Deepwind 2021 conference

Wind farm set point optimization with surrogate models for load and power output targets

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Background

The main objective:

Device set-points reflecting the optimal balance between WPP power production and cost of WPP loading from an economic perspective

Acknowledgement:

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Objectives of this study

- Develop a methodology for wind turbine set-point selection for de-rating strategies, which allow **loads and power output targets** as optimization criteria

- This involves changing rotor speed and blade pitch set-points of **individual turbines** in the wind farm

Assumptions and other requirements

- We use fatigue loads as a proxy for costs (e.g. due to design lifetime consumption, O&M costs)
- A more advanced cost function based on a combination of loads & power output is also applicable to the same procedure
- We need a model which can predict both power and loads in a computationally efficient manner
- We use gradient-based methods, so any model output needs to be at least L-1 continuous (to make differentiation possible)
- Wake effects and upwind turbine de-rating to be considered simultaneously
- We look at quasi-static (open-loop) strategies on a 10-minute scale

Definition of objective functions

- **Variable types:**

P: Power output

ΔD: Fatigue damage accumulated over a reference period (10min)

$DEL \propto (\Delta D)^{\frac{1}{m}}$: Damage-equivalent loads

- **Potential optimization problems for a farm with N_T turbine units:**

A) Power maximization:

Maximize $\sum_{i=1}^{N_T} P_i$

subject to: $DEL_i \leq DEL_{max}, for\ all\ i = 1 \ldots N_T$

B) Fatigue minimization at target power:

Minimize $\sum_{i=1}^{N_T} DEL_i$

subject to: 1) $\sum_{i=1}^{N_T} P_i = P_{target}$

2) $DEL_i \leq DEL_{max}, for\ i = 1 \ldots N_T$

Suggested approach

1. Definition and implementation of potential derate strategies

2. Variable space definition (e.g. environmental, operational regimes, farm geometry)

3. Hawc2 simulations on a DoE filling the variable space

4. Surrogate model mapping power output and loads vs. environmental inputs and derate strategies

5. Set up a constrained optimization routine using surrogate model predictions

6. Exploration of the derate strategy space to find optimal strategies

1. Definition of derate strategy

Derate index: $DI \in [0,1]$

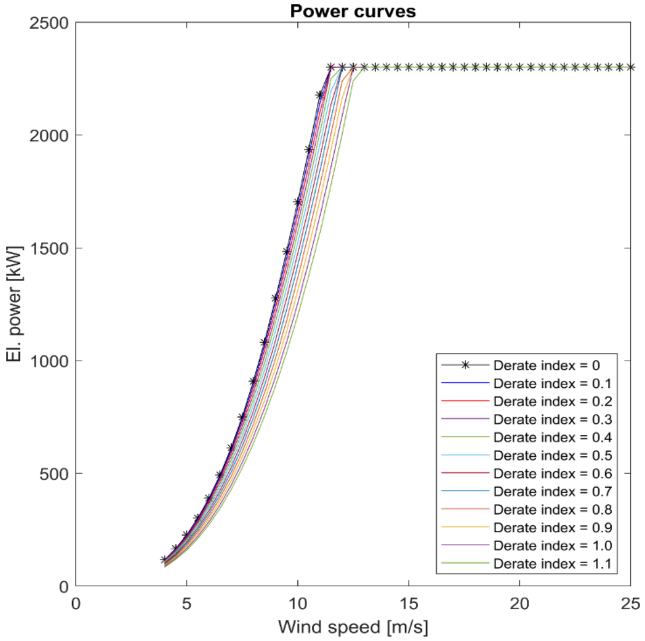
Minimum pitch setting: $\varphi_{min} = -1 + 5DI$

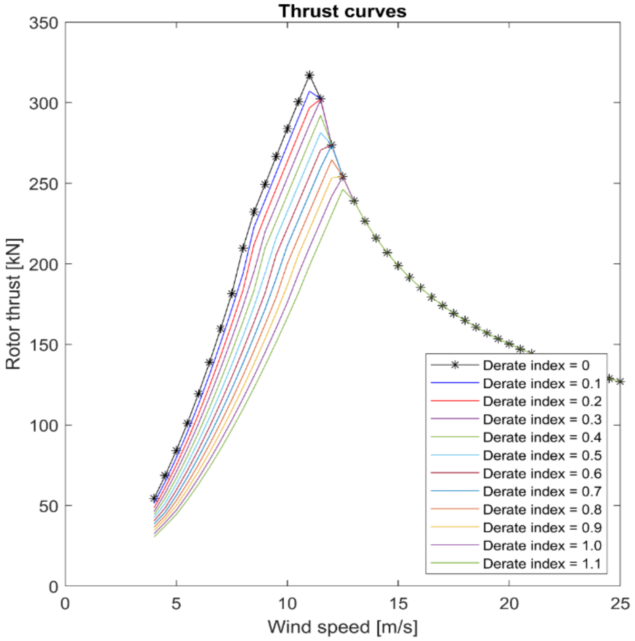
Torque demand multiplier setting: $K = 0.7 + 0.4DI$

(K controls the generator torque through the relationship $T_g = K\omega^2$)

Modifying thrust/torque settings – controlled by a single "derate index"

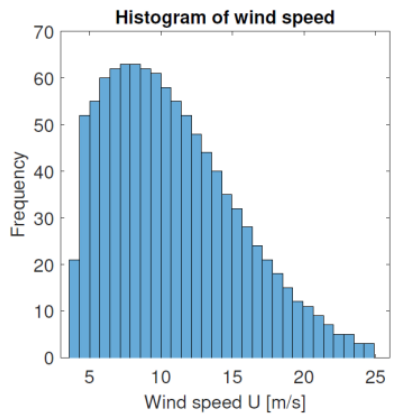
- Allows for the derate effect to be controlled by a single variable => easy to simulate
- Consistent with strategies applied to same turbines in earlier studies

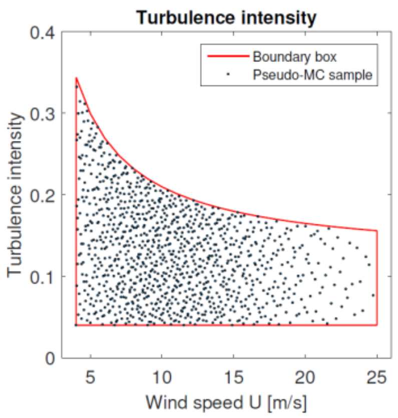


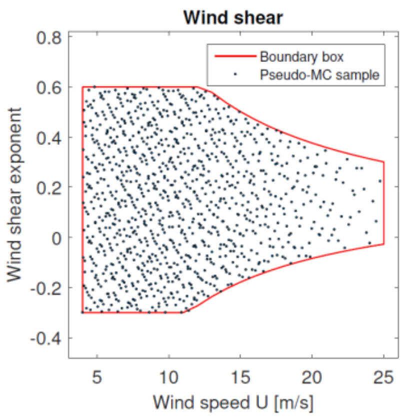


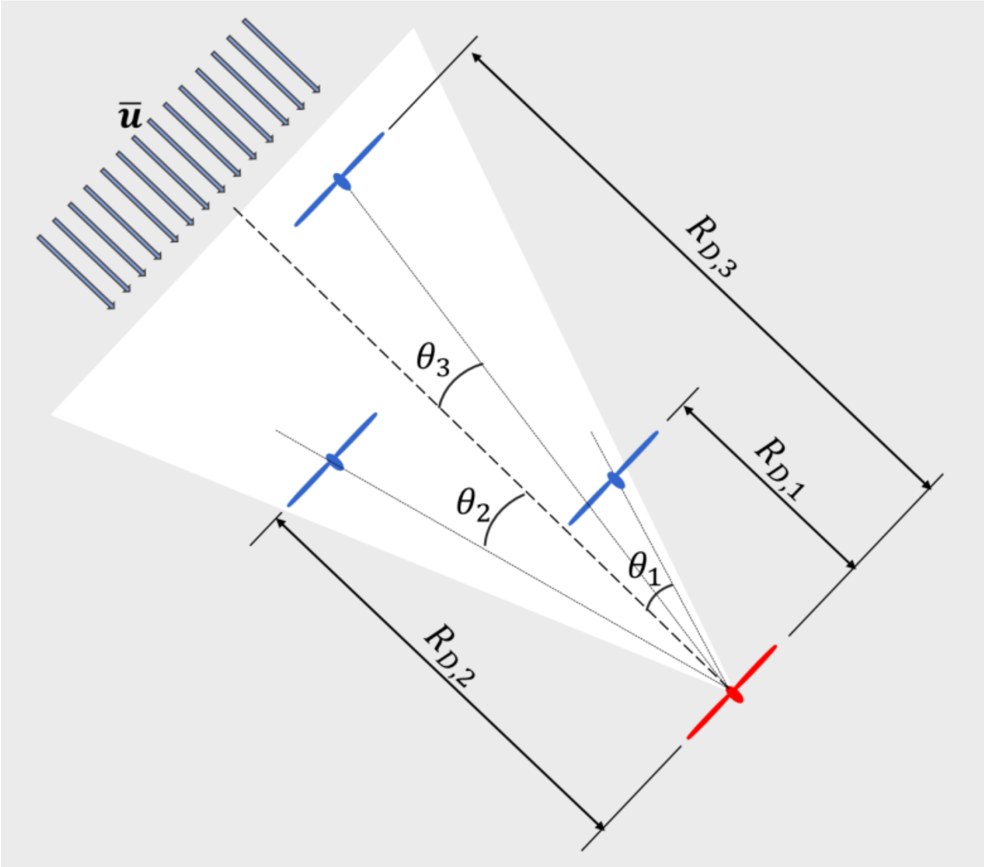
2. Variable space definition

- Wind speed (cut-in to cut-out)
- Turbulence
- Wind shear
- Derate index on the simulated turbine
- Derate index of disturbing turbines
- Relative position of disturbing turbines (parameterized)



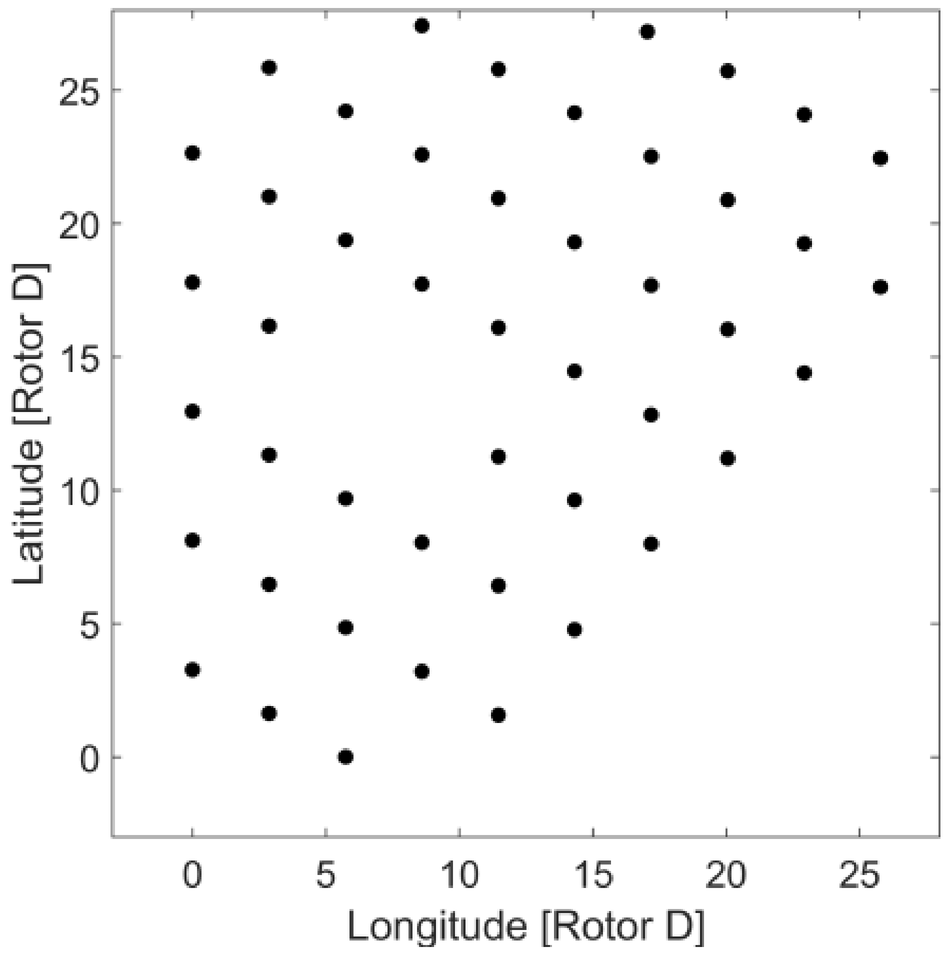






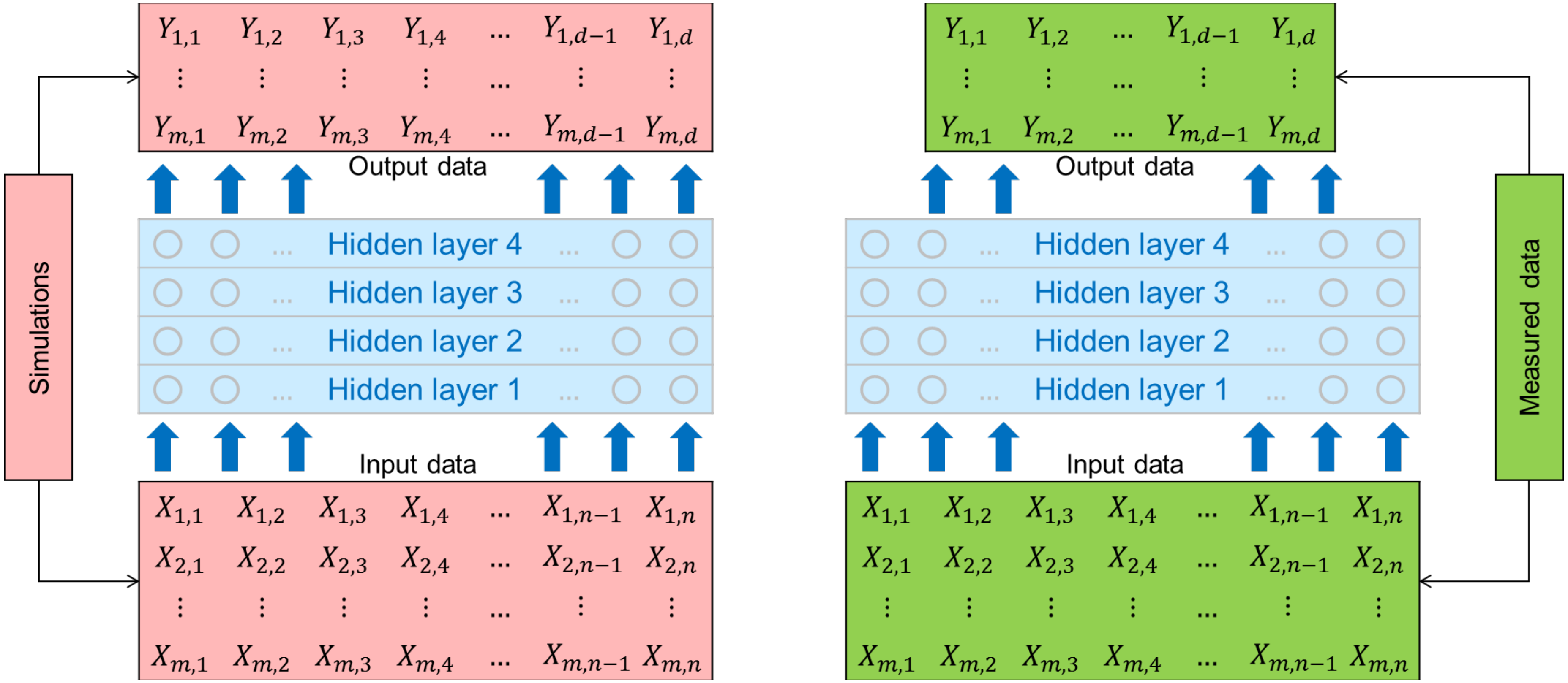
3. Hawc2 simulations - algorithm

- Full wind farm simulated with the DWM in each simulation
- For each simulation instance, random wind direction and random turbine from the farm are picked up. Other turbines are input as wake sources in DWM.
- All wake sources are assigned a specific derate index which translates to wake deficit parameters in DWM.
- The turbines considered upwind from the simulated turbine are selected based on the wind direction and a relative angle range (e.g $\pm 15\text{deg}$). Their relative positions and derate indices are defined as input features for the surrogate model training.
- Other variables (wind speed, turbulence) follow their predefined distributions



4. Surrogate model fitting

- Artificial Neural Network (ANN)
- Can be used both based on simulations or measured data (or both)

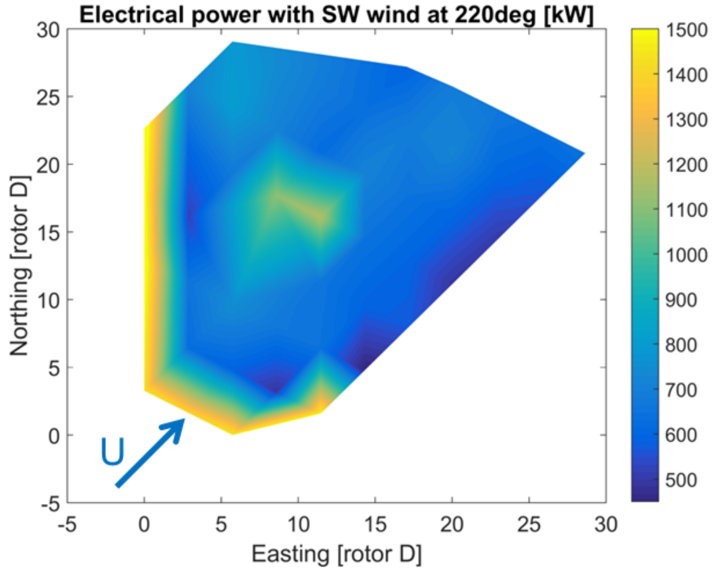


Validation with Lillgrund data without derating

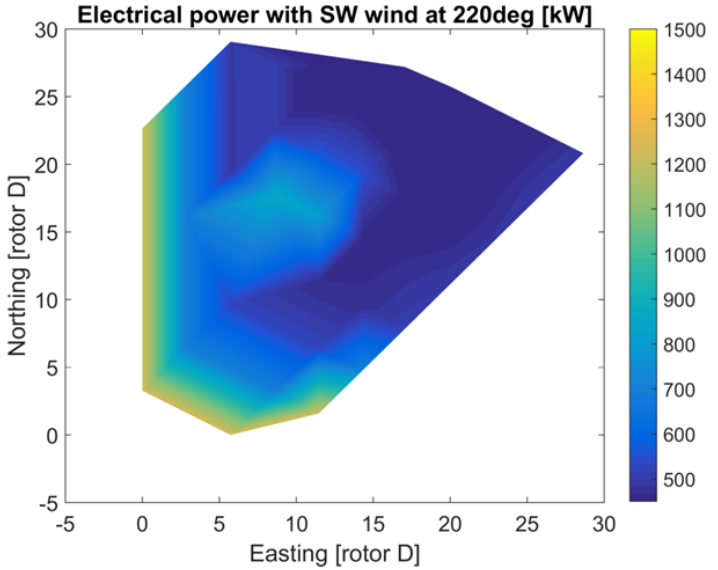
- Load and power predictions with the surrogate model approach compared to measured data **without de-rating**:
  - Power from SCADA on all turbines
  - Blade loads on C-08

- Different models (purely simulation-based as well as entirely data-driven) are tested

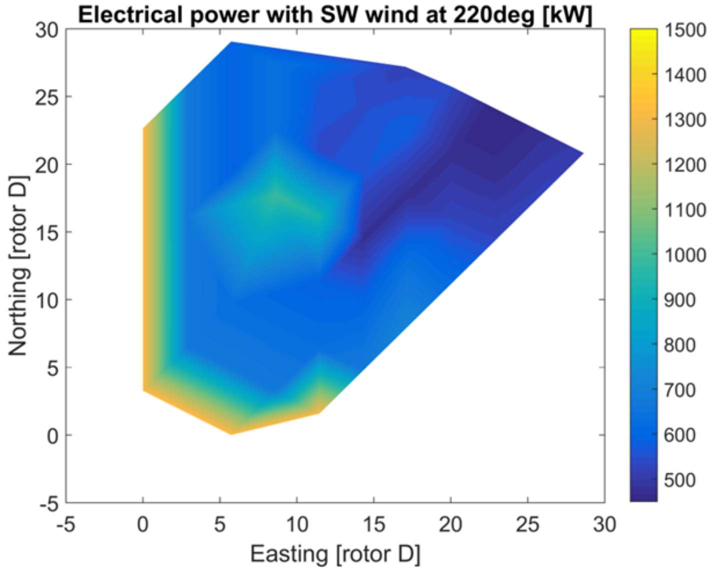
Measured data



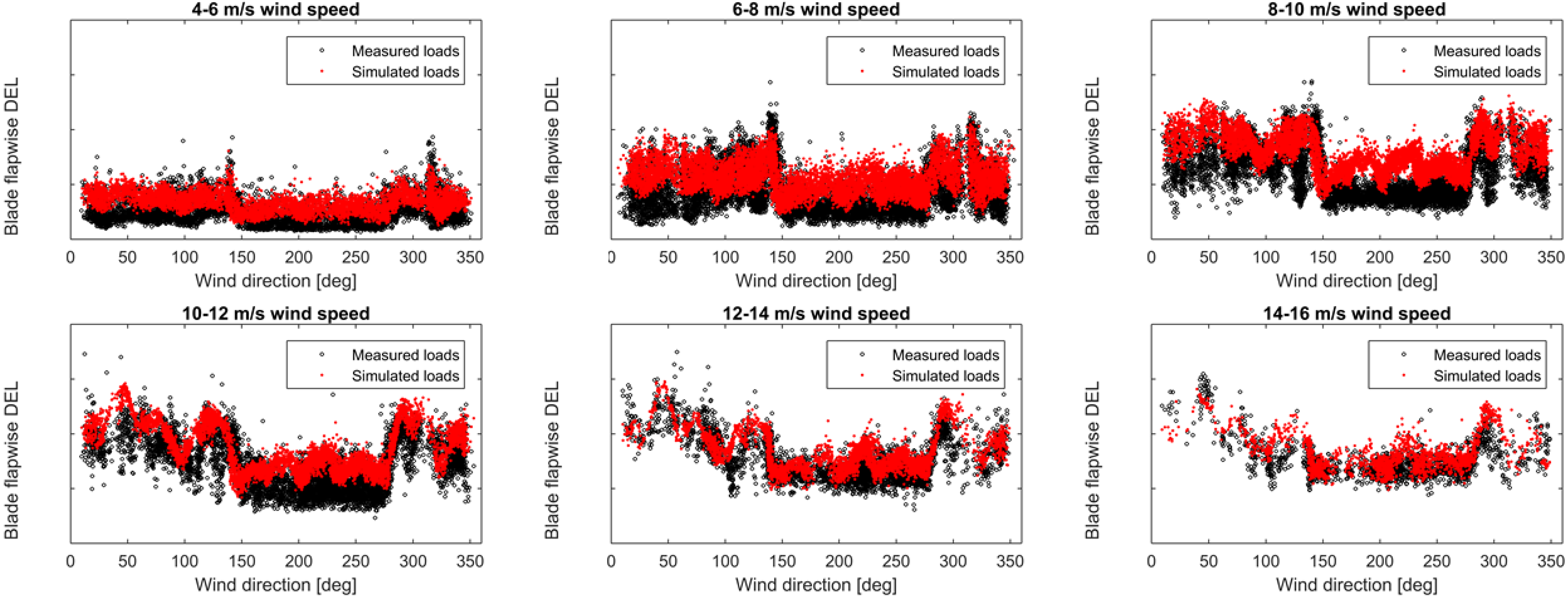
Simulation-based ML



Data-driven ML

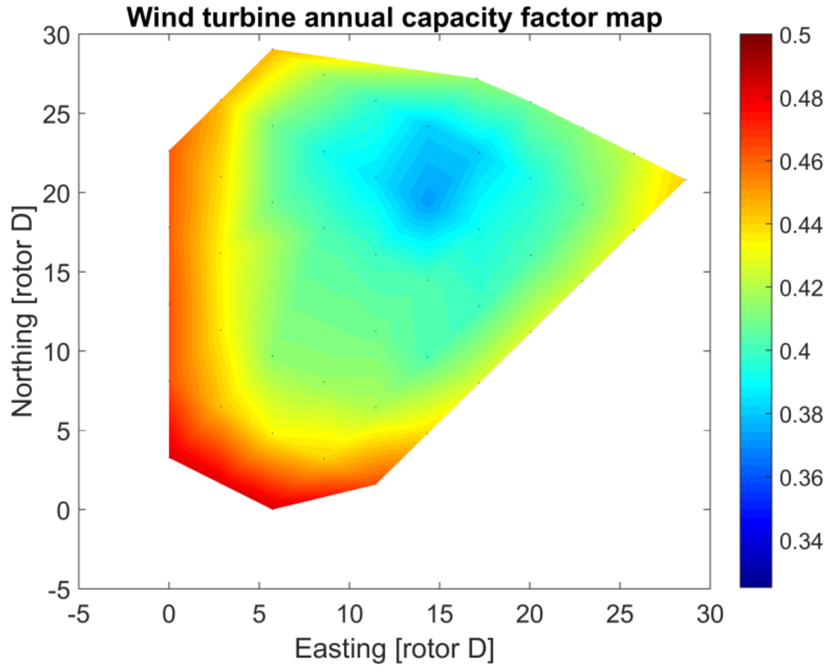


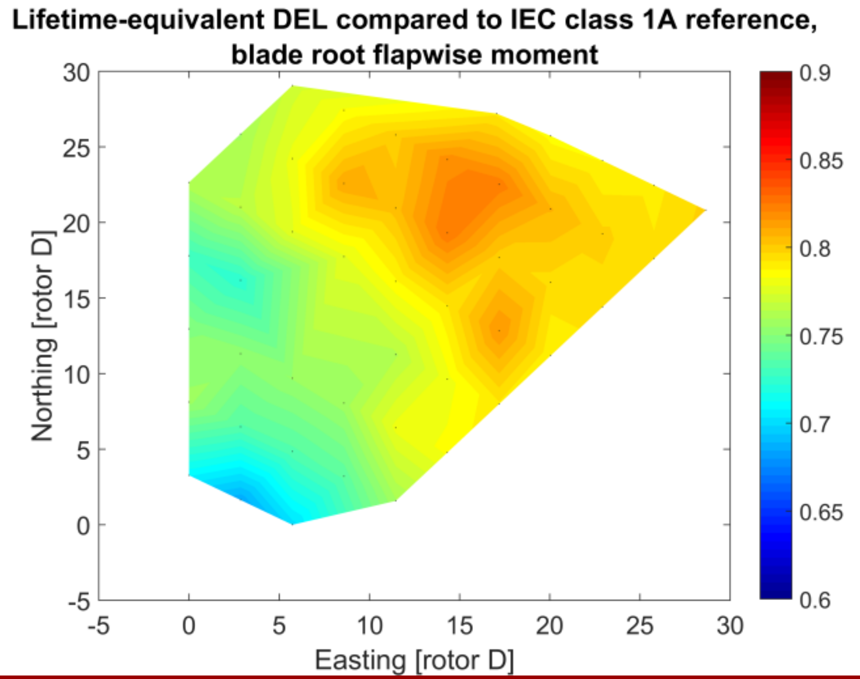
Validation with Lillgrund data (blade loads on C-08)



Lillgrund annual capacity factor and fatigue lifetime maps

- The surrogate model can be usedin weighted integrations / Monte Carlo simulations (including reliability analysis)
- Here, annual capacity factor map and blade root fatigue map computed using a weighted integration over wind speeds, directions, turbulence
- Estimate based on Lillgrund site-specific wind conditions





5. Optimization problem setup

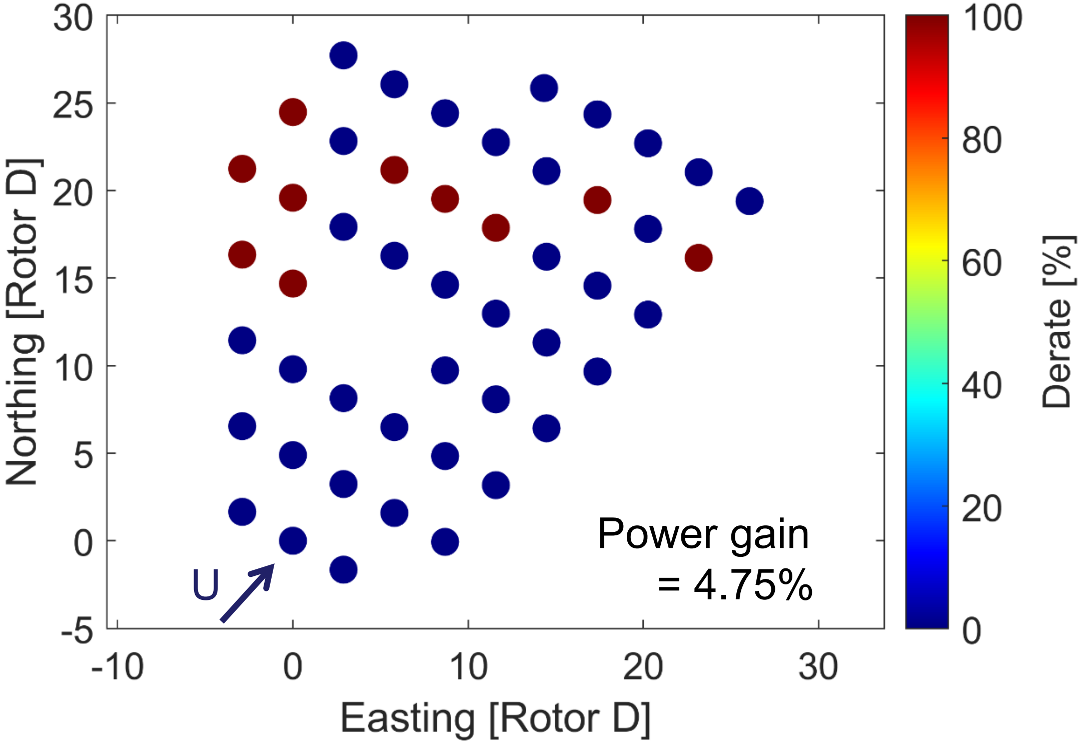
- We apply gradient-based constrained minimization
- A scalar objective function (either total power or total fatigue accumulation – on farm level)
- Constraints:
  - Individual wind turbine load constraints
  - Total farm power output as equality constraint (when minimizing loads)
- Using the interior-point algorithm implementation in Matlab

6. Exploration of the strategy space

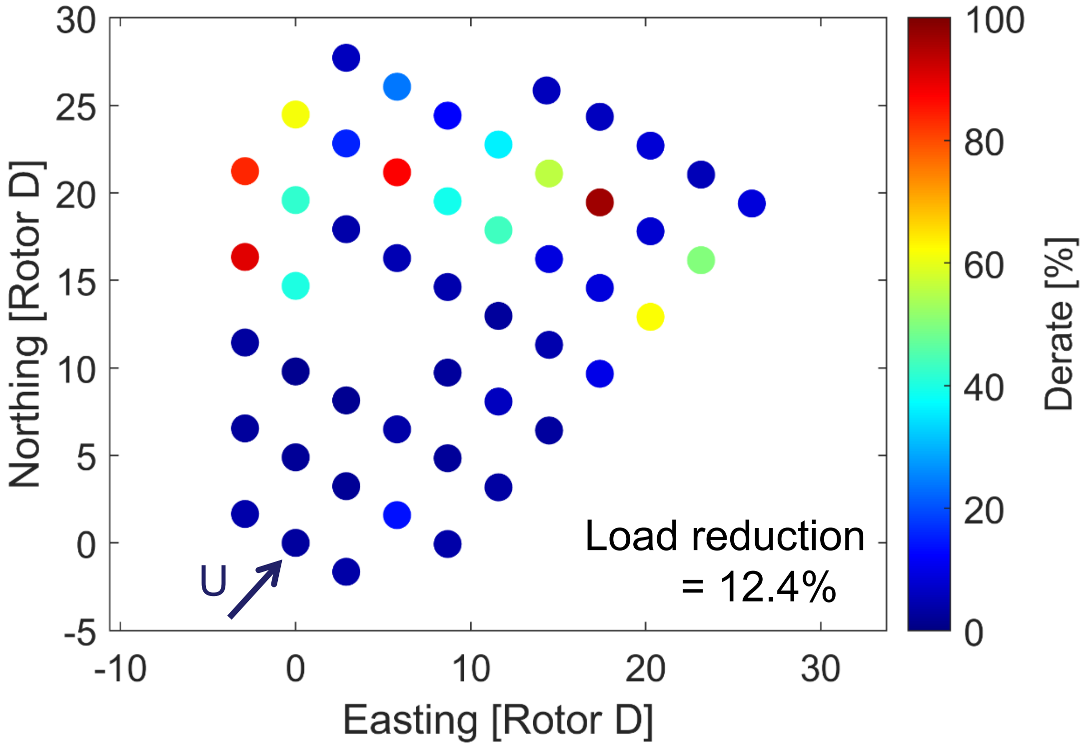
Optimization of total farm outputs

Wind direction: 220deg   Wind speed: 5m/s   Turbulence intensity: 5%

Power maximization with no constraints



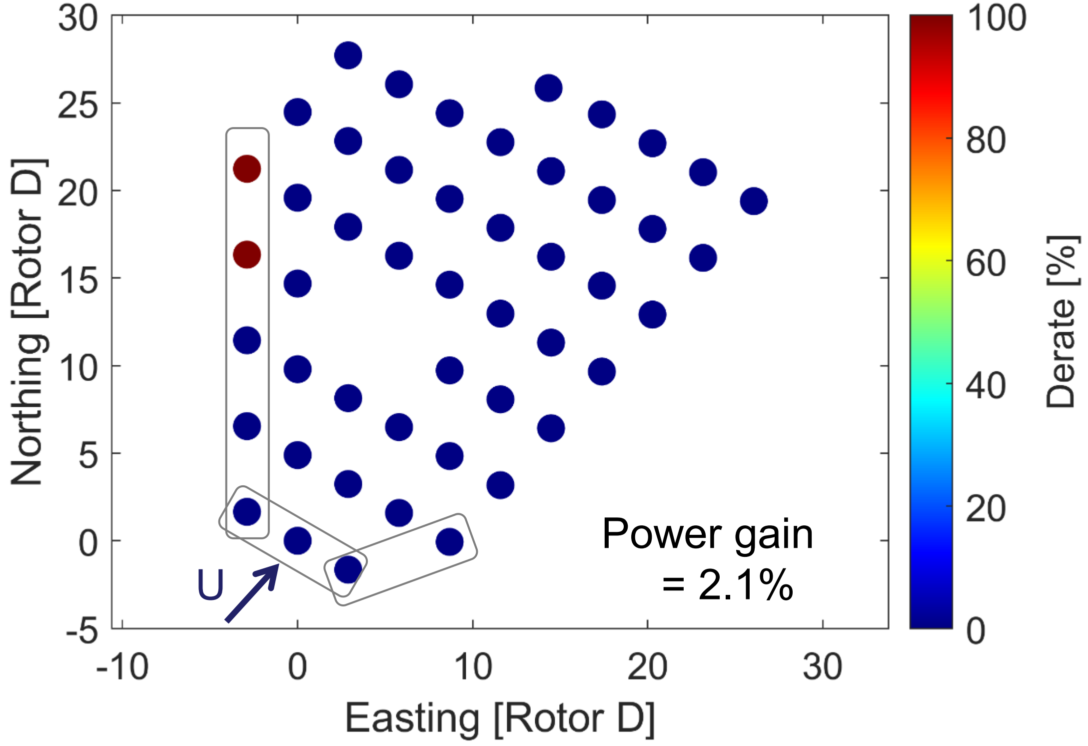
Load minimization under nominal farm power output



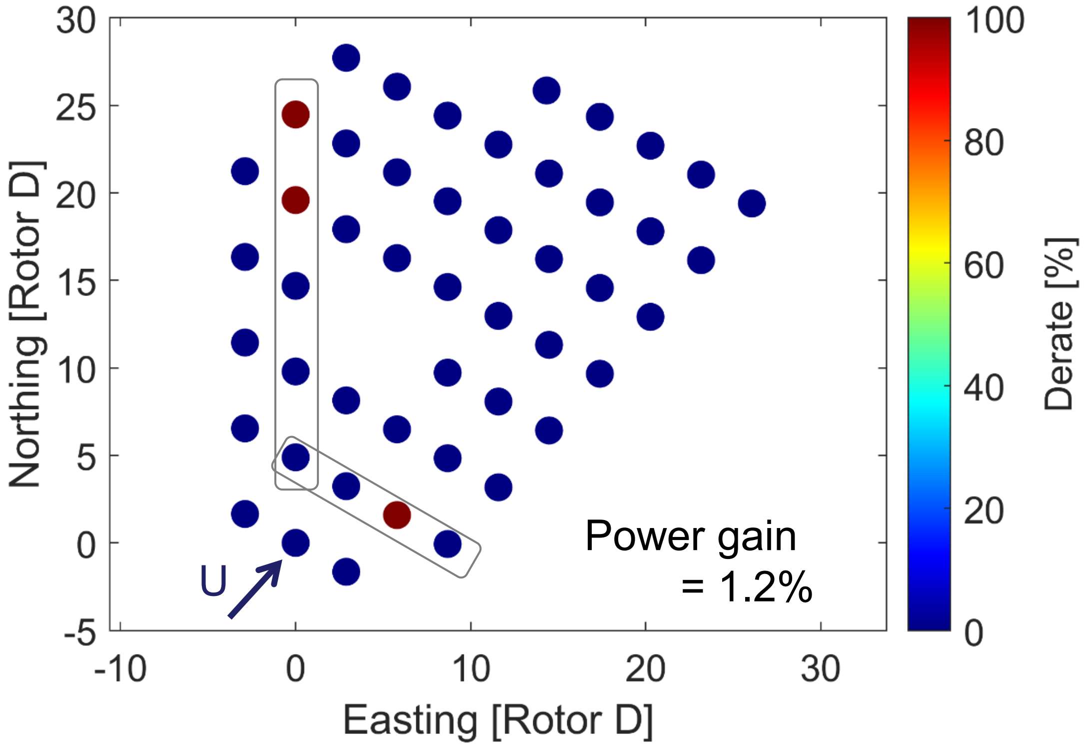
Optimization for single-row control strategies

Wind direction: 220deg   Wind speed: 5m/s   Turbulence intensity: 5%

De-rating limited to first row only

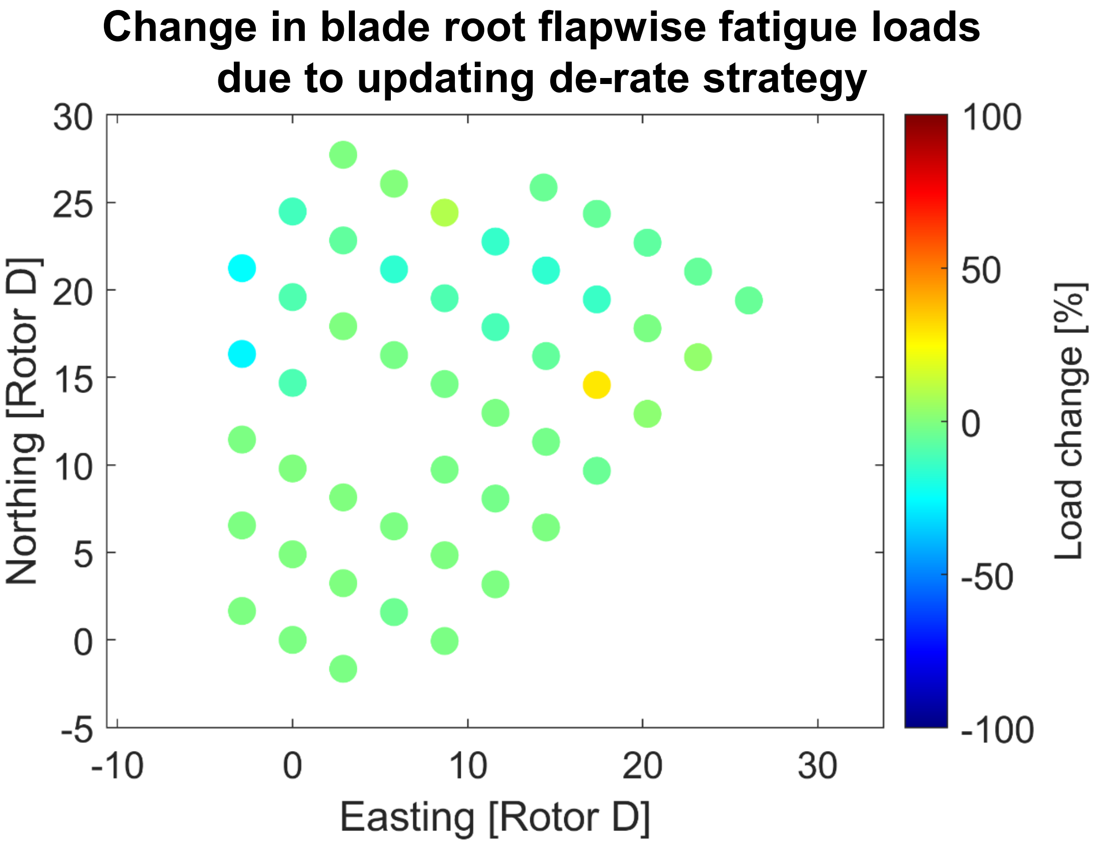


De-rating limited to second row only



Effect on loads

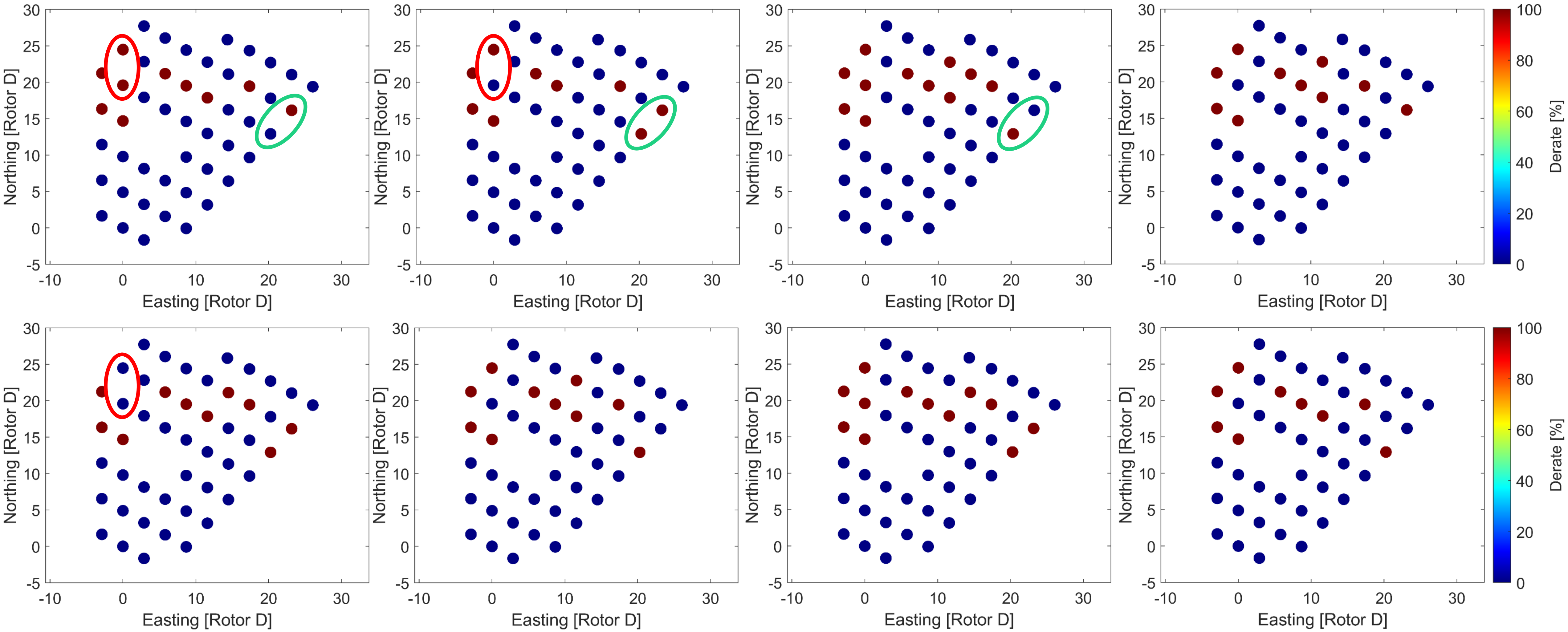
Wind direction: 220deg Wind speed: 5m/s Turbulence intensity: 5%



- This is the load-minimization case with nominal power output as constraint
- De-rated turbines generally get lower loads
- A few turbines get load increases but these are below the loads experienced by turbines working in free wind (hence, no active individual turbine load constraints)
- Net load reduction is 11%

Robustness of optimal point predictions

- Run multiple optimizations with random initialization (random initial de-rate level in the range 0 – 0.2)
- Resulting solutions are similar but with small variations
  showing that we don't have a well-defined global maximum



Conclusions and future work

- We developed and demonstrated a procedure which allows individual set point optimization for all turbines in a wind farm, under multiple optimization criteria

- Pro's:
  - The surrogate-based approach makes it very computationally efficient, once the simulation results have been generated
  - Can work with multiple constraints and objective functions, allows considering both power output, loads and reliability
  - Same principle can be directly applied with more advanced objective functions such as e.g. LCOE or reliability (as long as these are derived from power and loads)

- Con's:
  - Surrogate model has uncertainty; many simulations required to narrow it down
  - Solution may be non-unique, multiple local maxima (e.g. due to geometry patterns and overfitting)
  - Accuracy of predictions is limited by the accuracy of the engineering wake model used in the aeroelastic code
- Future work:
  - Focus on uncertainty reduction (wake model and surrogate modelling approach)