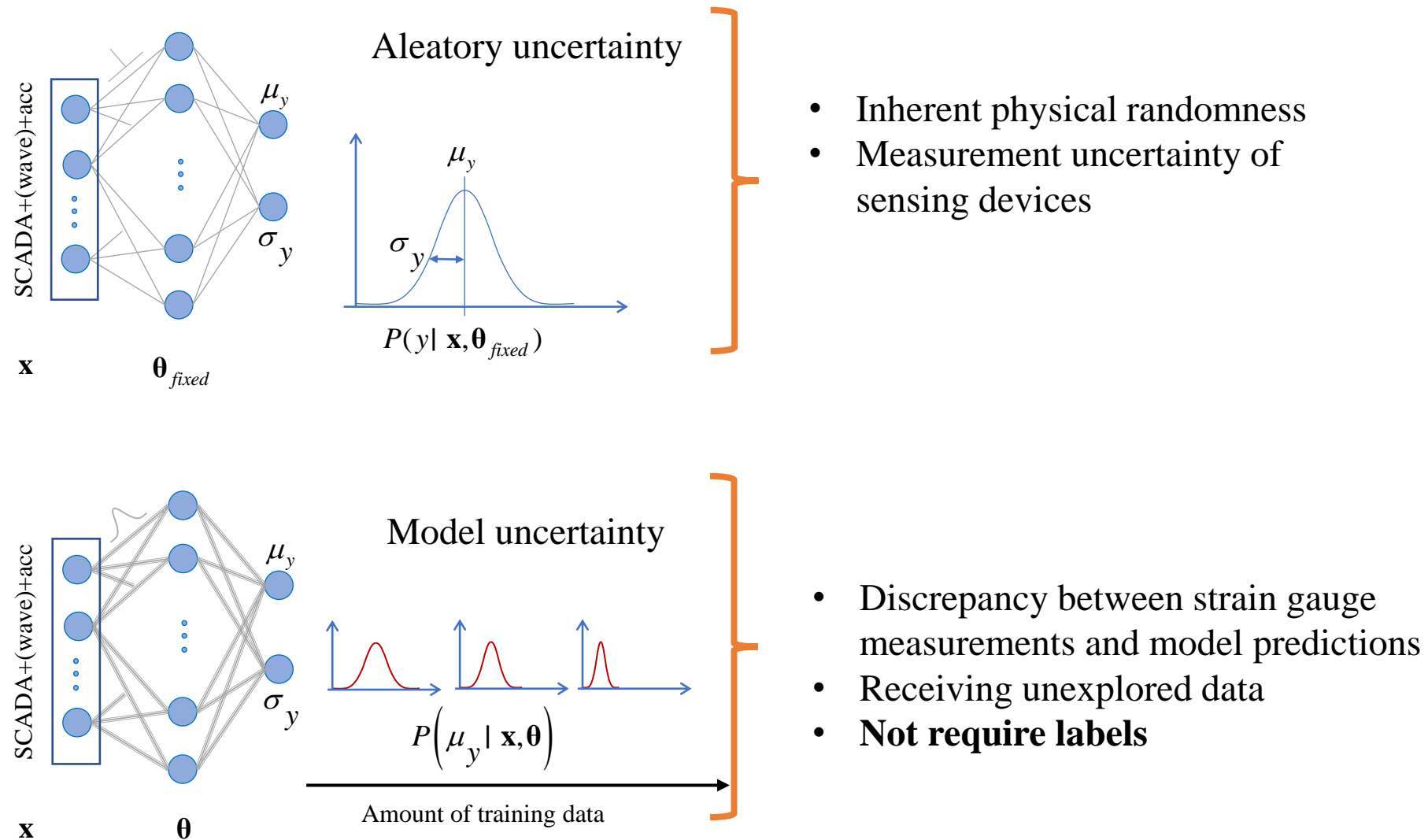
DEM_{tl}
 DEM_{tn}

Selection of input monitoring signals

- Aimed for farm-wide application

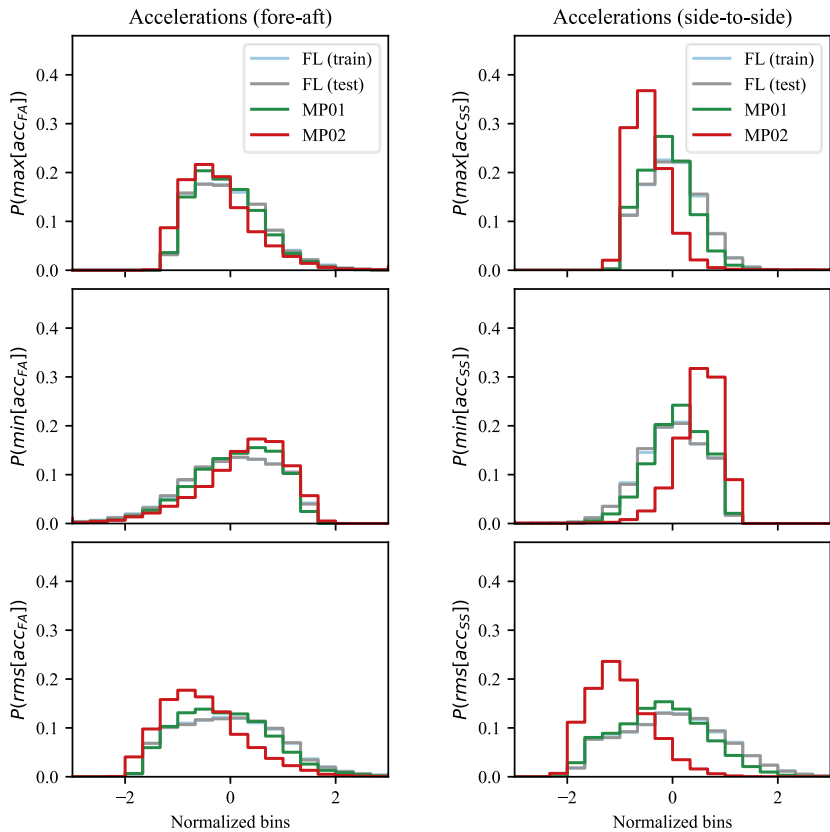
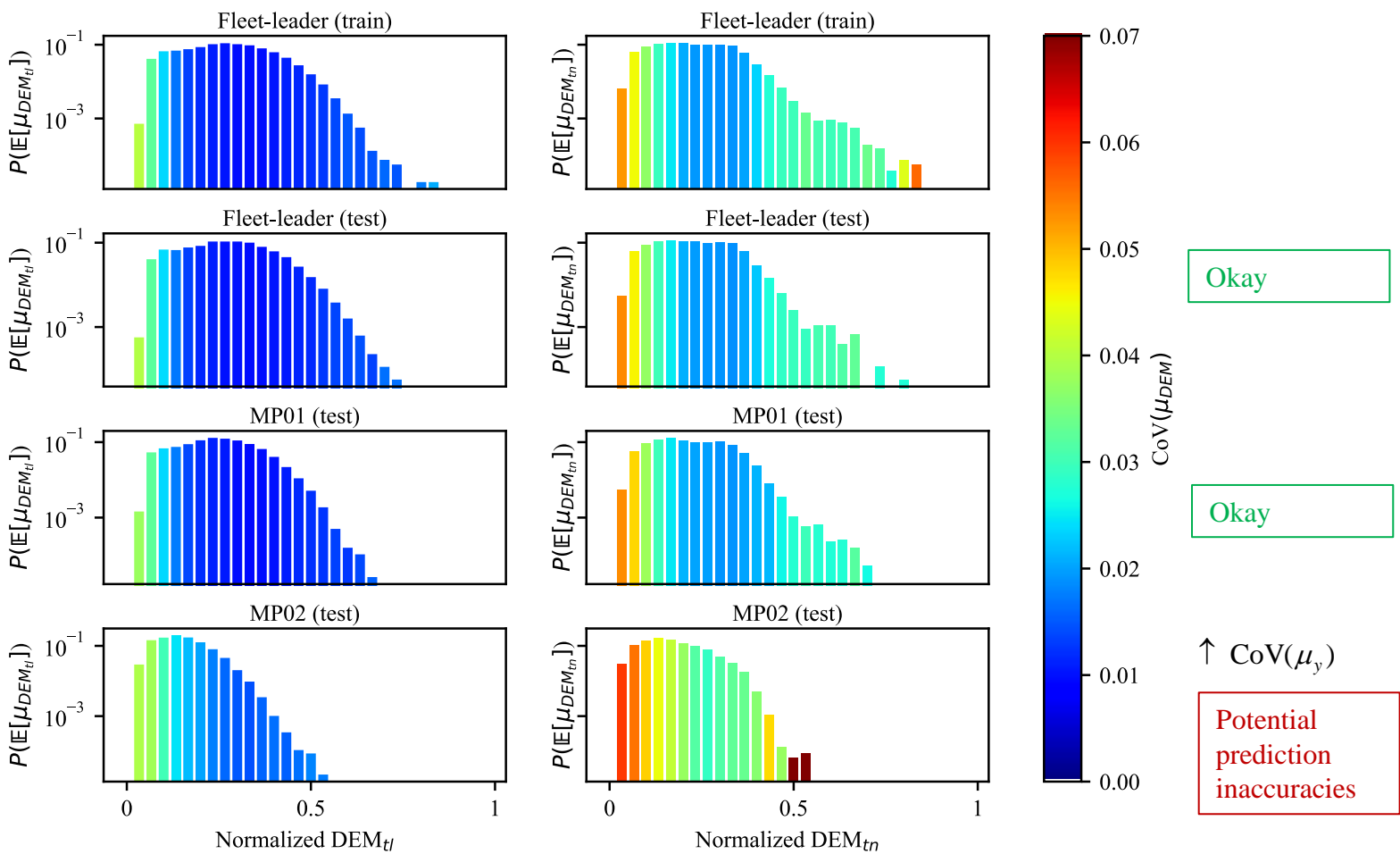


Uncertainty quantification of load predictions



Farm-wide deployment

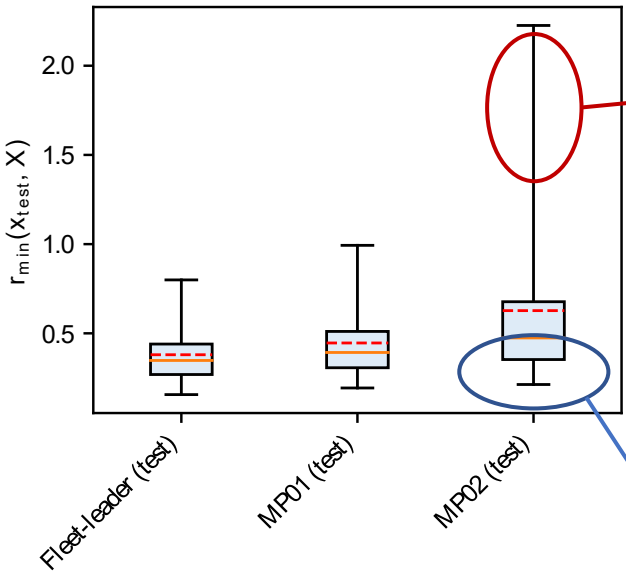
Distribution of DEM (side-to-side and fore-aft) and model uncertainty



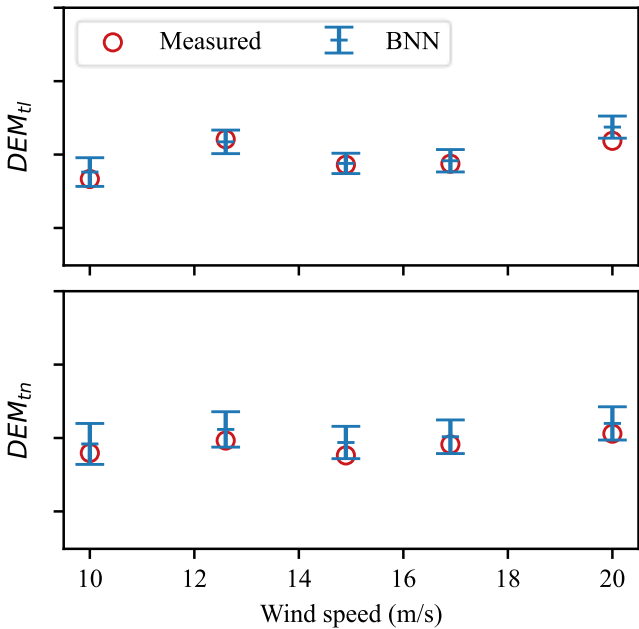
The BNN is receiving some unexplored data when deployed for MP02.

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

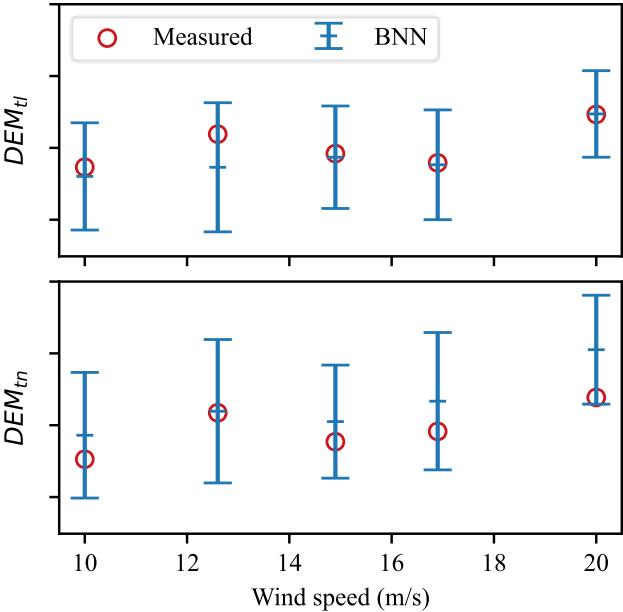
Minimum Euclidean distance to the nearest training point.



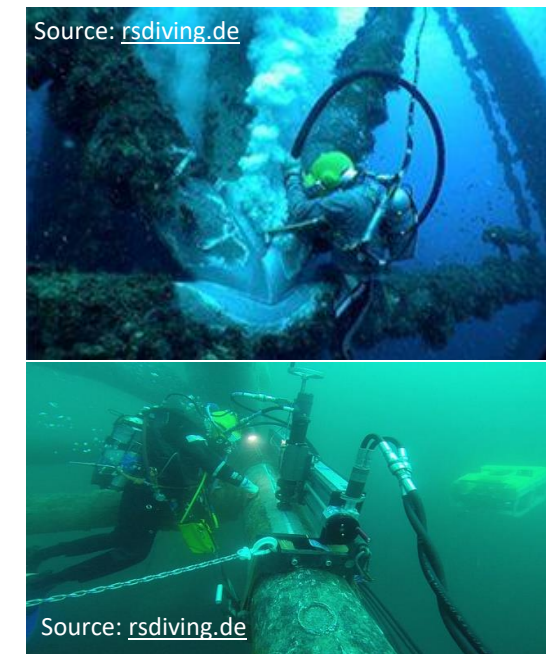
In-training test samples.



Out-of-training test samples.



- To thoroughly compare DNNs and BNNs.
- To compare with kernel-based methods, e.g., Gaussian processes.
- To implement in decision-making for life-cycle management.



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For questions and comments:

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