

#### Innovation Fund Denmark



# Leading edge erosion defect forecasting and its coupling to wind farm control

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### **Presentation outline**

- Introduction to the Blade Defect Forecasting (BDF) project
- Data (weather and blade inspections)
- Modelling
- Results
- Perspective to wind farm control



### Introduction to BDF

#### **Motivation:**

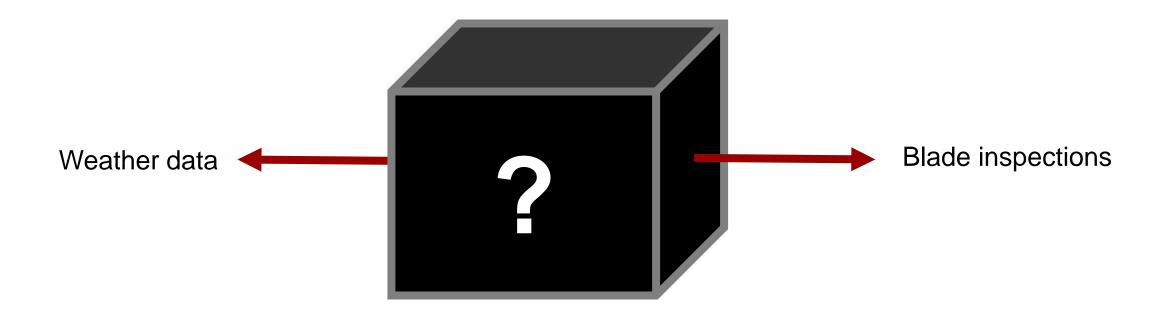
- Unplanned blade repairs account for a major added operational expense
- Wind turbine blade maintenance plans are typically based on assumptions
- There is a need for site-specific blade maintenance planning for:
  - 1. Already operating wind farms
  - 2. New sites

#### **Objectives:**

- Develop a blade defect forecasting tool that can be used to estimate the expected defects based on environmental parameters
- Identify inter-relations between blade degradation and environmental conditions
- Establish a comprehensive environmental parameter database for Northern Europe based on mesoscale weather data

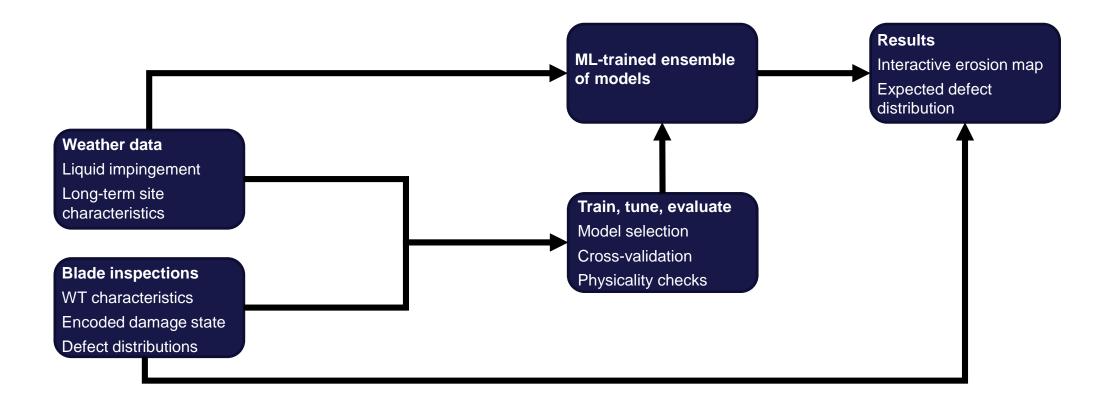


# **Modelling problem**



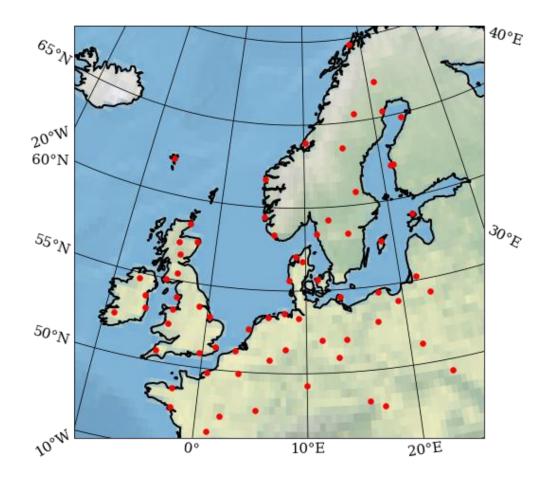


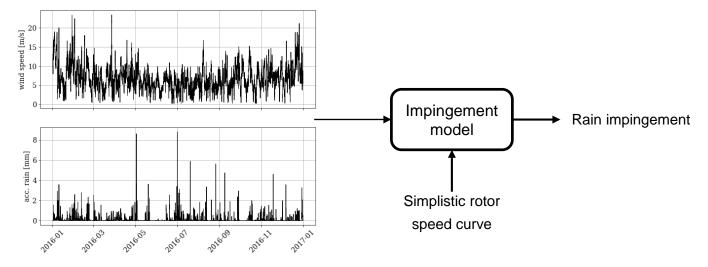
# Proposed modelling workflow





## Weather data





- Provided by DMI's NWP model HARMONIE
- 106 sites located in Northern Europe
- Mesoscale data with:
  - Horizontal resolution: 2.5 km
  - Temporal resolution: hourly
- Data format:
  - Accumulated hourly surface fields (e.g., precipitation)
  - Model level fields (e.g., wind speed, wind direction, TKE)
- Rain impingement how much rain has hit the tip of the blade



# **Blade inspections**

- 12 inspections on 7 different wind farms in Northern Europe
- Inspections are performed manually, ground- or drone-based
- 678 blades inspected with more than 14,000 defects observed on the leading edge
- Defects are categorized by defect type and severity
- Sequences of weather data with blade inspections gives us damage states at the start and end of each sequence → 18 samples in total

2009	2010	20	2011		2012 2013		13	2014		2015		2016		2017		2018		2019		2020	
Wind farm 1																					
Wind farm 2																					
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# Defect encoding to damage state

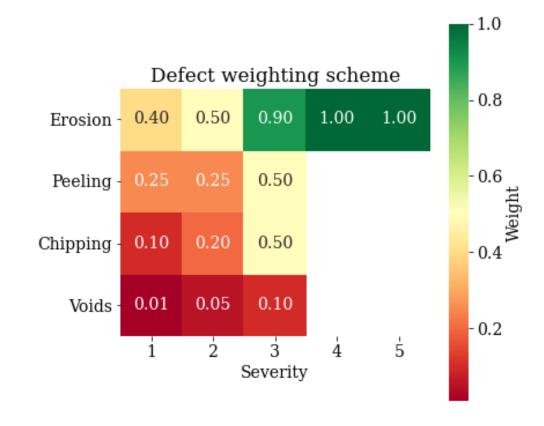
**Problem**: We need to encode a full wind farm inspection into a numerical value that can be used for modelling

#### Solution:

- 1. Assigning weights to each defect category that reflects the urgency for repair
- 2. Per inspection  $\rightarrow$  per blade  $\rightarrow$  max defect

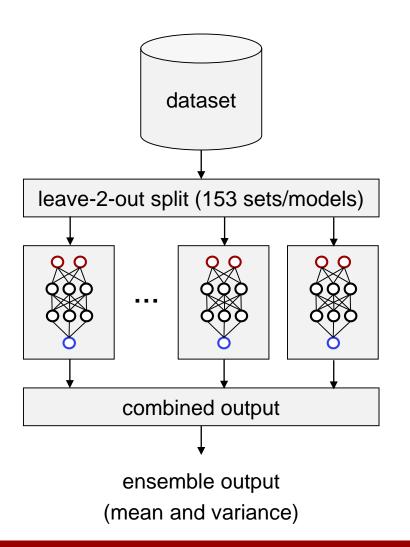
#### Output:

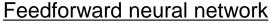
- 1. An encoded damage value per inspection that represents the state of the wind farm
- A joint distribution of defects (type and severity) that is conditioned by the encoded damage state





# **Ensemble modelling**





Model architecture:

#### Inputs:

- impingement
- encoded damage state at start

#### Output:

encoded damage state

#### Hidden layers:

- two hidden layers with 10 neurons in each
- relu activation
- no regularization
- kernel initializers = RandomNormal( $\mu = 0.5$ ,  $\sigma = 0.5$ )

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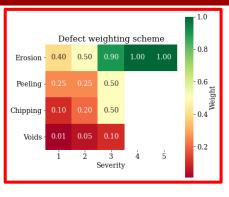
bias initializers = Zeros()

#### Loss:

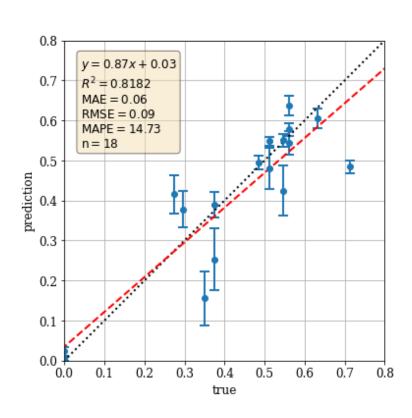
mean squared error

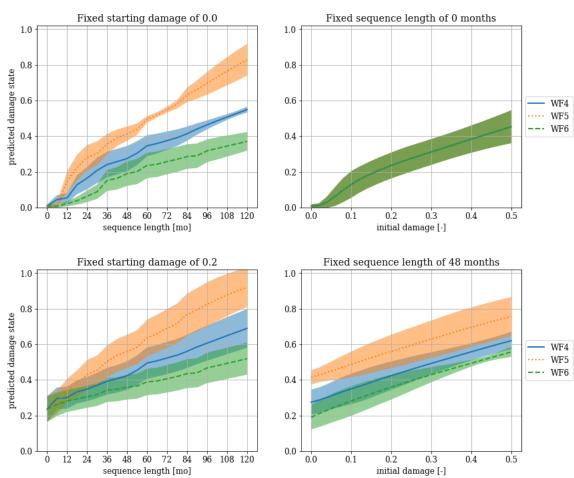


# **Model performance**



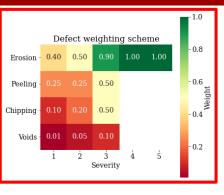
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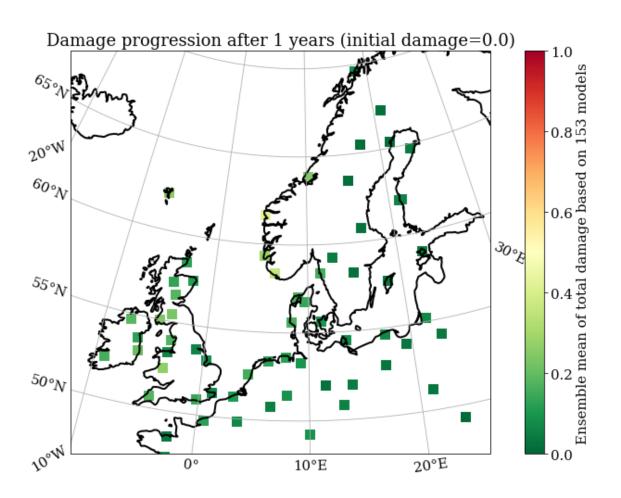


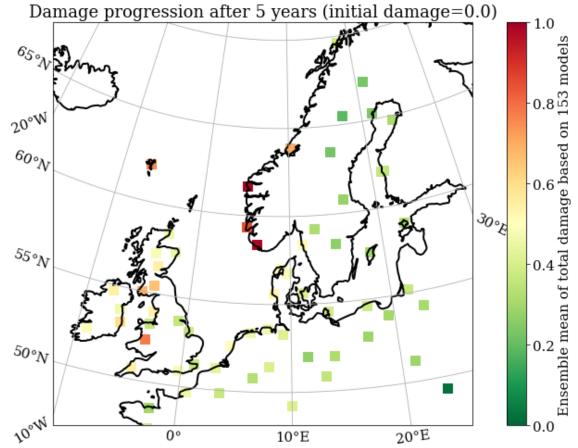


# Results – mapping tool



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#### **Future work**

#### **Short-term:**

- More sites → better populated erosion map
- Decoding damage state back to expected distribution of defects
- How does input uncertainty propagate through the model?

#### **Long-term:**

- More inspections → better uncertainty quantification
- Implement the defect forecasting model into a wind farm control framework

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# Perspective to wind farm control

#### **Concept of BDF tool for optimal LEE control:**

Rotor speed curve → impingement model →

BDF tool

→ Expected damage state

#### Wind turbine:

- Design variables: Rotor speed curve and rain threshold
- Single WT control → not considering added effects on farm level

#### Wind farm:

- Design variables: Rotor speed curve(s!) and rain threshold(s!)
- Combined WT-specific control → wake effects, loads

# Questions