

## Abstract

The scheduling of planned maintenance for offshore wind farms often does not take into account the value of the energy lost whilst maintaining individual wind turbines. Typical strategies involve the use of a passive scheduling strategy : this work demonstrates that the passive approach is inefficient based on real offshore wind farm data and quantifies the benefit of active optimisation strategies.

We developed a methodology to actively schedule maintenance activities based on a day-ahead power forecast. In the study, we use a physics-based mesoscale model to simulate a month-long case study of a mid-latitude offshore wind farm in the summer and winter. We then compare the following maintenance scheduling approaches: ACTIVE, ADVERSE and REALISTIC.

## Objectives

The purpose of this study is to

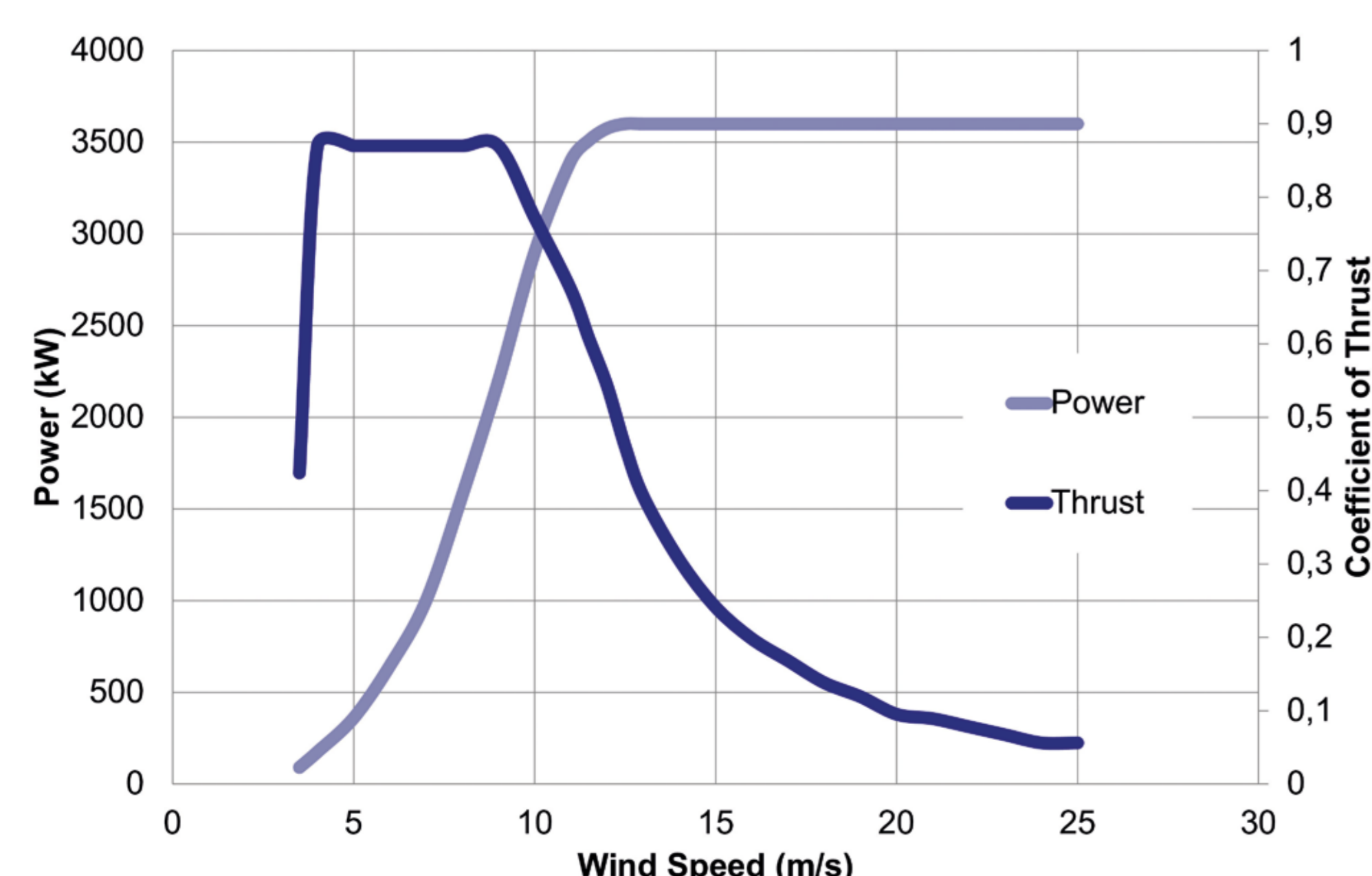
- Investigate the suitability of WRF for forecasting offshore wind farm power production in an operational setting.
- Investigate the suitability of using SCADA-generated Power and Thrust curves, in the absence of manufacturers' information.
- Quantify the potential savings in implementing an active maintenance optimization strategy.

## Methods

### Wind-Turbine Model Configuration

SCADA information is used to reconstruct

- Power Curve – correlating power output with wind speed measurements.
- Thrust Curve – using a unsteady Blade-Element Method [1], the aerodynamic characteristics of the wind-turbine is recreated to match SCADA measurements.

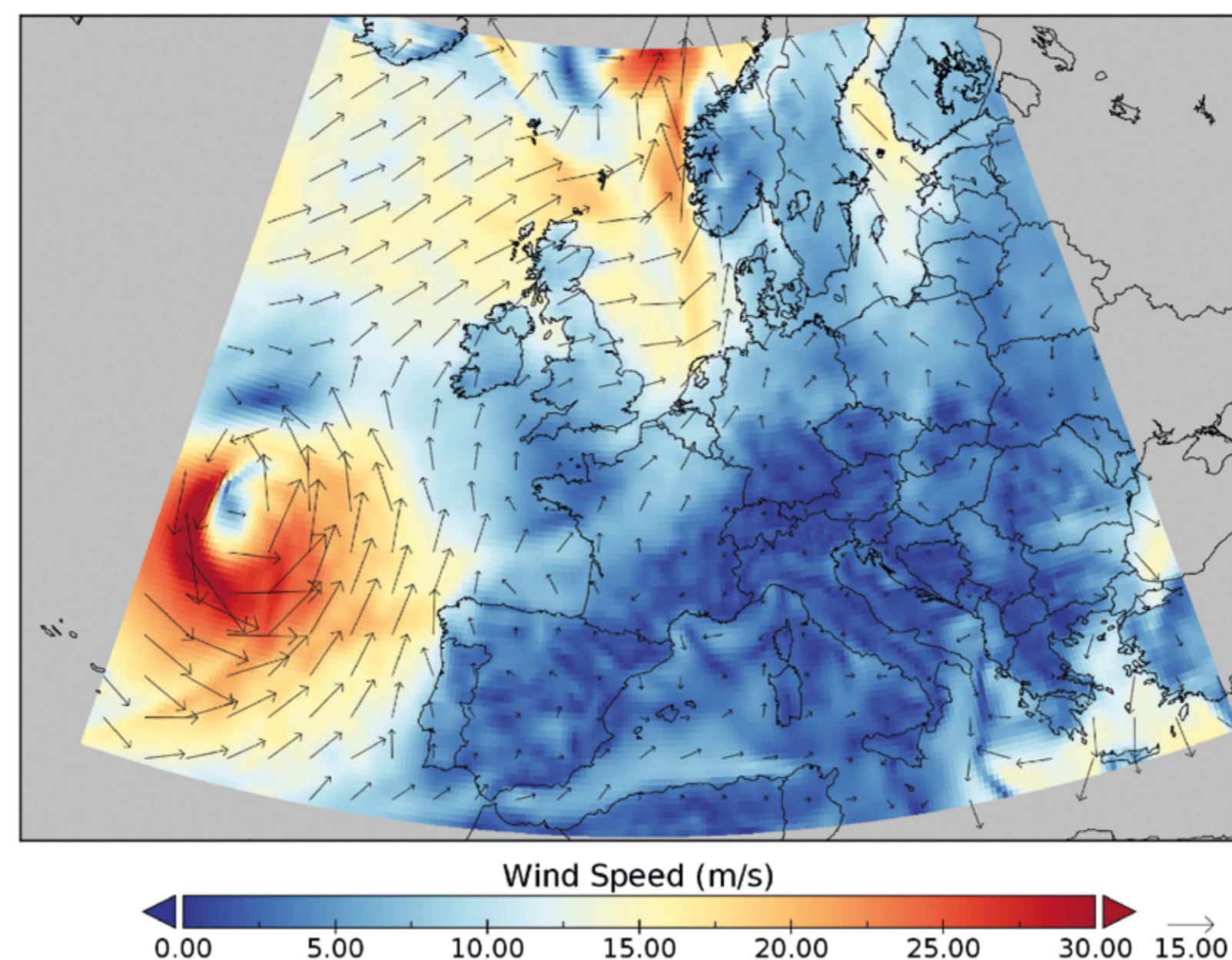


## Methods

### Mesoscale Model Configuration

- Mesoscale Model: WRFV3.7.1

ERA5 - Wind Speed at 100m Hub Height



- ERA5 initialization dataset shown above

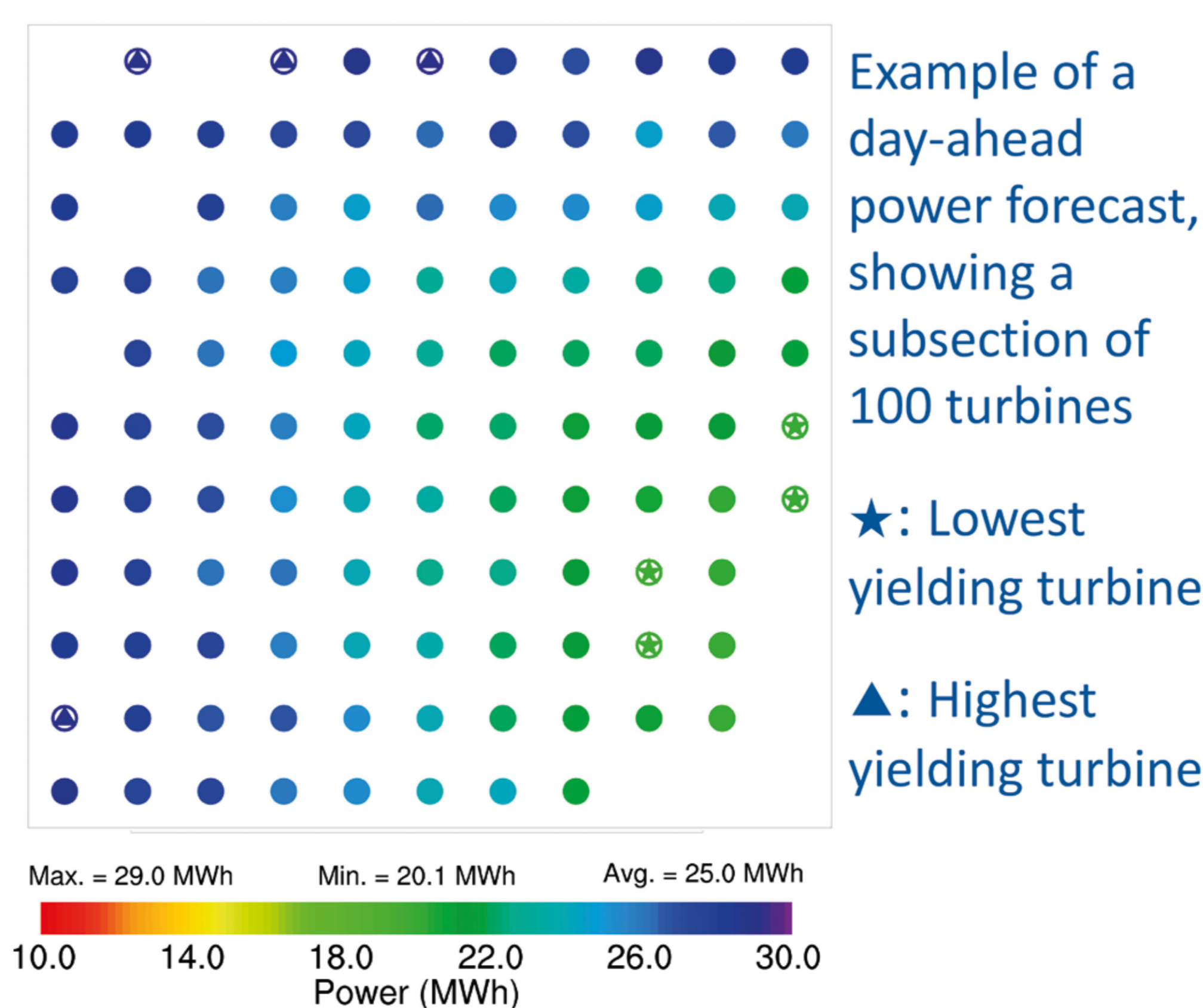
Initializing Dataset	ERA5
Time Period	JAN 2016 JUL 2016
Number of Domains	3
Domain Size	100x100x60 ( $N_x \times N_y \times N_z$ ) for all
Domain Resolution	25 km, 5 km, 1 km
PBL Scheme	MYNN2.5
Wind Farm Parameterization [2]	Enabled

- 10-min frequency output used in analysis.

### Active Maintenance Strategy

All simulated turbines are kept operating 24/7 to calculate opportunity cost of power production during actual downtime. We assume on each day, 4 selected turbines are shut-down and maintained for 8 daylight hours.

	Turbine Selection Criteria
ACTIVE	4 Lowest yielding turbine
ADVERSE	4 Highest yielding turbine
REALISTIC	<ul style="list-style-type: none"> <li>• Daily list of turbines generated from SCADA measurements.</li> <li>• Power forecast is compared against maintaining the same number of turbines on that day using the ACTIVE strategy</li> </ul>



## Results

### Mesoscale Model Accuracy

As the maintenance strategies outlined rely on the accuracy of the forecasts by WRF, the average error for each turbine is quantified:

	WIND	POWER
BIAS	- 0.40 m/s	- 0.18 MWh
MAE	2.28 m/s	0.59 MWh
Correlation	0.77	0.77
RMSE	3.12 m/s	0.95 MWh

These metrics are in line with similar studies such as the NREL WIND toolkit validation study [3] and deemed acceptable.

### Comparison of Maintenance Strategies

The theoretical maximum savings based on ACTIVE and ADVERSE is shown here:

	JAN	JUL
ACTIVE (MWh)	1635.43	893.79
ADVERSE (MWh)	2108.67	1438.97
Reduction in Downtime Loss (MWh)	473.24	545.18
Reduction in Downtime Loss (%)	22.4	37.8

The REALISTIC comparison based on SCADA:

	JAN	JUL
ACTIVE (MWh)	2223.06	560.27
REALISTIC (MWh)	2529.30	830.77
Reduction in Downtime Loss (MWh)	306.24	270.5
Reduction in Downtime Loss (%)	12.1	32.5

## Conclusions

The current WRF configuration, together with the SCADA reconstructed power and thrust curves, is shown to be an acceptable model for day-ahead power forecasts.

There are quantifiable savings to be gained through an active maintenance strategy approach.

Further improvements to mesoscale modelling of wind farms and optimization of active scheduling approaches can result in further reduction in downtime loss, hence increasing project revenue

## References

1. Singapore Wala, A. A (2017, May). Aerodynamics modelling of floating offshore wind turbines. Phd Thesis. *Nanyang Technological University*
2. Fitch, A. C., Olson, J. B., Lundquist, J. K., Dudhia, J., Gupta, A. K., Michalakes, J., & Barstad, I. (2012). Local and mesoscale impacts of wind farms as parameterized in a mesoscale NWP model. *Monthly Weather Review*, 140(9), 3017-3038.
3. Draxl, C., Hodge, B. M., Clifton, A., & McCaa, J. (2015). Overview and meteorological validation of the wind integration national dataset toolkit. *NREL/TP-5000-61740. Golden (CO): National Renewable Energy Laboratory (forthcoming), Tech. Rep.*

