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Digital Twins for Wind Energy and Leading Edge Erosion Detection

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Wind Energy: Opportunities and Challenges

- US has **73,000+** turbines, which generate over **150 GW**.
- **Maintenance costs** are a large share of the energy price.[5]
- **Blade faults include:**
  - Cracks
  - Skin/adhesive debonding
  - Delamination
  - Fiber breakage
  - Edge erosion

Image Source: `demoinesregister.com`

[5] J. Tautz-Weinert S.J. Watson, *Using SCADA data for wind turbine condition monitoring*, IET Renewable Power Gen.,11 (2017), pp. 382-394

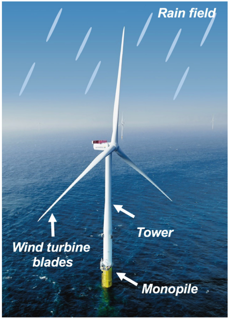
Remote Monitoring

Image Source: energyintel.com

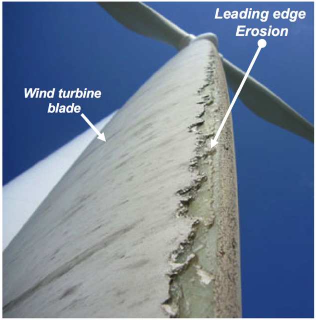
Image Source: industry.sitka.com

Early fault detection via remote sensor data improves maintenance and safety.

Leading-Edge Erosion



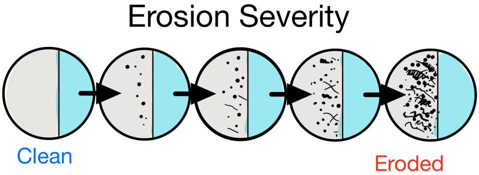
(A)



(B)

- Decreases lift/drag ratio.[7]
- Difficult to detect.
- Scarce data.

⇐ Severe erosion build up.[8]

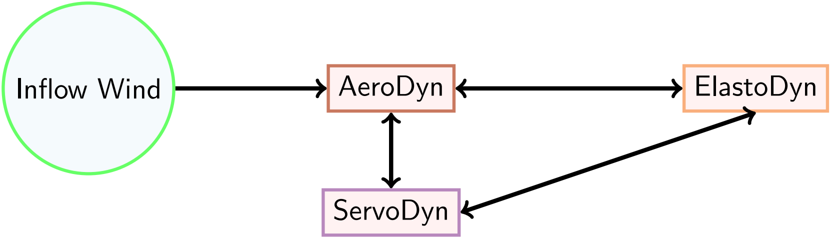


[7] A. Sareen et al., *Effects of leading edge erosion on wind turbine blade performance*, Wind Energy, 17 (2014), pp. 1531-1542

[8] A. Shankar Verma et al., *A probabilistic long-term framework for site-specific erosion analysis of wind turbine blades*, Wind Energy, 24 (2021), pp. 1315-1336

Simulation

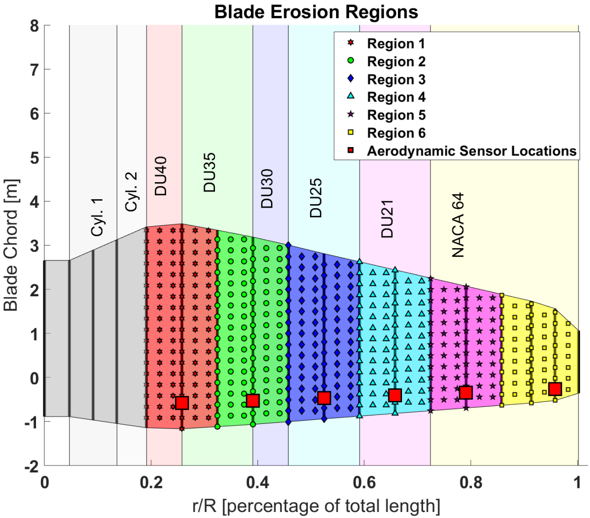
Definition: *OpenFAST*, from the National Renewable Energy Laboratory (NREL), couples multi-physics modules to model turbine responses to realistic wind/weather simulations.[9]



- **InflowWind:** wind conditions
- **AeroDyn:** aerodynamics: lift, drag
- **ElastoDyn:** structural motions
- **ServoDyn:** control inputs/outputs

[9] J. Jonkman, *The new modularization framework for the FAST wind turbine CAE tool*, in Proceedings of 51st AIAA aerospace sciences meeting including the new horizons forum and aerospace exposition, 2013

Edge-Erosion Simulator Design



Our Edge-Erosion model is a new adaptation of the OpenFAST framework.

OpenFast Inputs and Outputs

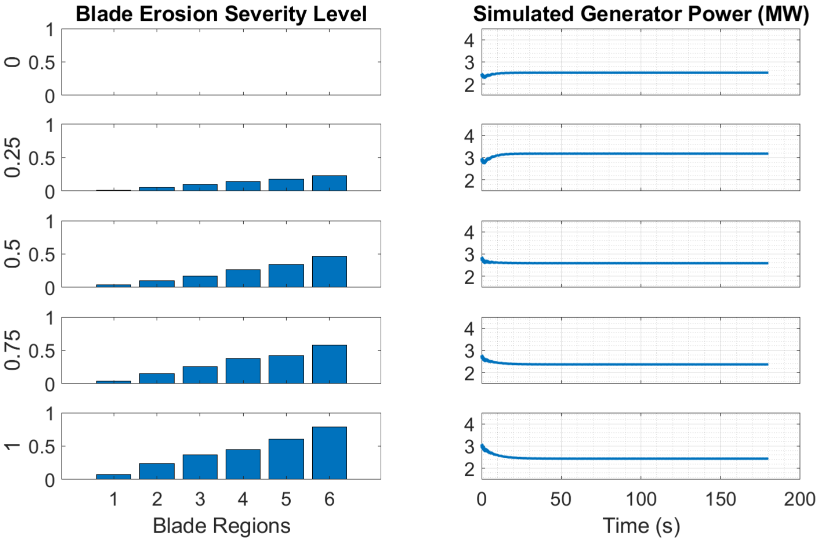
OpenFAST Erosion Model Input Parameters

Input	Nominal Value	Range	Units
Wind Direction	0	[-15, 15]	(m/s^2)
Wind Speed	11.4	[3, 25]	(m/s)
Air Density	1.225	[1.1, 1.42]	(kg/m^3)
Wind Shear Coefficient	0.2	[0, 0.5]	(-)
Erosion Severity	0	[0, 1]	(-)

OpenFAST Erosion Model Output Quantities

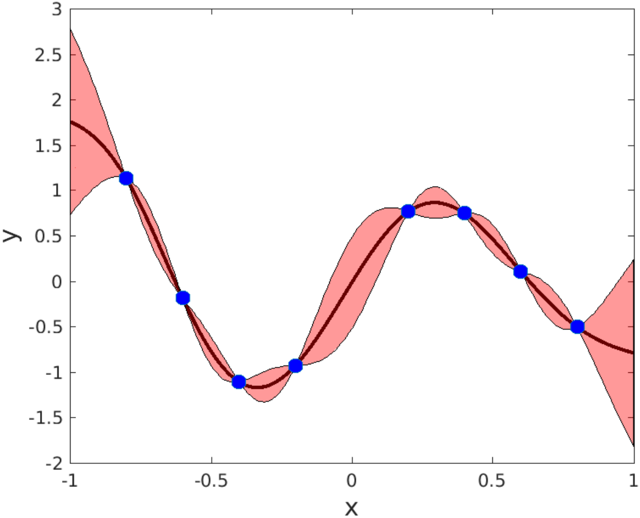
Output	Units	Description
Blade Tip Acceleration	(m/s^2)	Blade local flapwise acceleration
Drag Sensor	(-)	Drag sensor located in blade region 6
Lift Sensor	(-)	Lift sensor located in blade region 6
Generator Power	(MW)	Generator Power after control and electrical effects
Blade Root Moment	$(kN - m)$	Blade edgewise moment (caused by edgewise forces) at the root of the blade.

OpenFAST Output



For this model, each simulation takes $\approx$ **45** seconds.

GP Predictive Emulator With Uncertainty[10]



[10] Sacks, J., Welch, W. J., Mitchell, T. J., and Wynn, H. P. (1989). Design and Analysis of Computer Experiments. Statistical Science, 4(4):409–435.

Gaussian Process Modifications

Surrogate modeling of a wind turbine must account for:

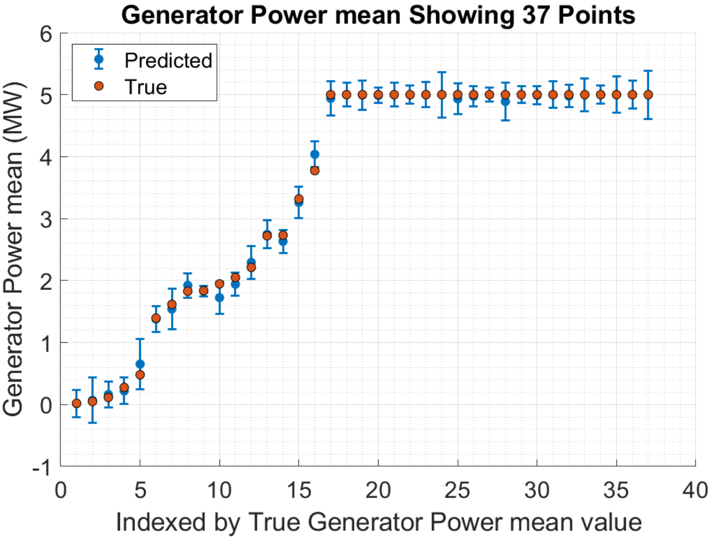
1. Vector Valued Outputs: turbines are equipped with a variety of sensors.
   - Solution: Parallel Partial Gaussian Process emulator [11]
2. Range Limited Outputs: e.g., generator power is constrained to $\leq$ 5MW.
   - Solution: zGP emulator [12]

Operation	Time
Simulation Routine	45.72 s
PPzGP Imputation (173 training points)	1415.85 s
Fit PPzGp (173 training points)	3.443 s
Predict from PPzGP	0.0093 s

[11] M. Gu, J.O. Berger, *Parallel Partial Gaussian Process Emulation for Computer Models with Massive Output*, Annals of Applied Statistics, (2016), pp. 1317-1347

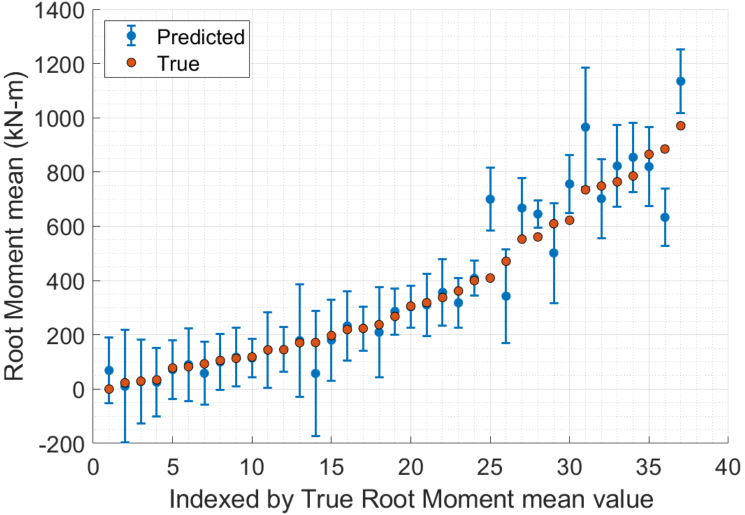
[12] E. Spiller et. al., *The Zero Problem: Gaussian Process Emulators for Range-Constrained Computer Models*, SIAM/ASA UQ, (2023), pp. 540-566

PPzGP Generator Power Predictions



- Training set size: 173 design points
- Testing set size: 37 points.

PPzGP Root Moment Predictions



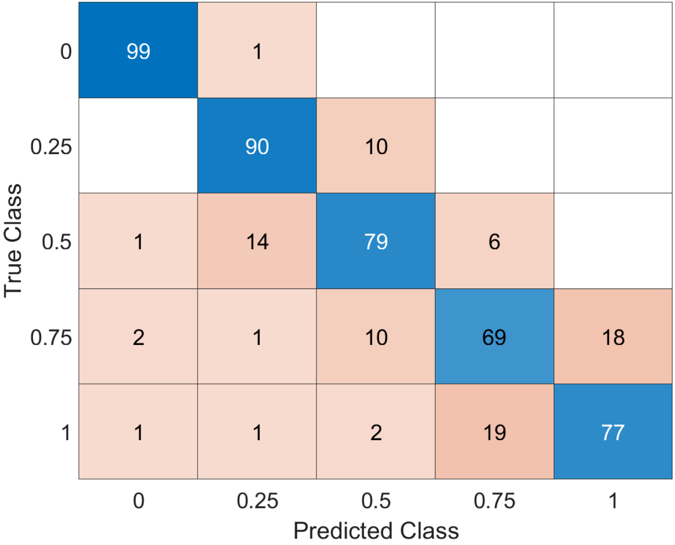
- Training set size: 173 design points
- Testing set size: 37 points.

Erosion Severity Classification Experiment

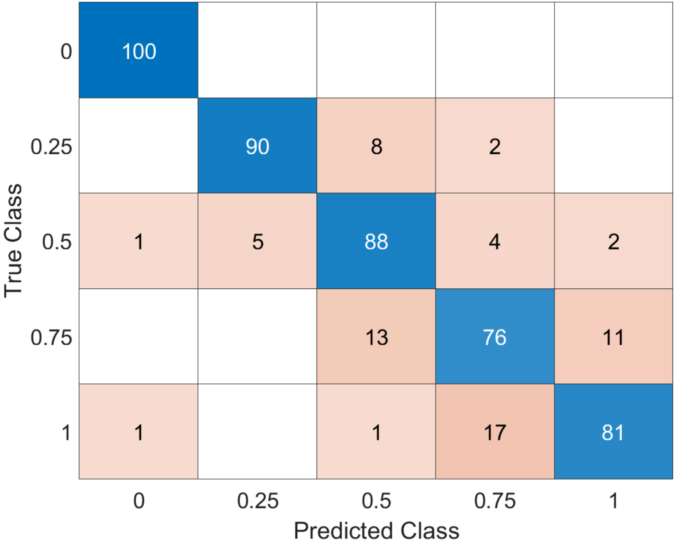
Objective: Use the **PPzGP** surrogate model to train an erosion severity classifier.

- Compare two random forest classifiers:
  - One trained on 500 OpenFAST simulated data points.
  - Second trained by sampling 5000 points from the emulator (very cheap, 2s total time).
- Experimental design space includes
  1. Randomly vary erosion within chosen level.
  2. From sensitivity analysis 3 most influential environmental parameters to vary for the design are wind direction, wind speed, and air density.
  3. train two classifiers using 10-fold cross validation and test on same data.
  4. Goal: classify erosion into 5 levels from no erosion (level 0) to highest erosion (level 1).

Results: Simulation Trained Classification Model



Results: Emulation Trained Classification Model



Conclusion: Emulation for Erosion Detection

	Simulation Trained	Emulation Trained
AUC mean	0.969	0.983
AUC std	0.026	0.015
% Improvement	(-)	1.508%
Accuracy mean	0.828	0.871
Accuracy std	0.037	0.045
% Improvement	(-)	5.169%

- Emulator functions as an accurate reduced order model of the full simulator.
- One OpenFAST simulation takes 45s.
- Emulator sampling/prediction takes 0.01s.
- Training the ML model on data directly from simulator and on data from emulator gives similar prediction accuracy.