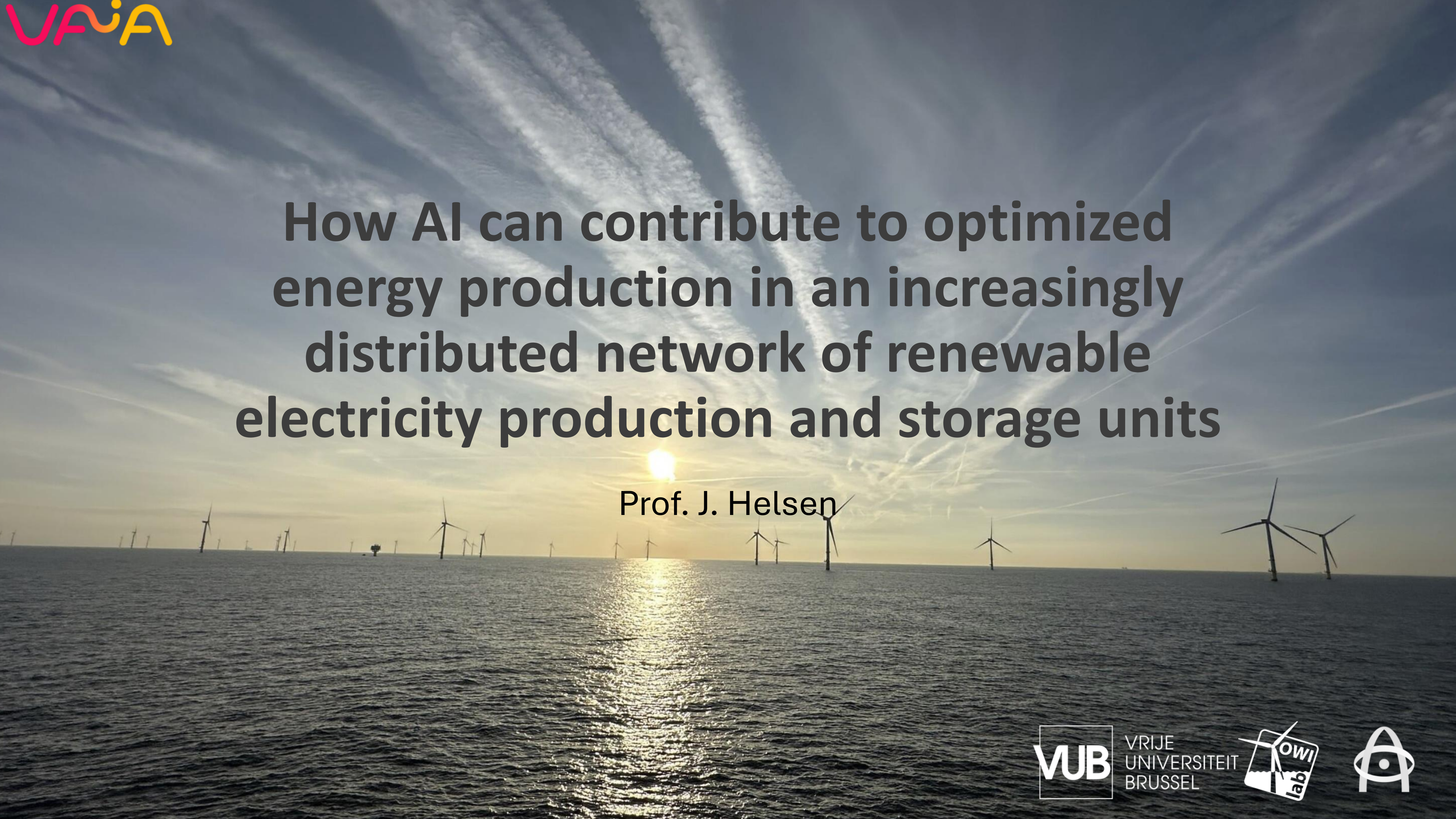
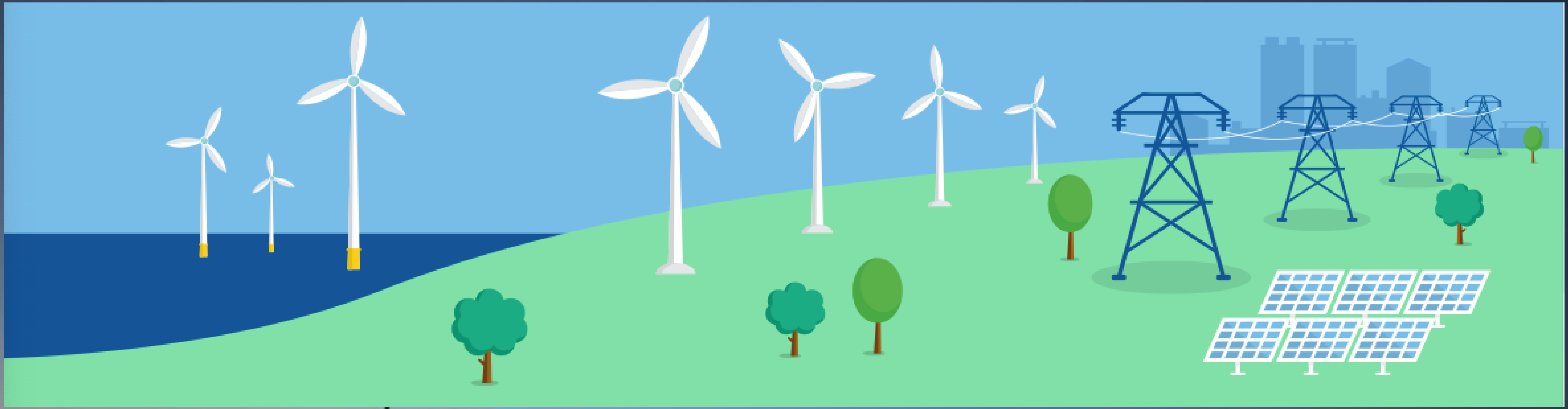
How AI can contribute to optimized energy production in an increasingly distributed network of renewable electricity production and storage units

Prof. J. Helsen

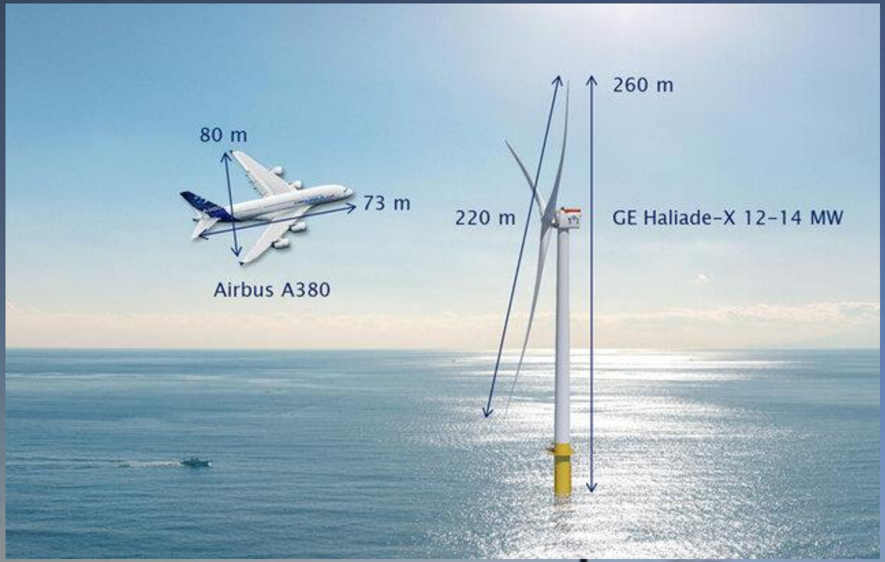


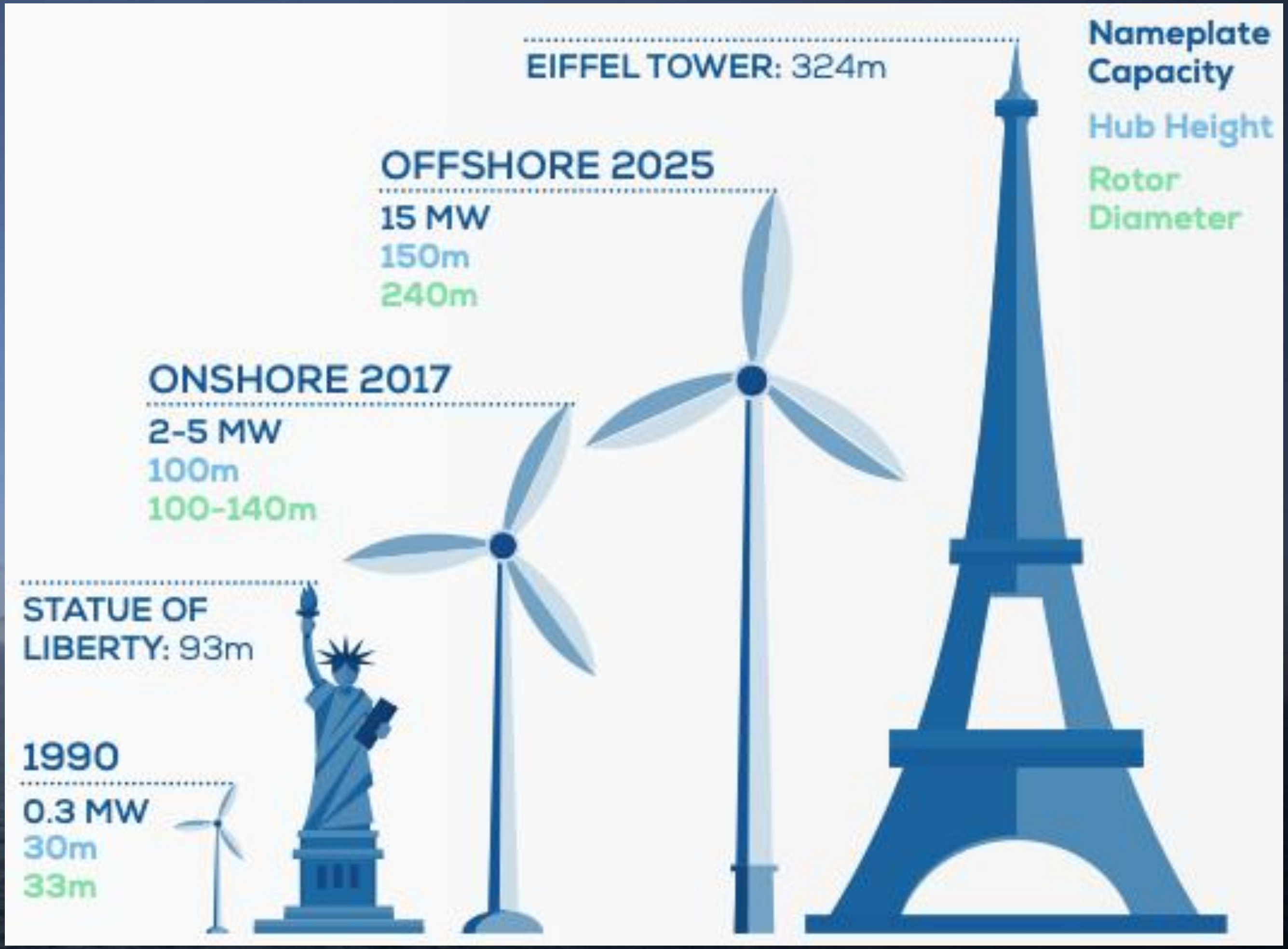
Renewable energy mix: production



In the near future
more & more
floating

Upscaling



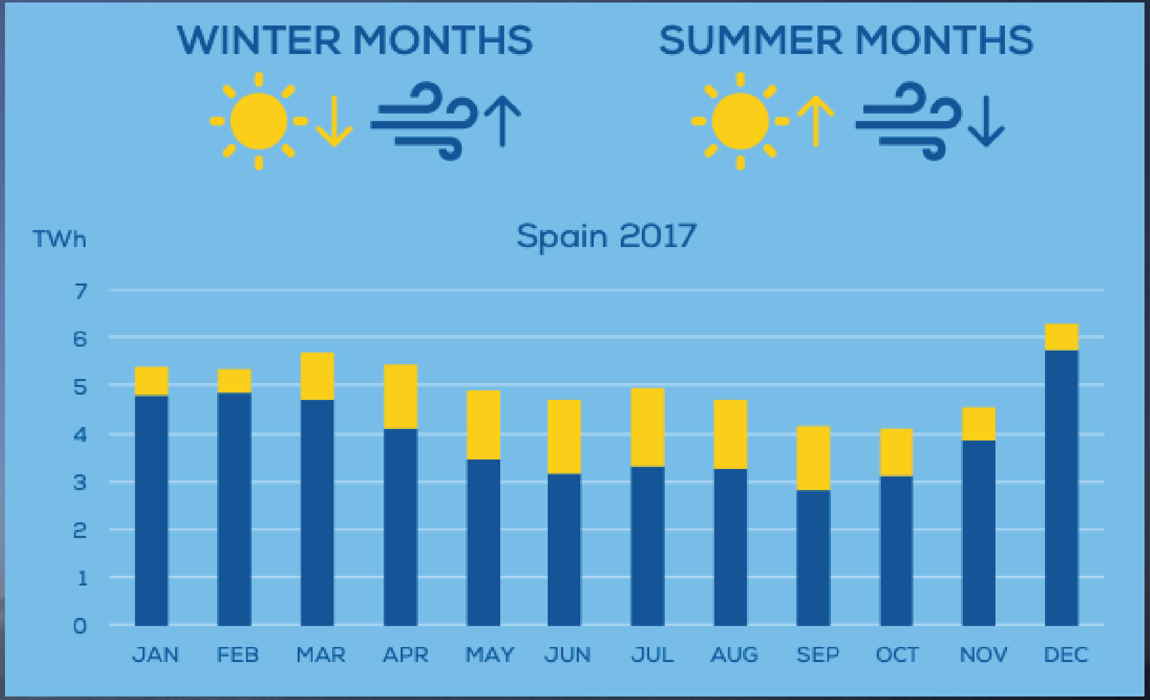


VUB VRIJE UNIVERSITEIT BRUSSEL

Solar and wind are complementary

Winter months are characterized by high wind while summer presents lower value

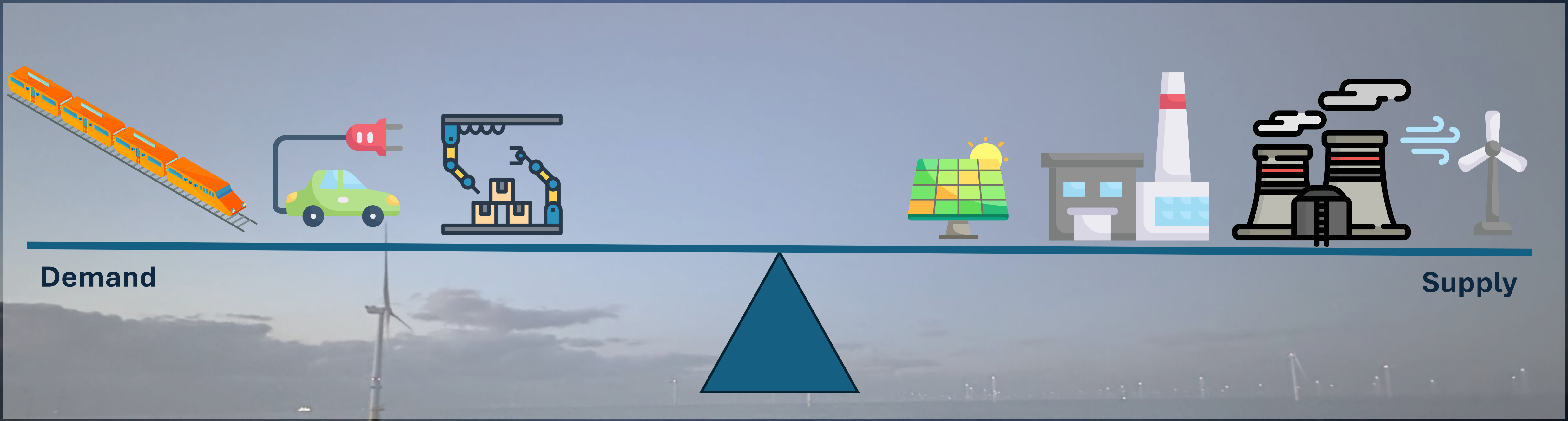
Solar PV resources have opposite attributes and are thus complementary



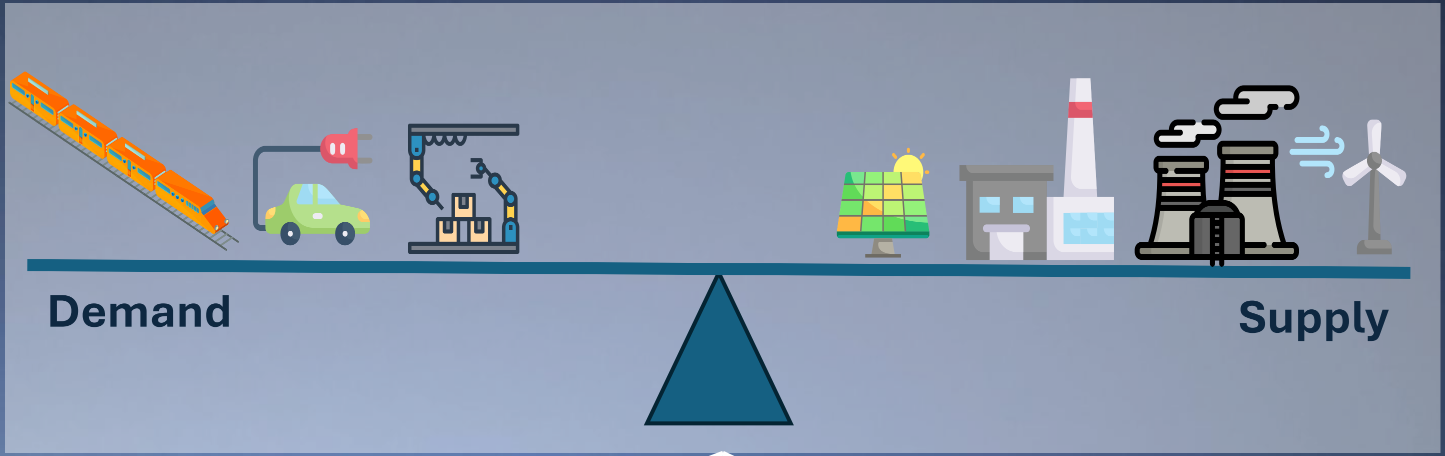
VRIJE UNIVERSITEIT BRUSSEL

Meeting demand and supply

Balancing



Role of the TSO to keep balance and thus 50Hz



PPA

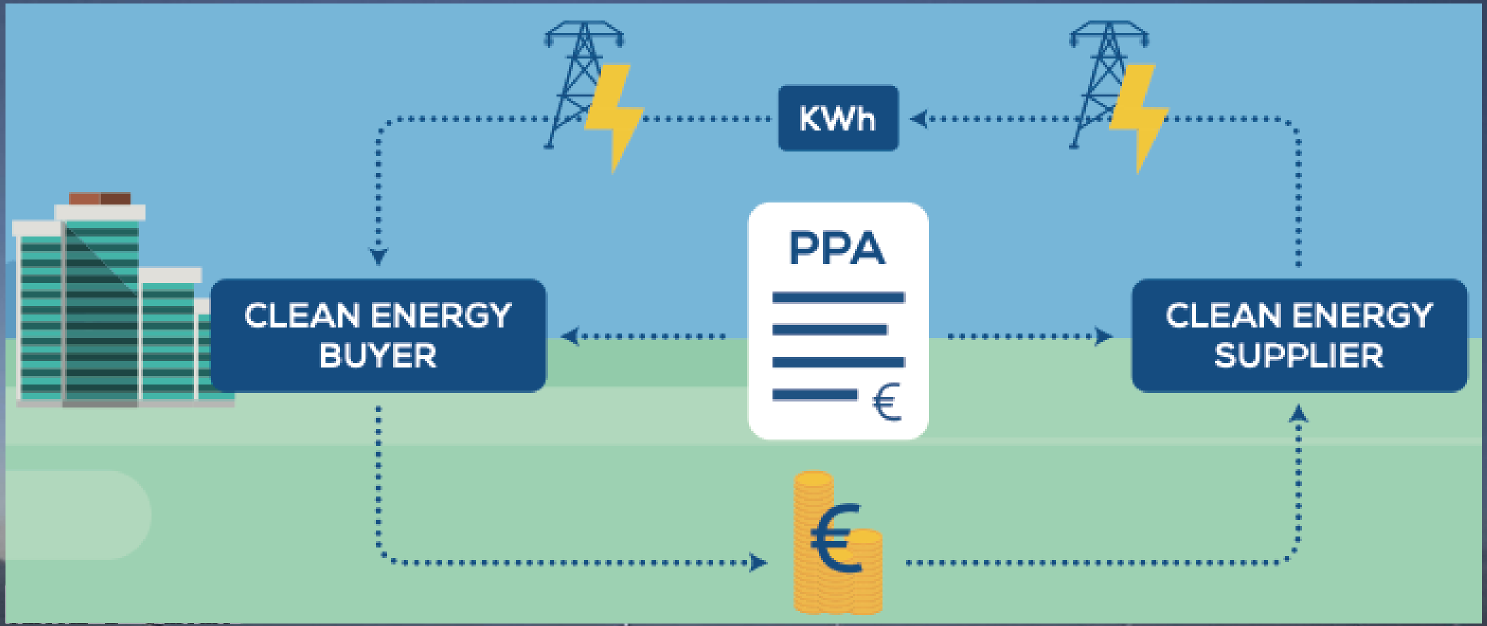
Smart power trading & curtailment

Advanced control

Storage

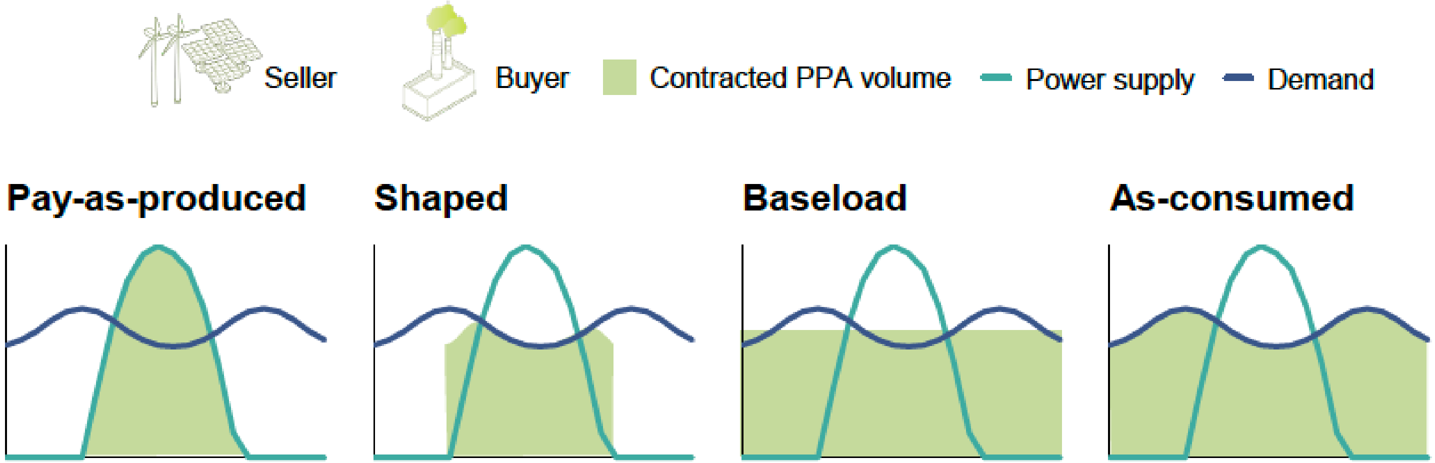
PPAs

Most common PPA structures



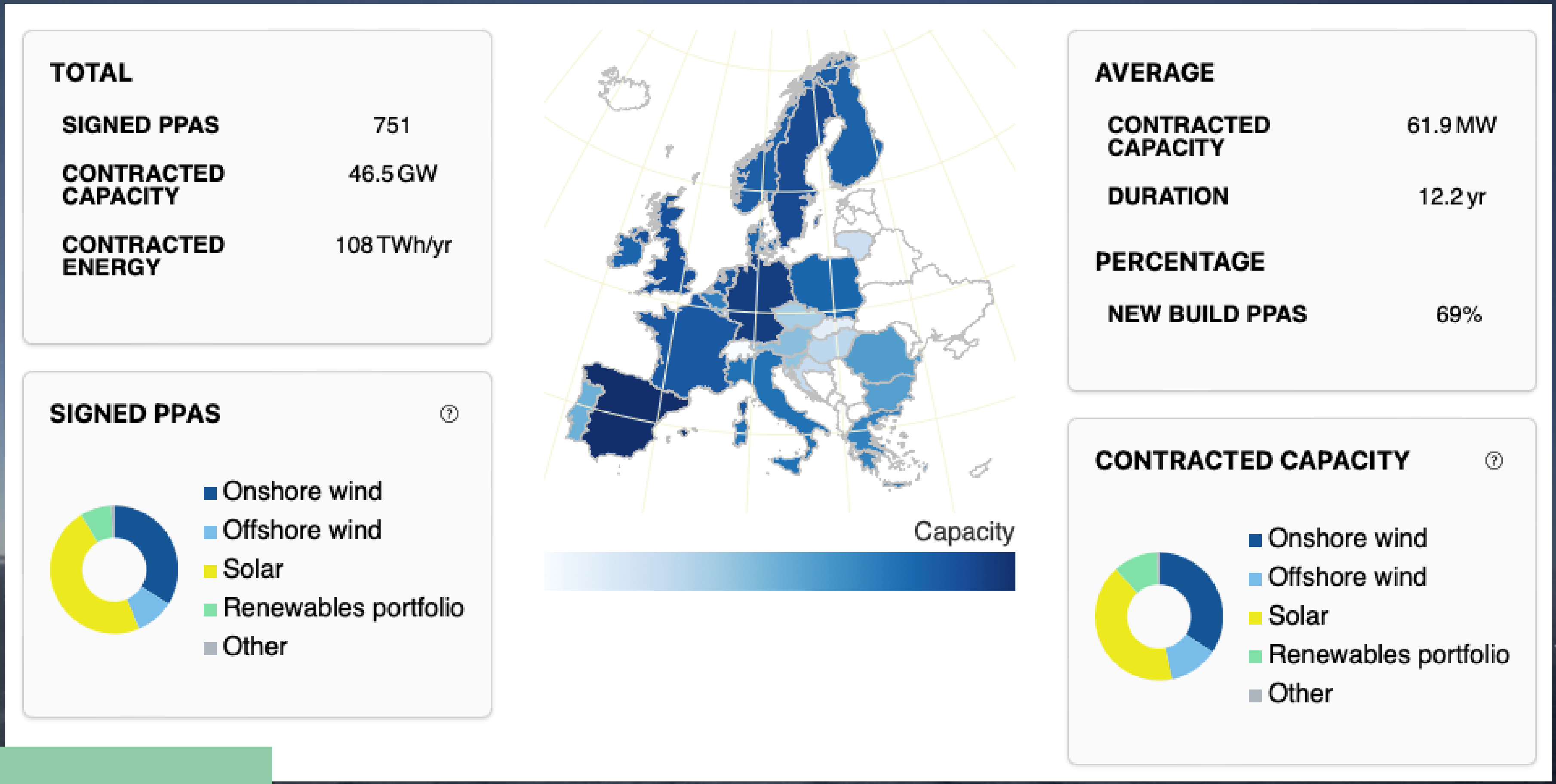
PPAs

Most common PPA structures



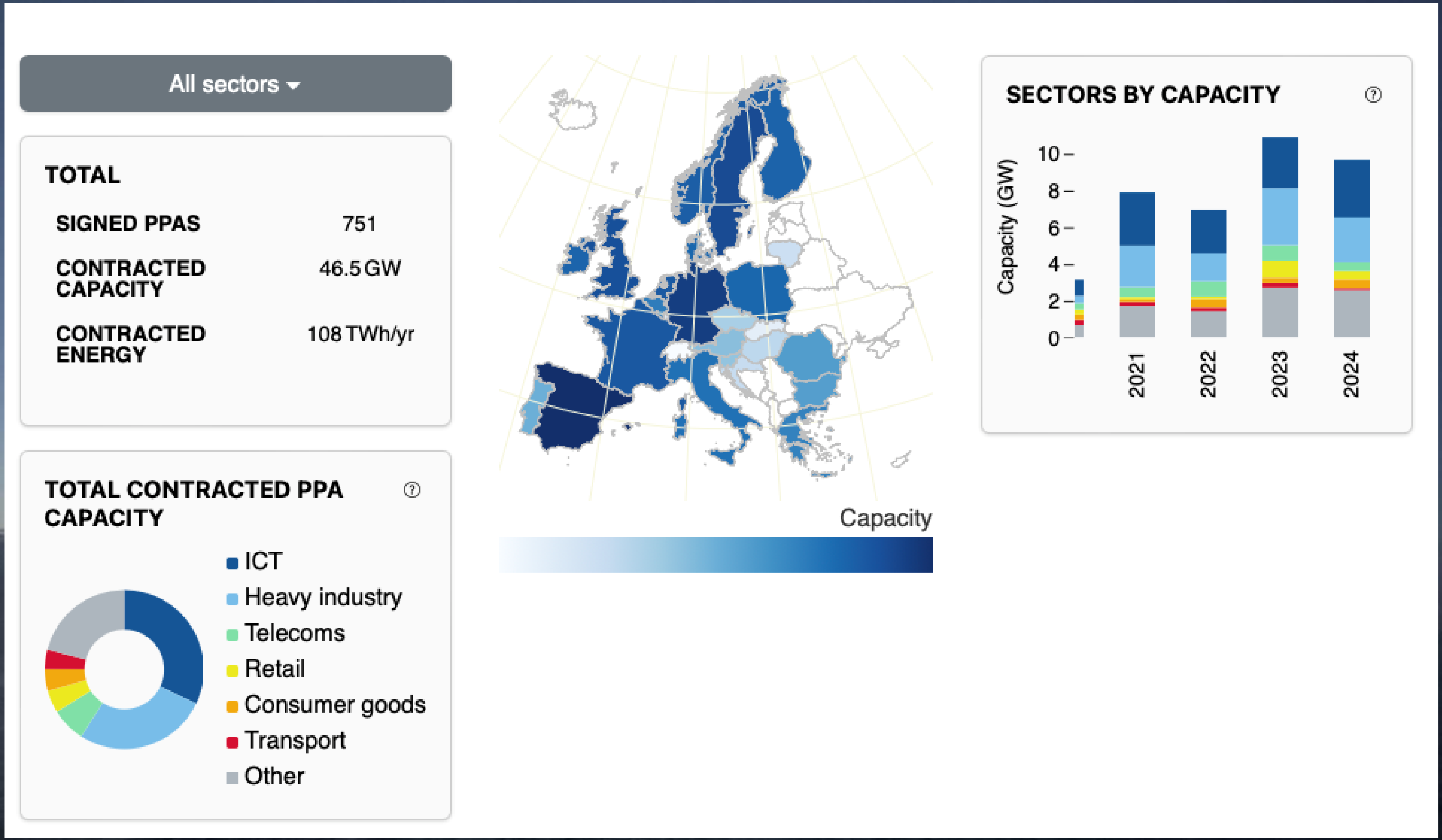
	Pay-as-produced	Shaped	Baseload	As-consumed
Description	The consumer buys the gross generation from the assets.	The seller converts the gross generation from the assets into a fixed shape over a year.	The seller converts the gross generation from the assets into a monthly/ annual baseload volume.	The PPA volume is the actual off-taker demand.
It has a higher price risk for…	The buyer, as the generation from the renewable assets is not fully predictable.	The seller, as it has to settle the difference between actual volume produced and the fixed shape at the market (resulting in a gain or cost).	The seller, as it has to settle the difference between actual volume produced and the baseload at the market (resulting in a gain or cost).	The seller. Only sellers with a large generation portfolio and flexibility assets can offer this type of PPA.

PPAs
A well-established approach



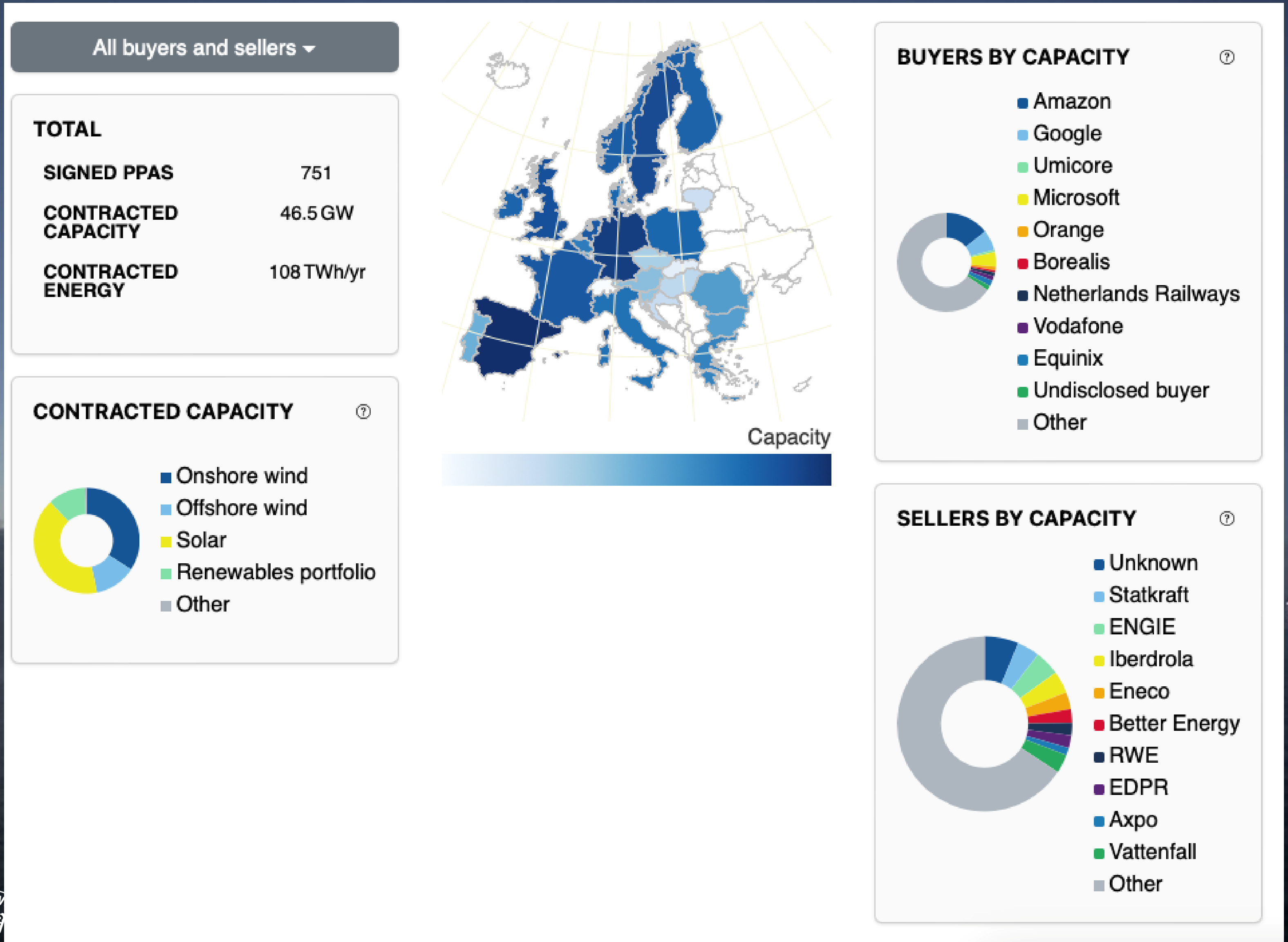
PPAs

A well-established approach



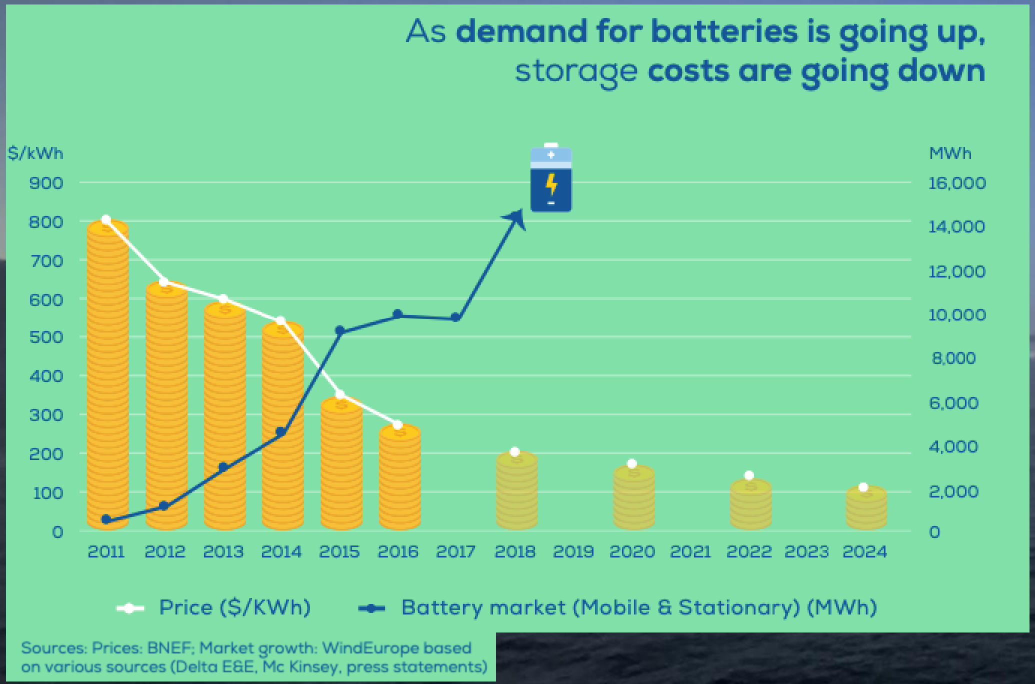
PPAs

A well-established approach



Introduction of flexibility

Add storage



VUB VRIJE UNIVERSITEIT BRUSSEL

Introduction of Flexibility

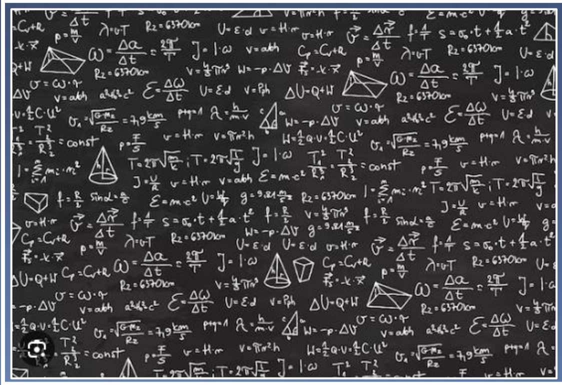
Power to X

e.g. Fraunhofer H2Mare

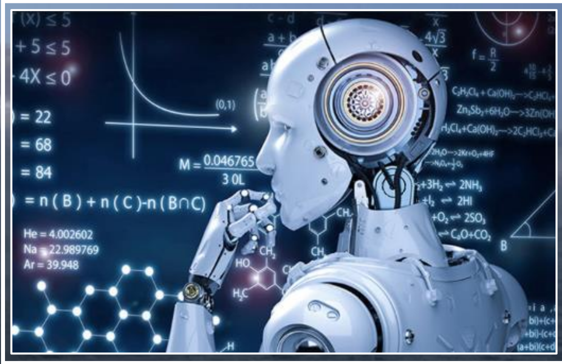
AI

Digital twin

Simulation Model



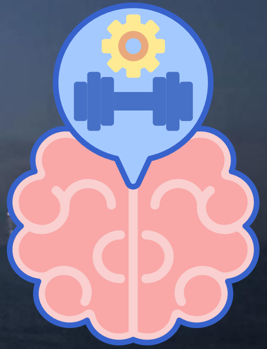
Physical-equations-based models



AI models

Need data for:

Validation



Training

It is all about data and AI

Some cases

Advanced weather forecast

Wind farm modeling and calibration for wake

Wind farm control combined with storage

Health assessment

“Testing lab”

Belgian offshore zone – A unique ecosystem

Combination of different turbine types → ideal to learn

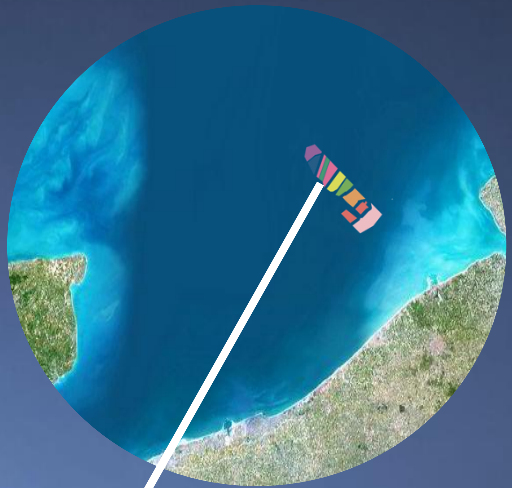
3MW

9MW

8.4MW

6MW

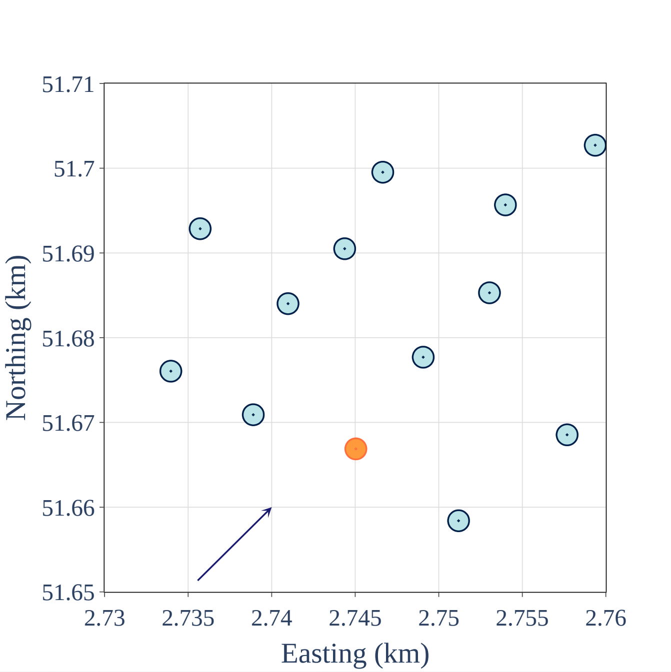
Offshore lab: lidar for wind insights

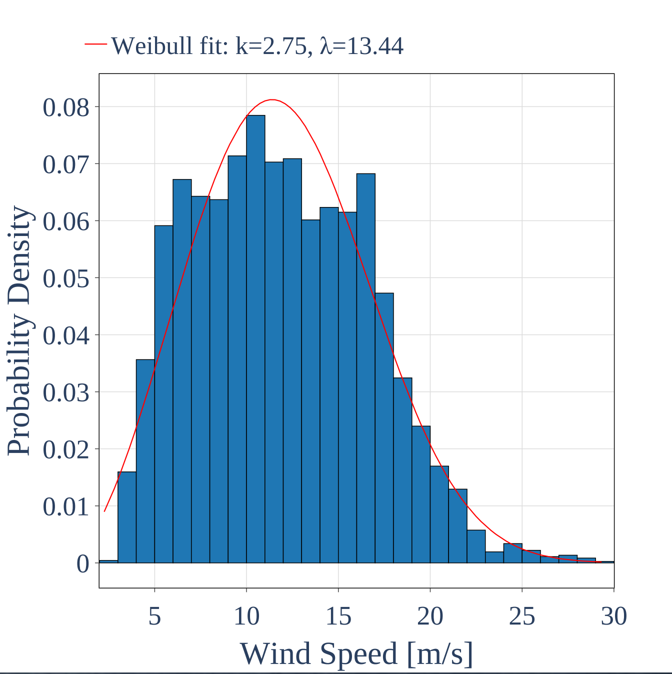


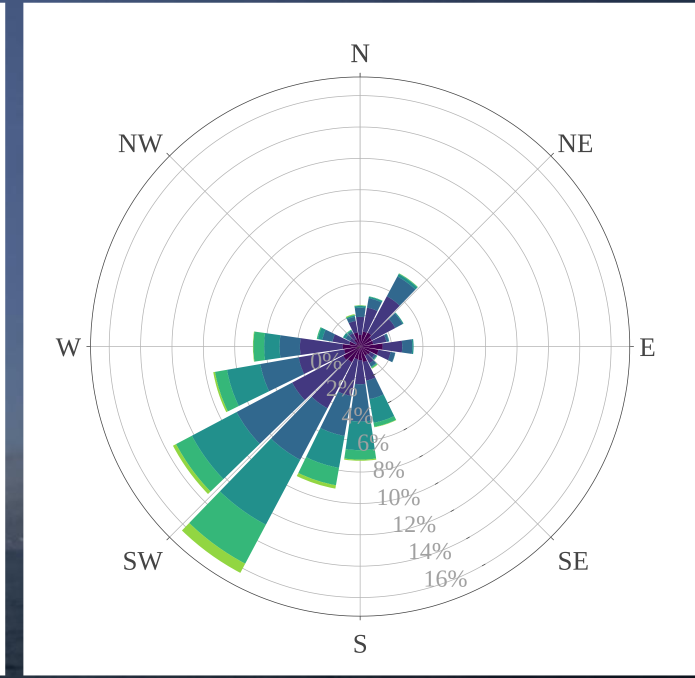
Wind speeds measured using laser

Measurement campaign

- Field experiment:
  - 10 Months in front row.



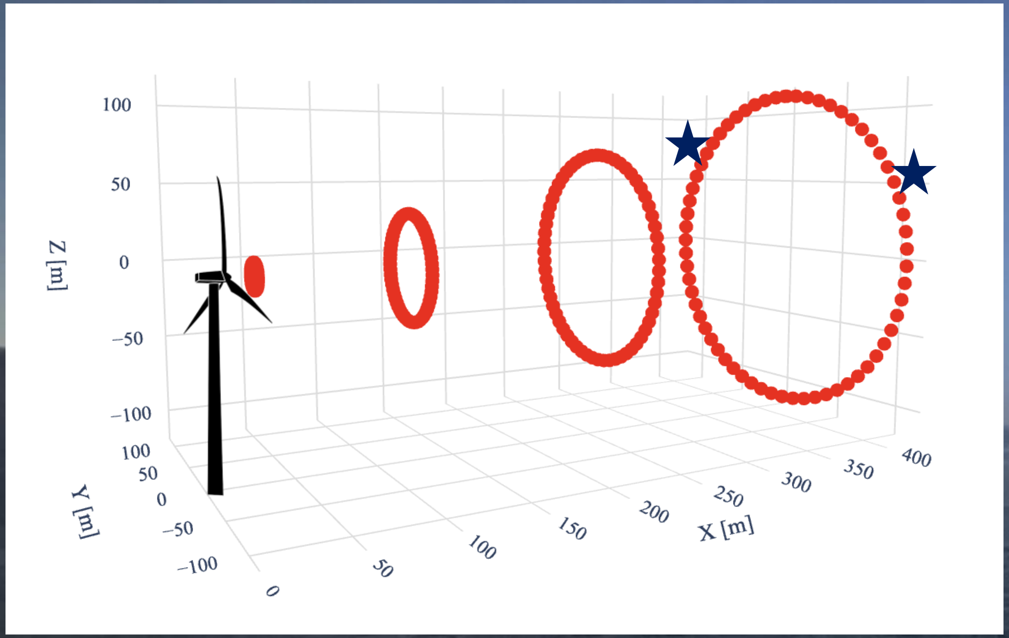


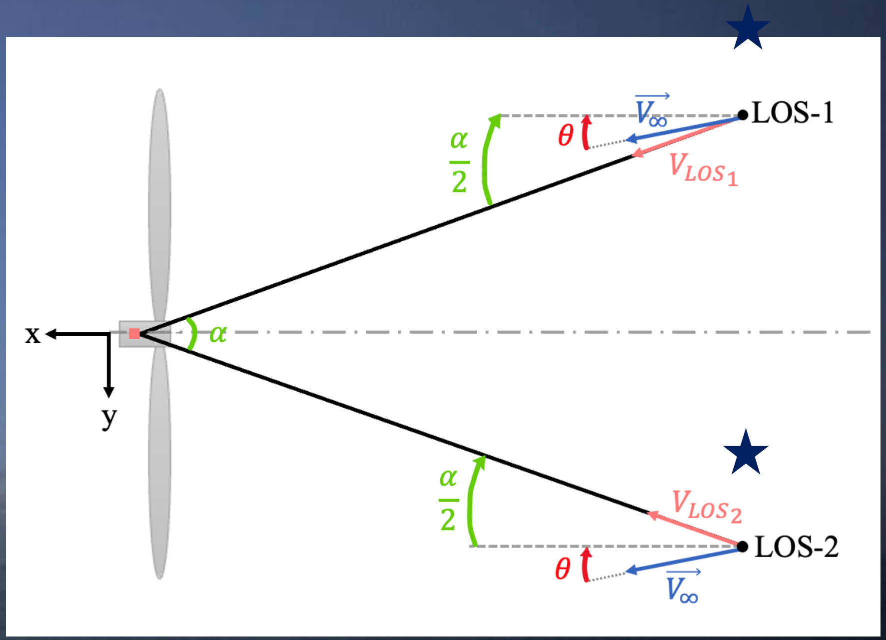


- Wind speed (left) and wind direction distribution (right).
- Site characterisation.

Wind Field Reconstruction

- This method uses two line-of-sight measurements to obtain wind parameters, such as wind speed.
- 2-Beam reconstruction is applied [1], with wind field simplifications:
  - Not tilted, i.e. no third component in the wind speed vector.
  - Horizontally homogeneous



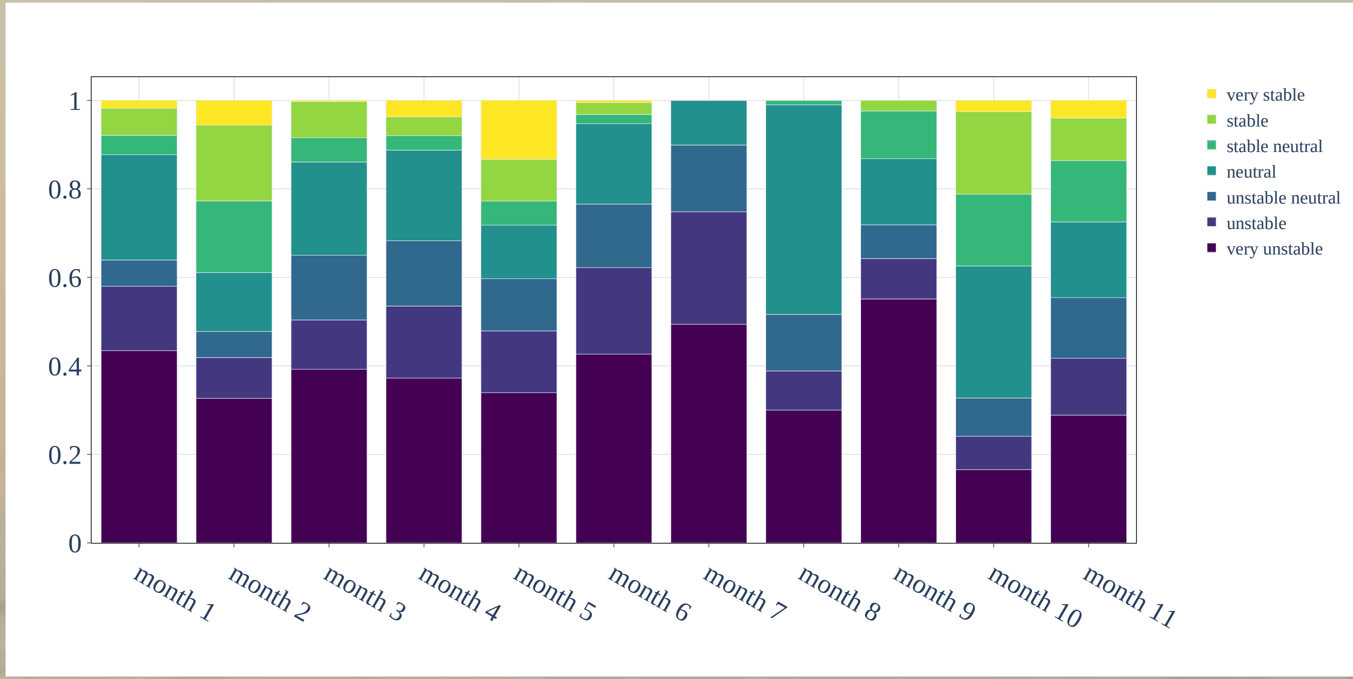


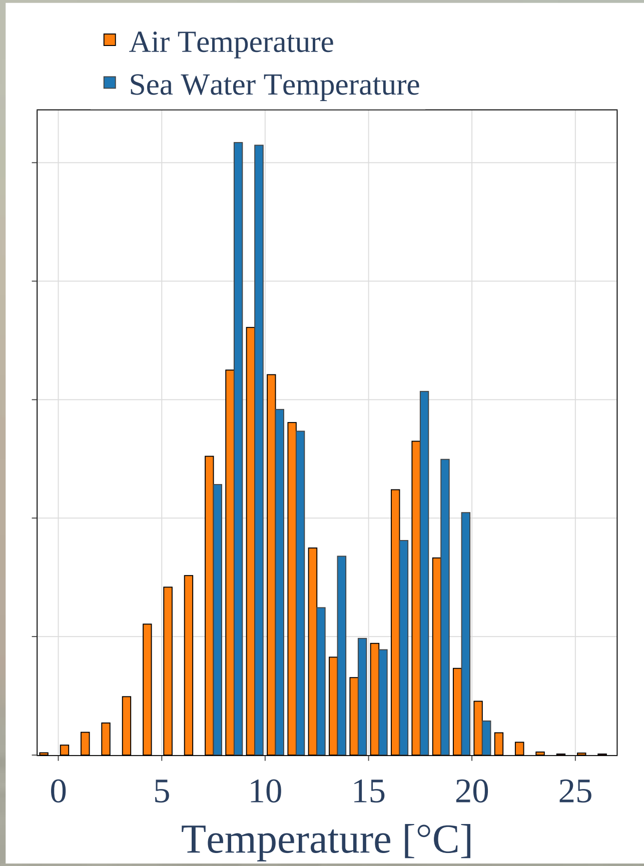
- Wind speed components (V_x and V_y) are estimated with the measurements in V_{LOS_1} and V_{LOS_2}.

[1] R. Wagner, T.F. Pedersen, M. Courtney, I. Antoniou, S. Davoust, and R.L. Rivera. Power curve measurement with a nacelle mounted lidar. Wind Energy, 17(9):1441–1453, 2014.

Weather conditions

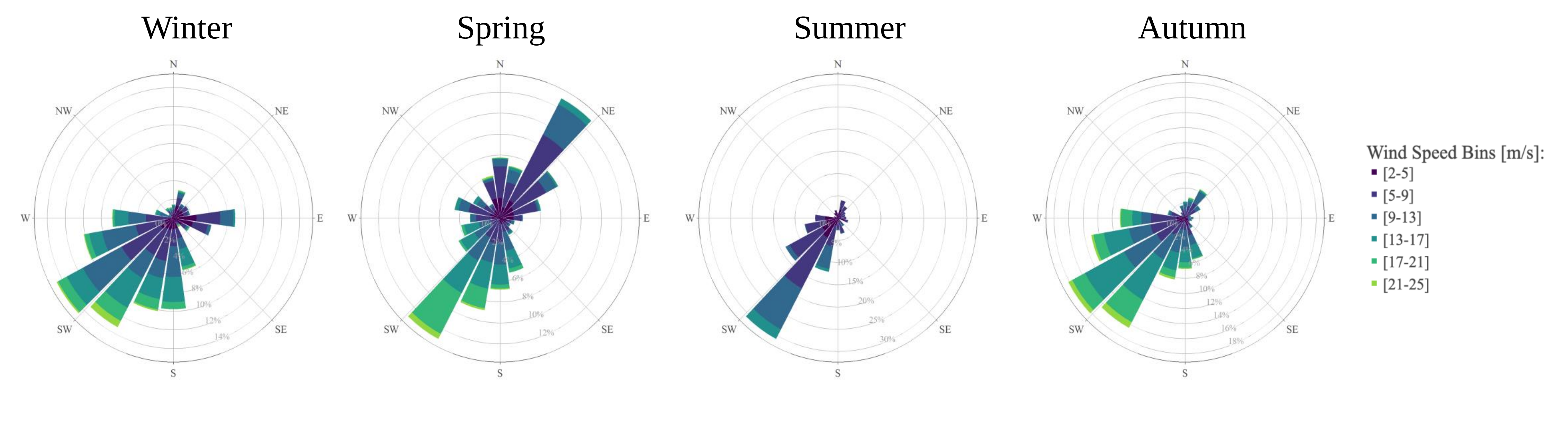
- Use of *Meetnet Vlaamse Banken* data to characterize local weather conditions:
  - Atmospheric stability.
  - Air and sea temperatures.
  - Wave and wind directions.
- Use of SCADA to calculate turbulence intensity.





Seasonal effects

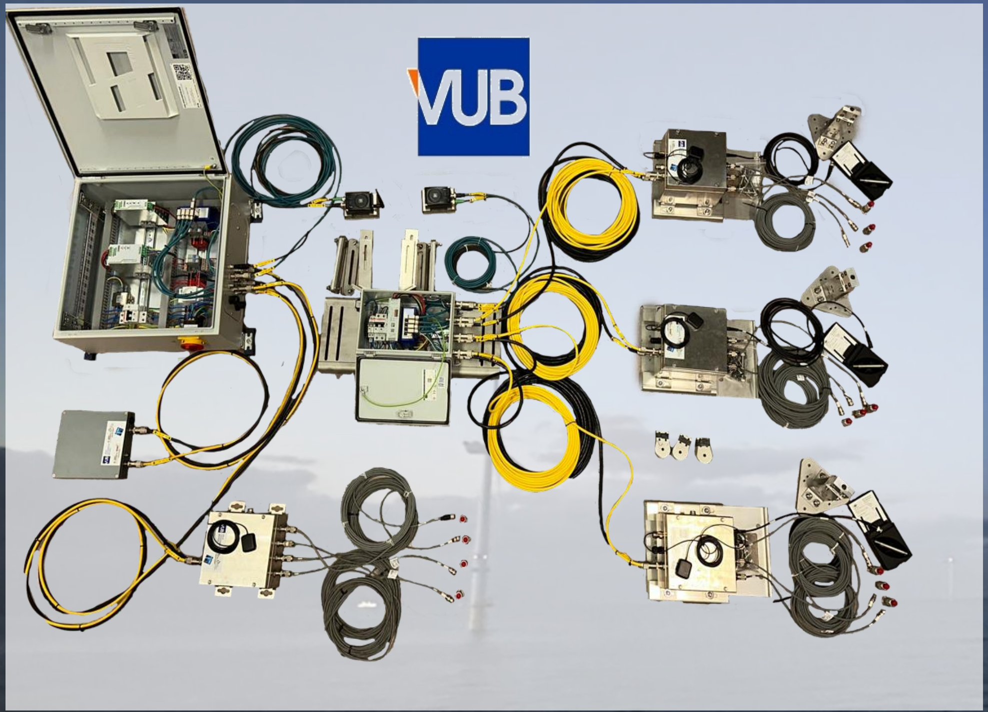
- Indicates variations in wind patterns that can impact turbine performance, highlighting the importance of continuous monitoring and adaptation to changing conditions.
- Used for:
  - Loads analysis.
  - Annual energy production / wind resource assessment.



Offshore lab: Turbine monitoring

Dedicated accelerometer instrumentation for turbine (incl. drivetrain) and foundation monitoring

20 turbines

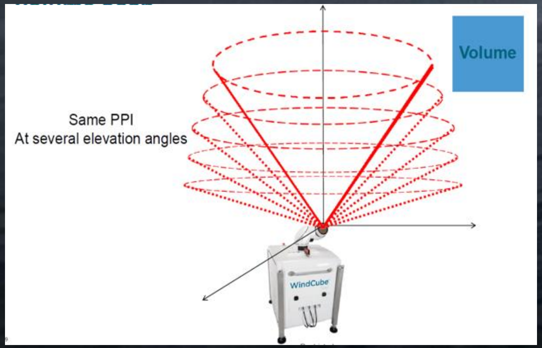


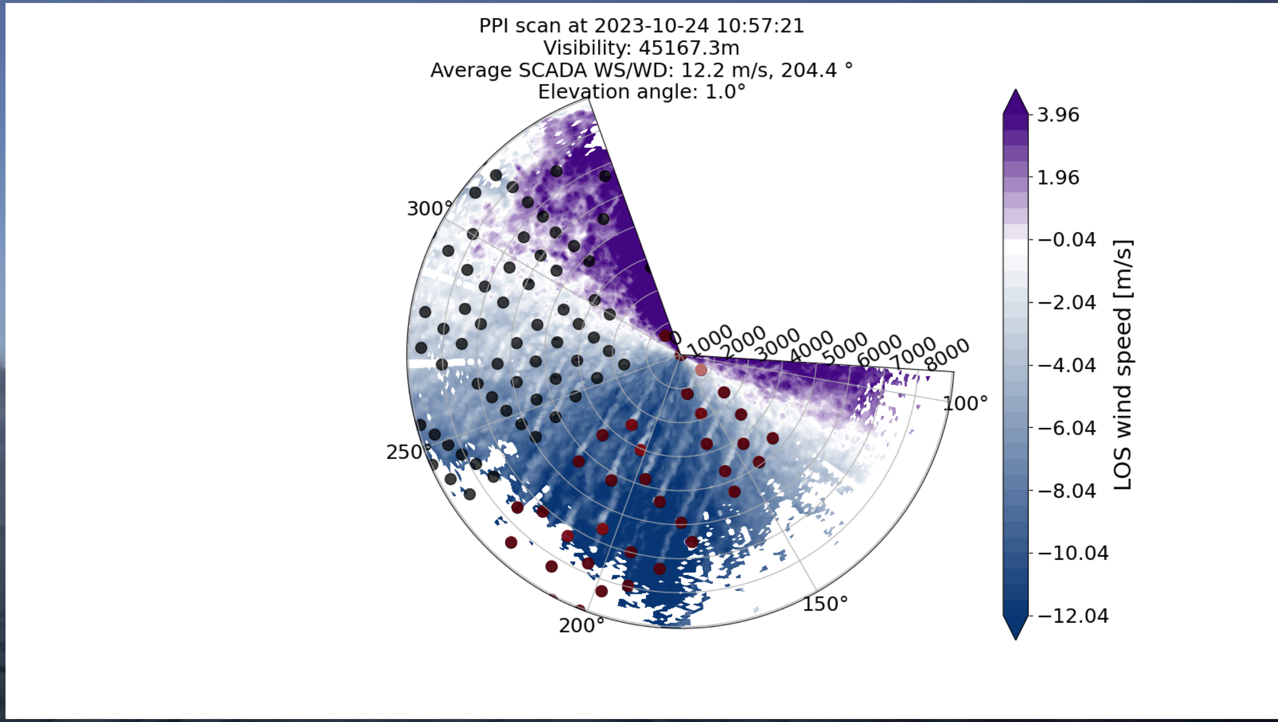
Offshore lab: Rain induced blade erosion

Dedicated rain instrumentation and weather station

In collaboration with:

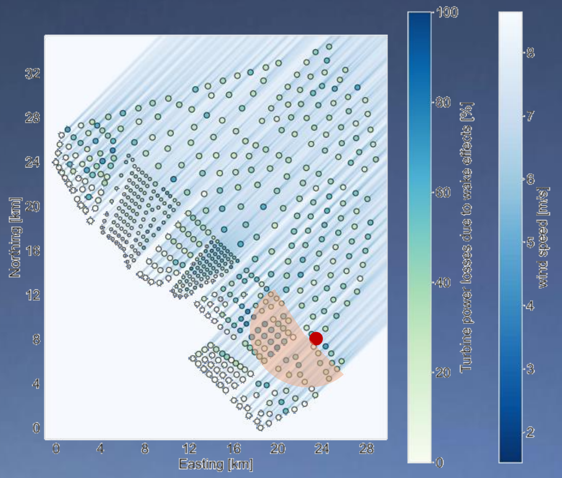
Offshore lab: Wake measurements

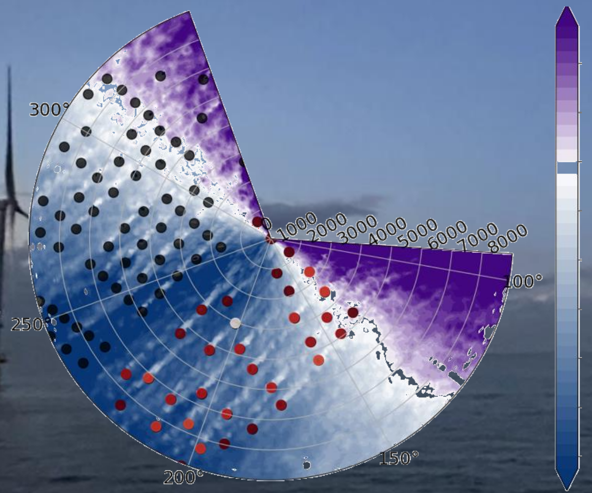


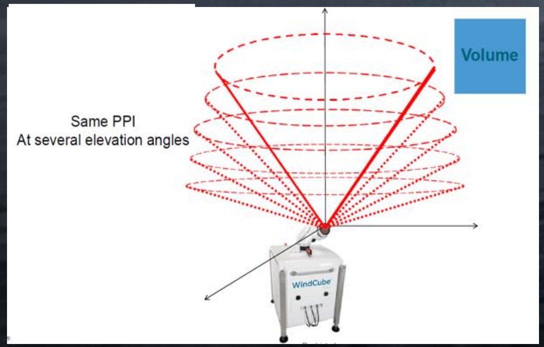


In collaboration with:

Digital twin of wakes at wind cluster level

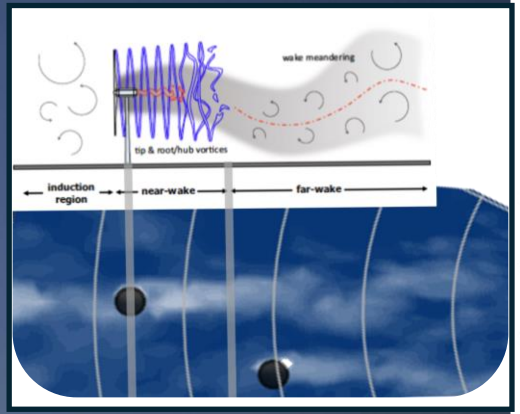


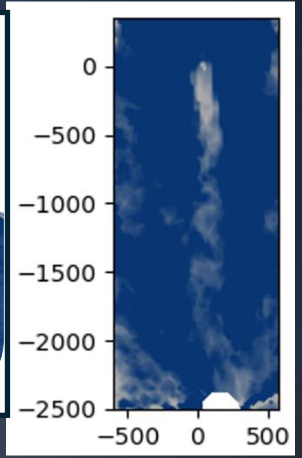


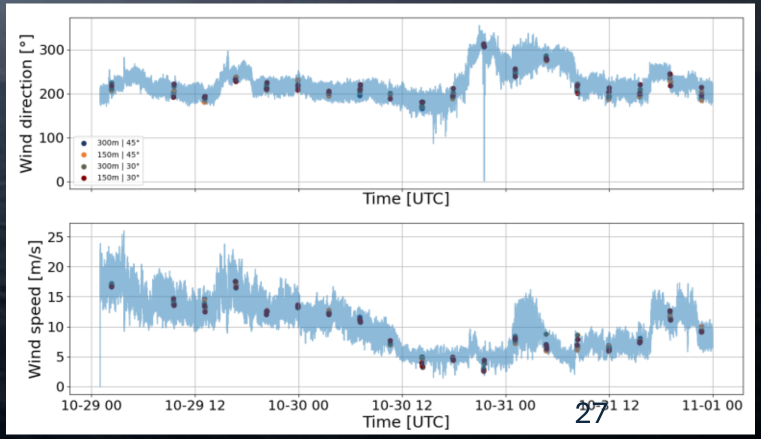


Simulation

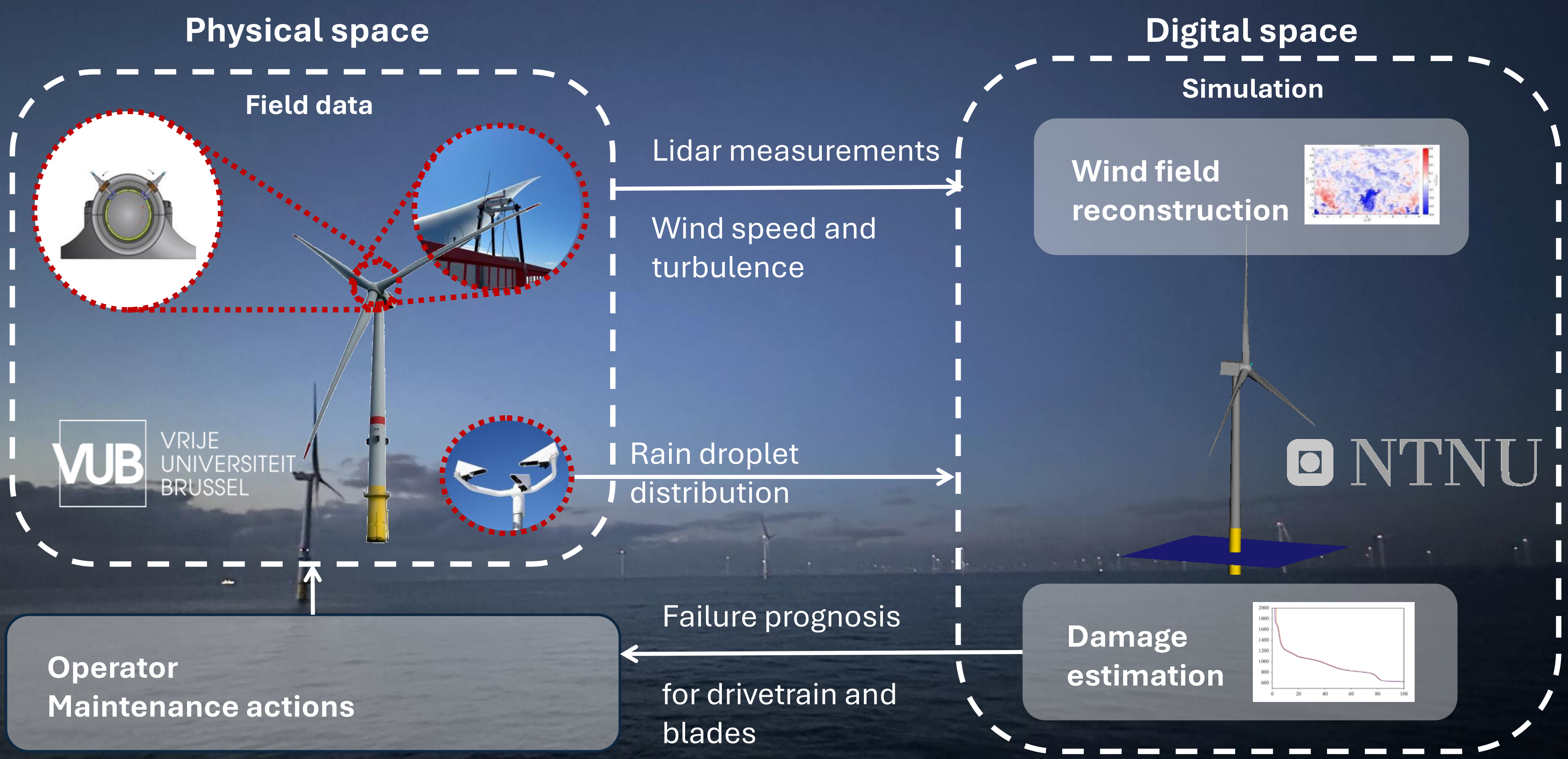
Validation







Digital twin at turbine level



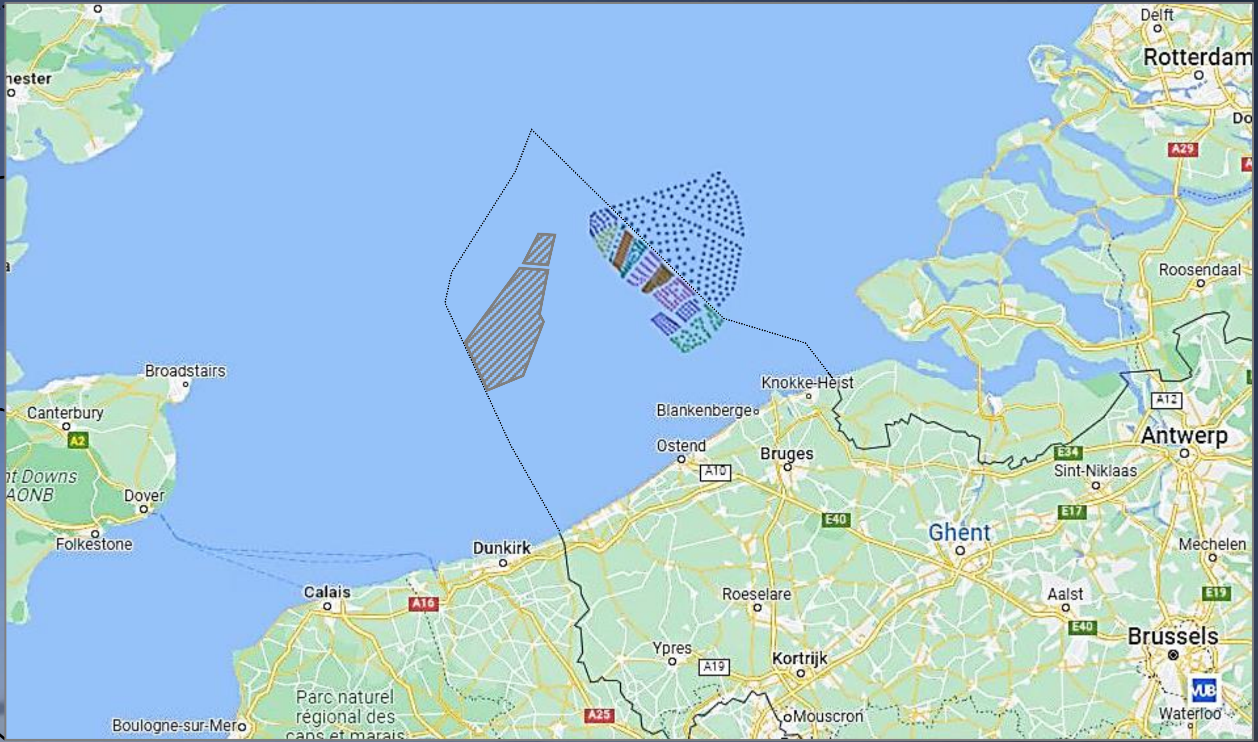
VRIJE UNIVERSITEIT BRUSSEL

Advanced weather forecast

VUB VRIJE UNIVERSITEIT BRUSSEL

Problem statement

Belgian-Dutch offshore wind farm cluster



- 13 wind farms
- 572 wind turbines (3764 MW)
- planning 2030: + 3500 MW

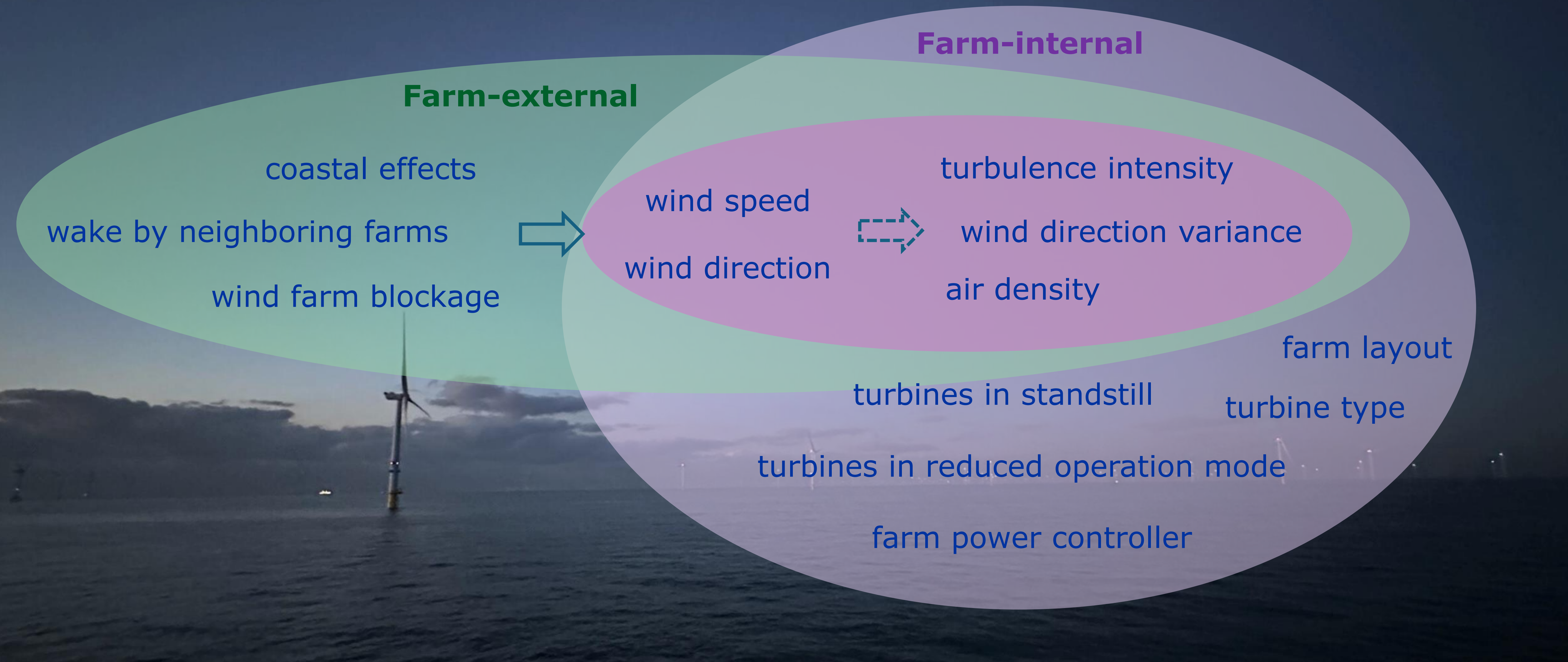
Large share of the total energy mix (>50%)
+ fluctuating nature

Wind farm operators: "Power production forecast for *my* wind farm ?"

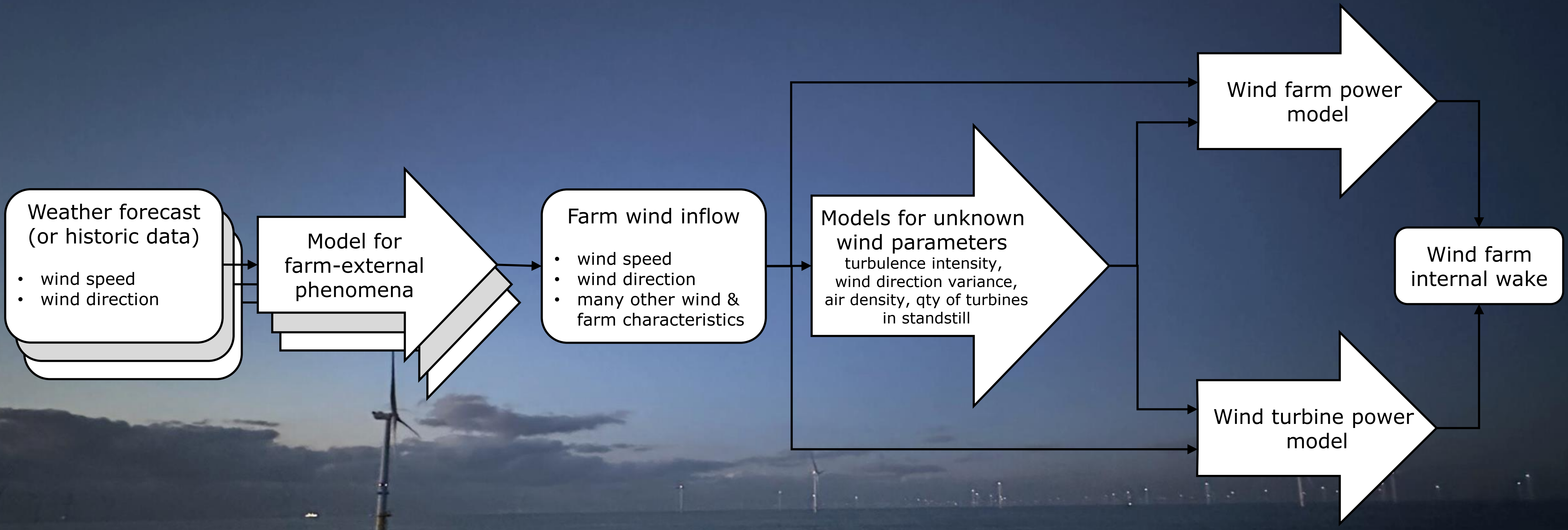
- different forecast horizons: day-ahead & intra-day energy trading, grid balancing services, …
- high speed predictions: real-time recommendation & control systems
- short time resolution: ~1 min.

VUB VRIJE UNIVERSITEIT BRUSSEL

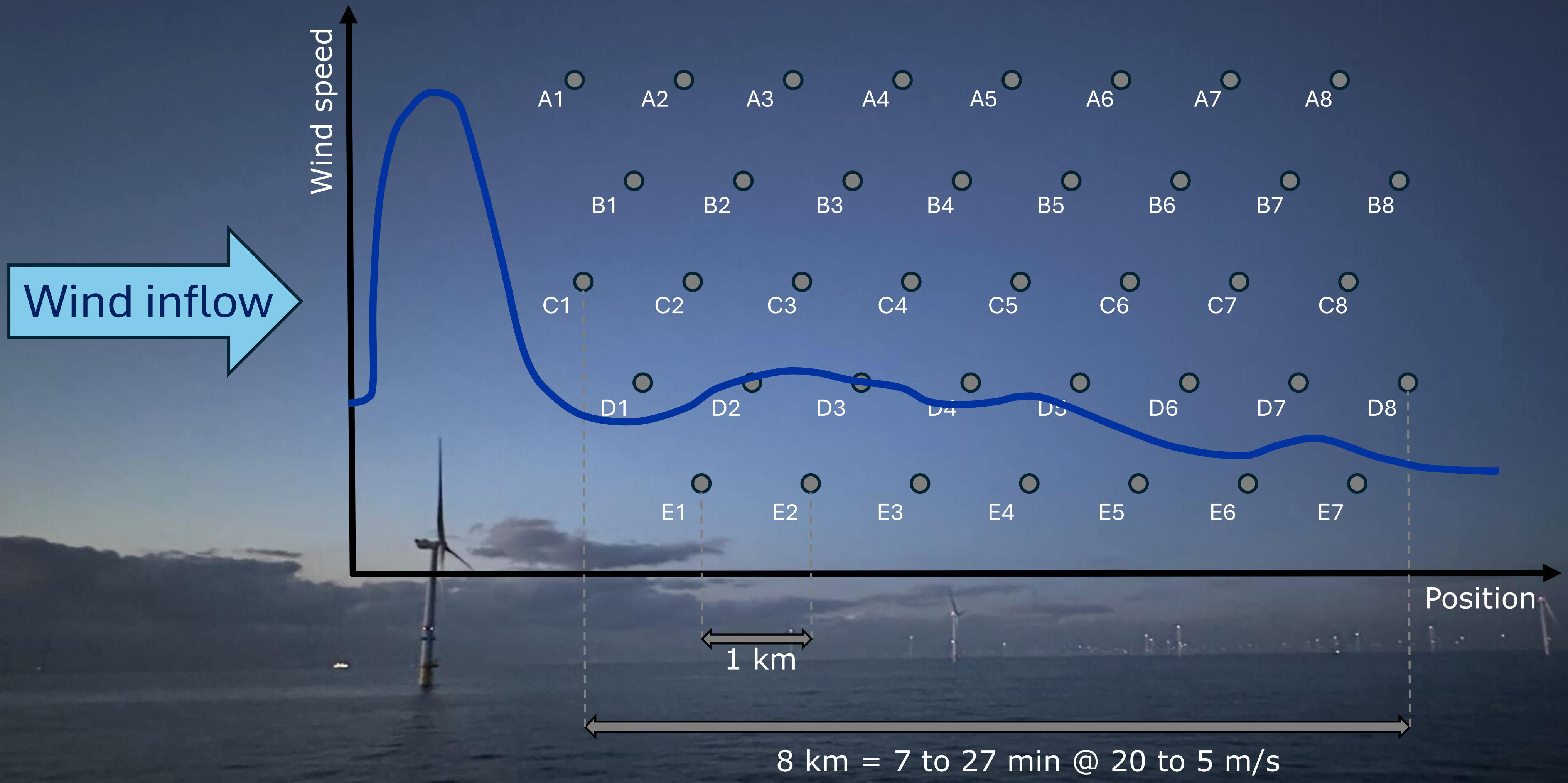
Parameters influence wind farm power



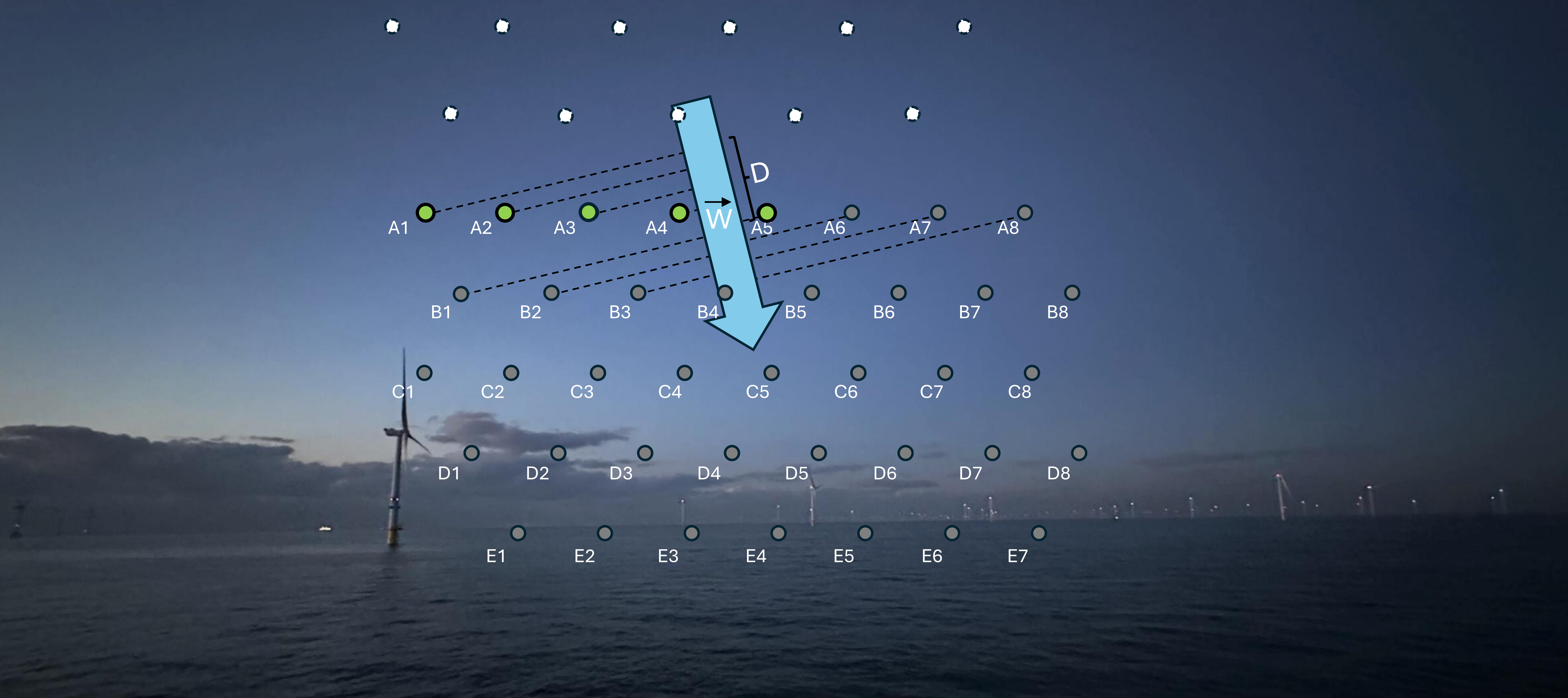
Modular deep learning structure



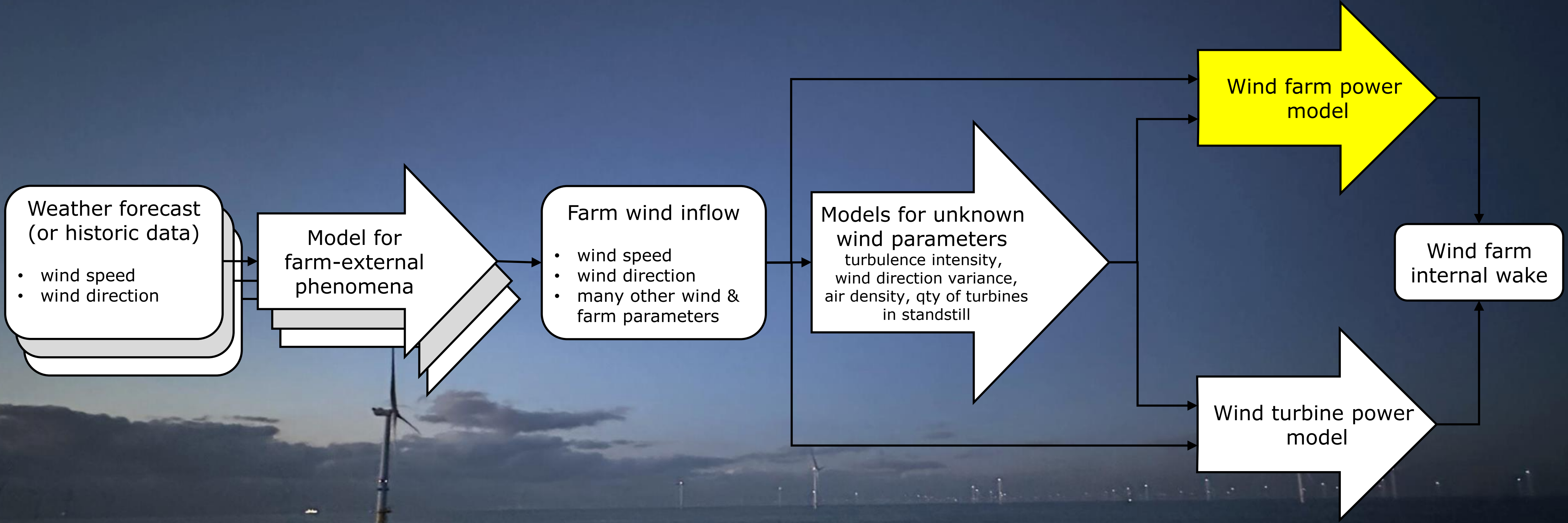
Farm wind inflow - dynamics



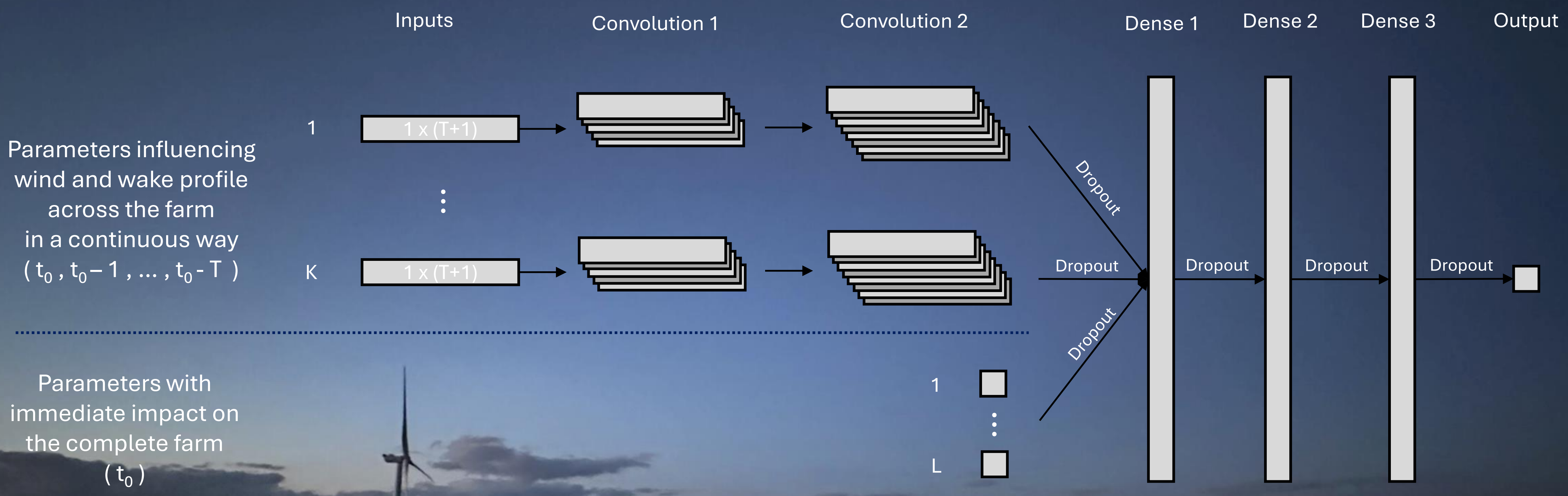
Farm wind inflow – upstream turbines



Wind farm production



Deep-learning model structure



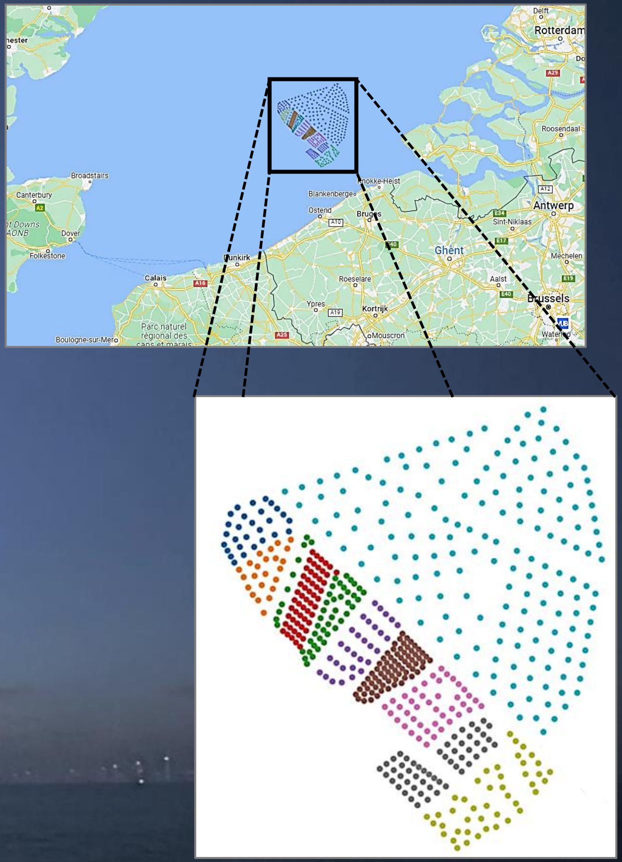
Uncertainty prediction based on: Monte Carlo dropout + Sigma-scaling

VUB VRIJE UNIVERSITEIT BRUSSEL

Test cases: two wind farms

- 2.5 years of 1-second turbine SCADA data
- pre-processed to 1-minute farm data features

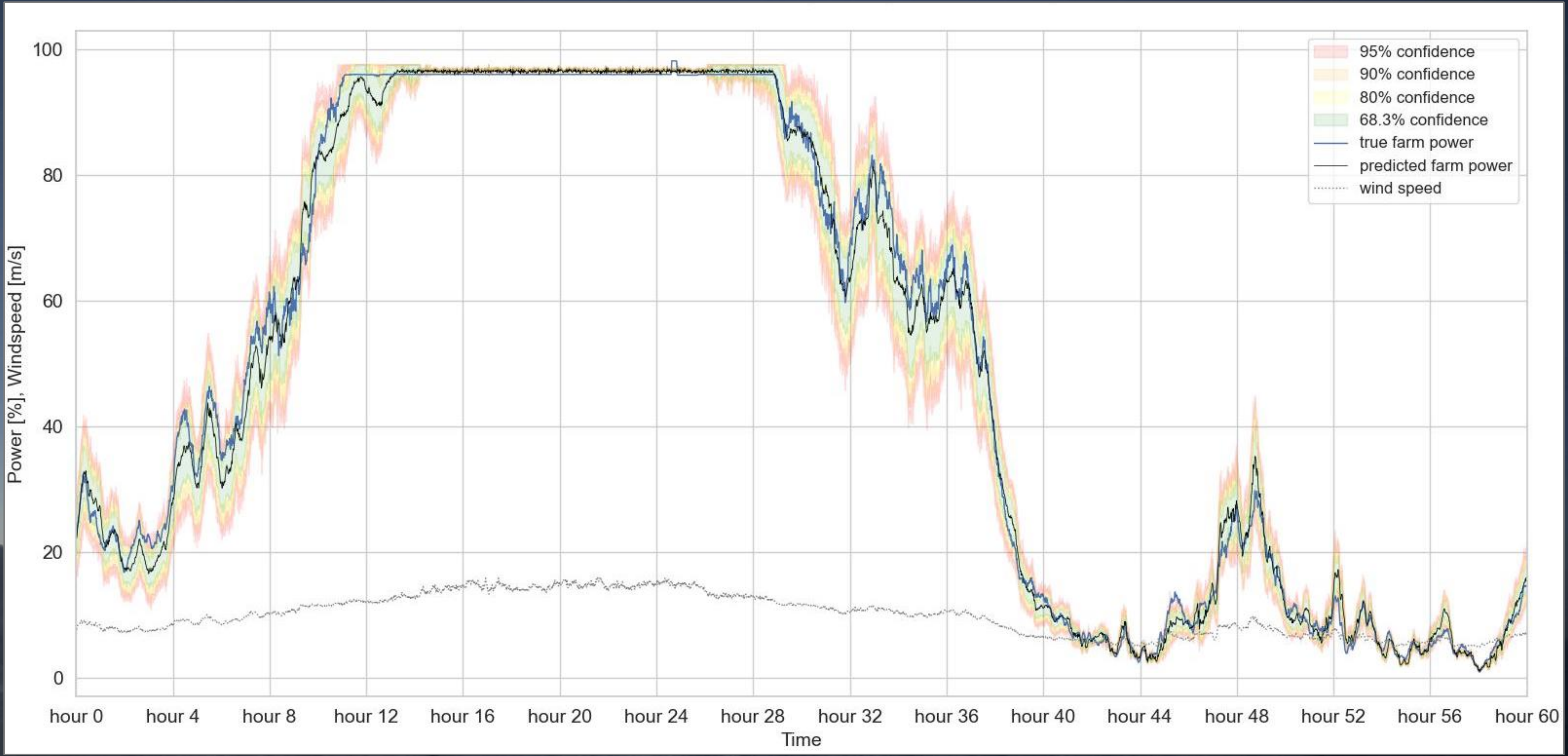
Data set	# Wind Farm 1	# Wind Farm 2
Training	960.695	978.008
Test *	292.996	292.078
Validation **	15.810	15.810
Total	**1.269.501**	**1.285.896**



* data blocks from days 2, 3, 4, 16, 17, 18 and 28 of each month
** 1 time sequence for 11 consecutive days

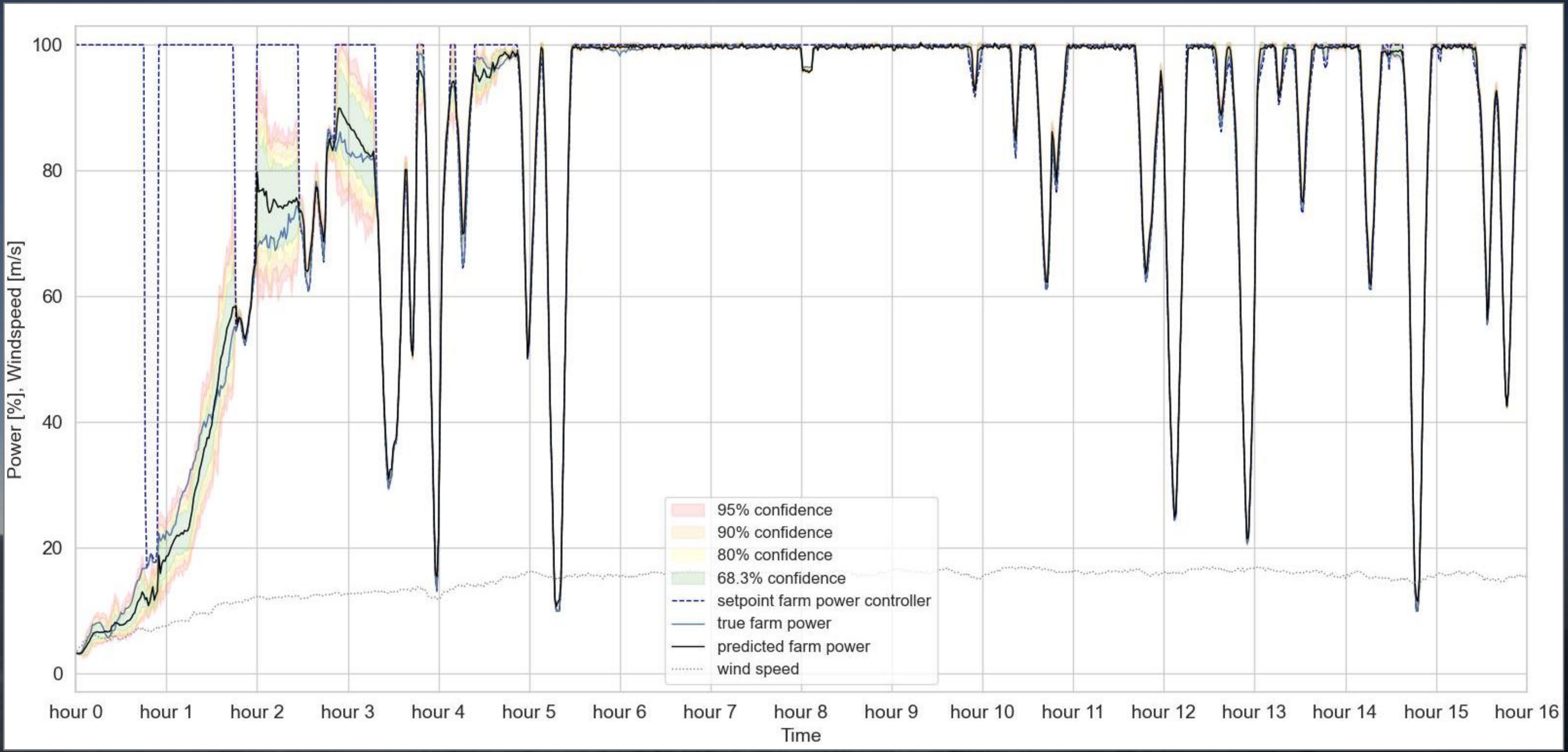
VUB VRIJE UNIVERSITEIT BRUSSEL

Validation time sequence



VRIJE UNIVERSITEIT BRUSSEL

Validation Time sequence – with farm power control

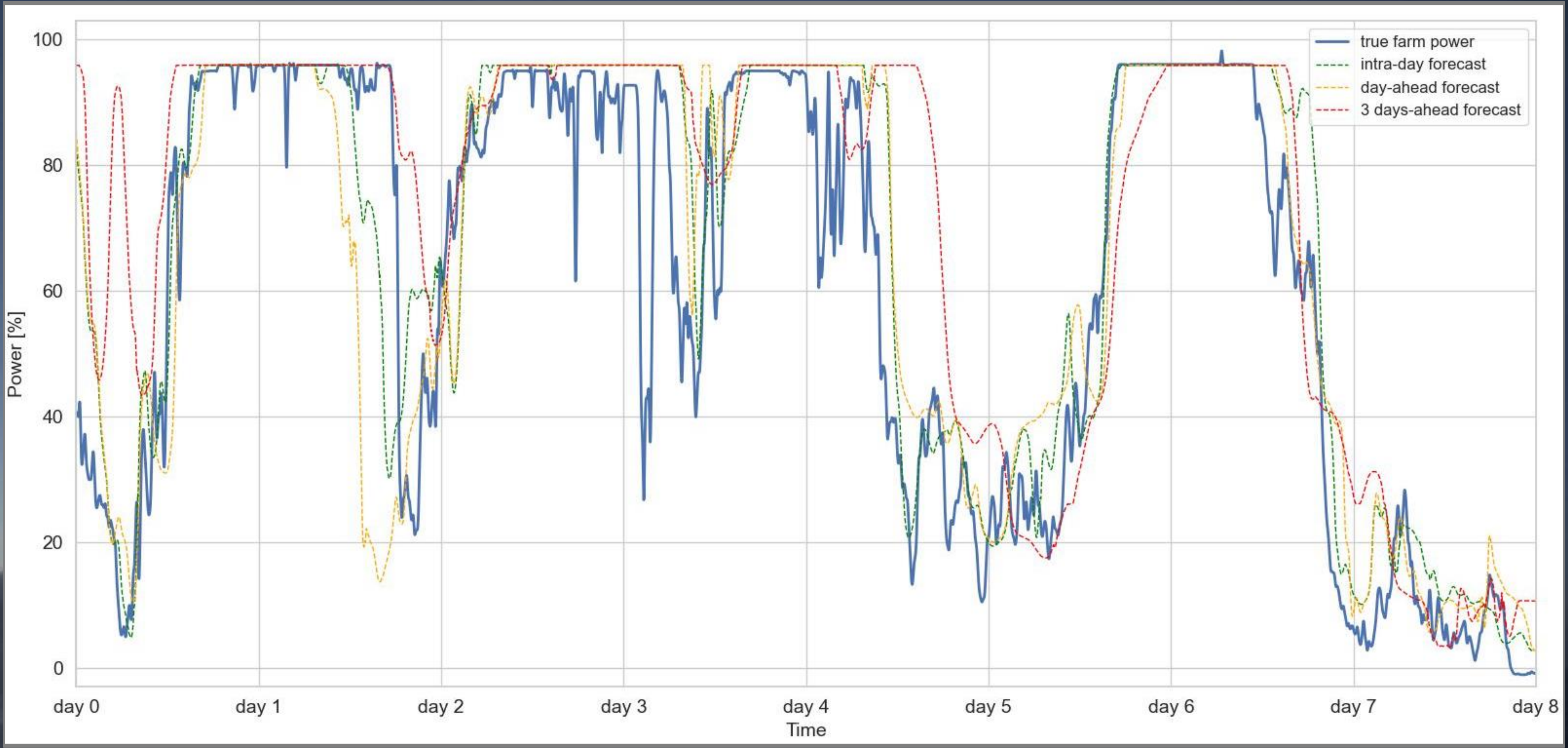


VUB VRIJE UNIVERSITEIT BRUSSEL

Performance metrics

	Wind Farm 1		Wind Farm 2	
Performance metrics	**training**	**test**	**training**	**test**
MAE	**2.22 %**	**2.42 %**	**2.15 %**	**2.14 %**
ME	-0.05 %	-0.17 %	-0.11 %	-0.10 %
RMSE	4.02 %	4.21 %	3.69 %	3.66 %
R2-score	0.99	0.99	0.99	0.99

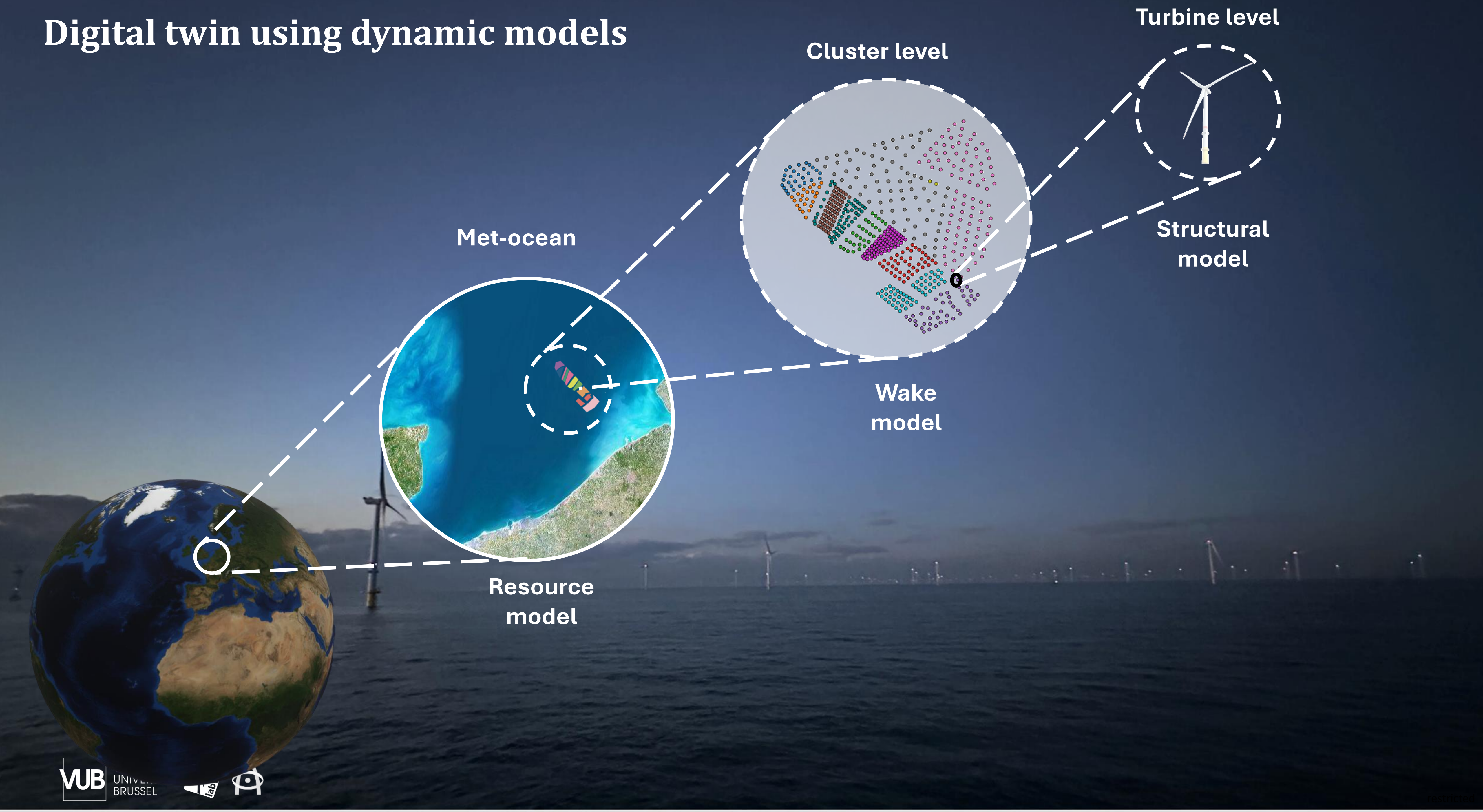
Farm power forecasts based on wind forecasts



Fleet-wide wake model calibration

VUB VRIJE UNIVERSITEIT BRUSSEL

Digital twin using dynamic models



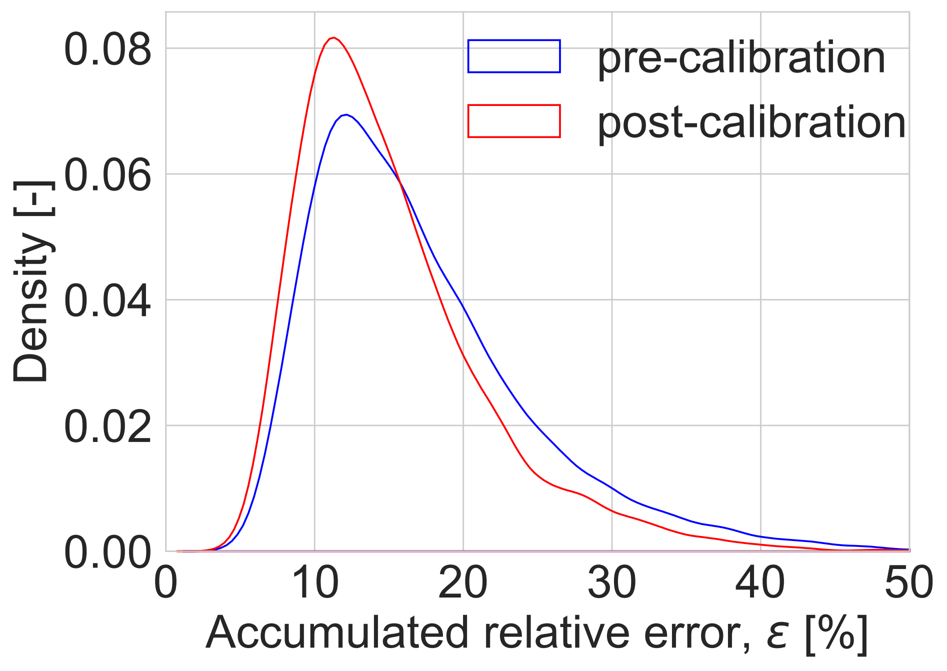
VUB UNIV... BRUSSEL

Step 1: Calibration at single farm level

Benchmarking:

- In blue: Pre-calibration:
  - Wind speed
  - Wind direction

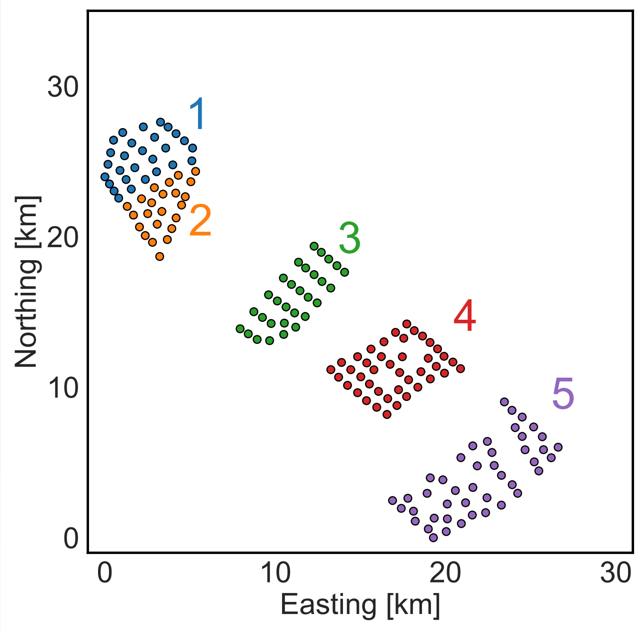
- In red: Post-calibration:
  - Tuning parameter
  - Wind speed
  - Wind direction

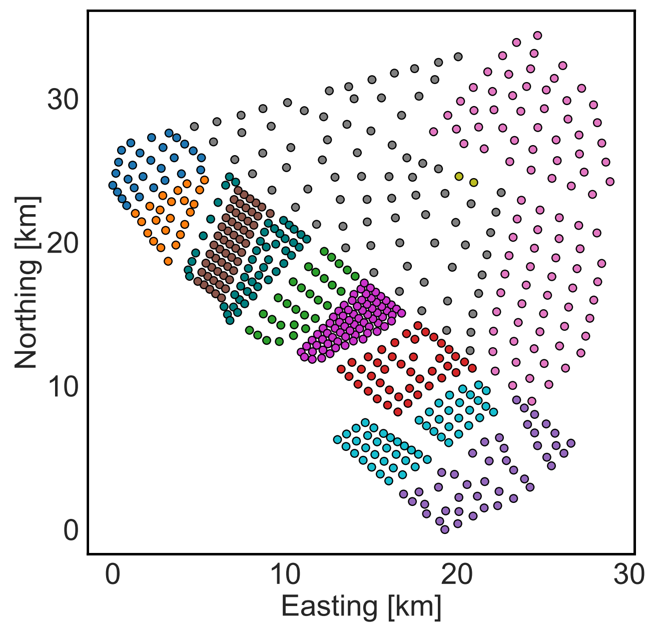


Clear improvement

$$\epsilon = \frac{\sum_{i=1}^{N_T} |\bar{P}_i - \hat{P}_i|}{\sum_{i=1}^{N_T} \bar{P}_i}$$

Step 2: Calibration at concession level



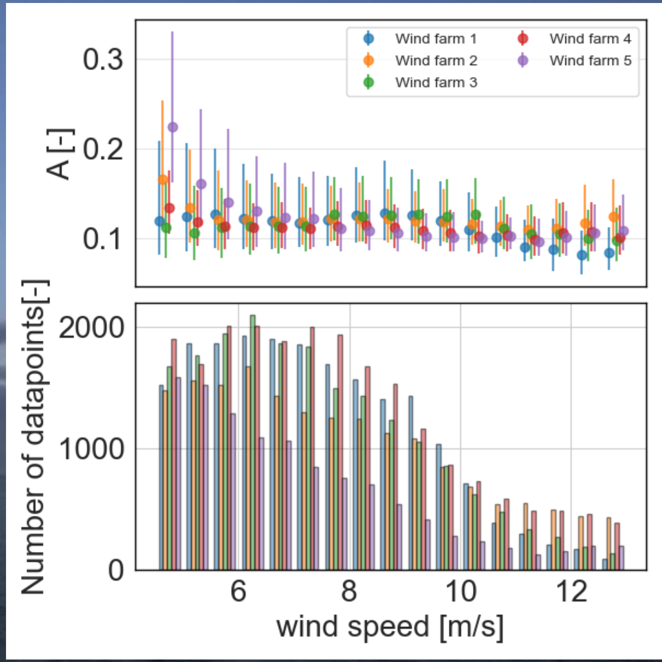


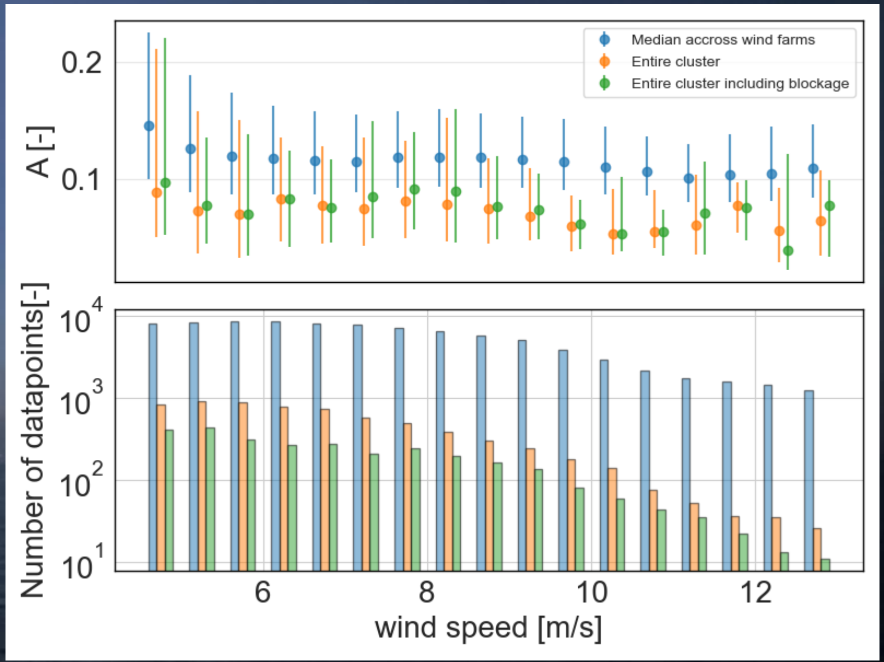
Step 2: Calibration at concession level

Comparison between results using different tuning procedures:

- Farm-wide tuning considering internal and external wake
- Concession-wide tuning

Example tuning parameter

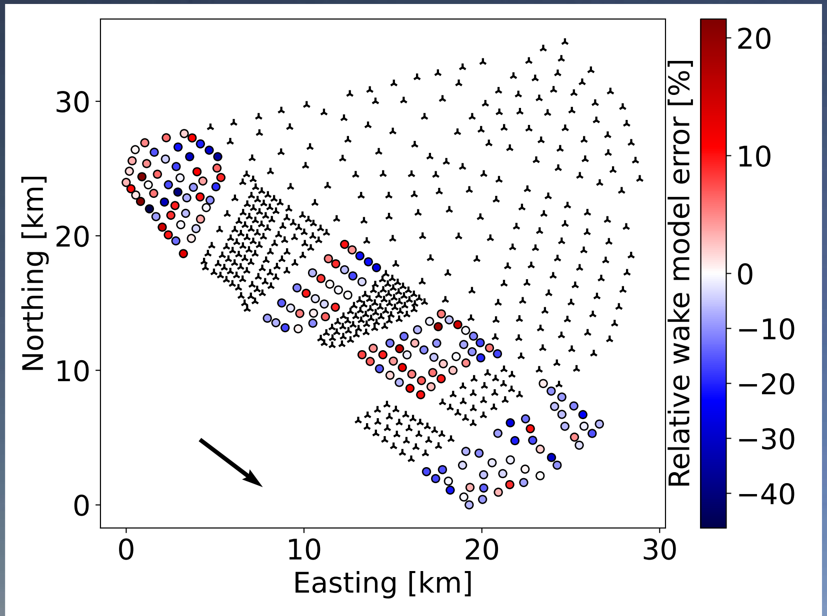




Internal + external wakes → Cluster wakes

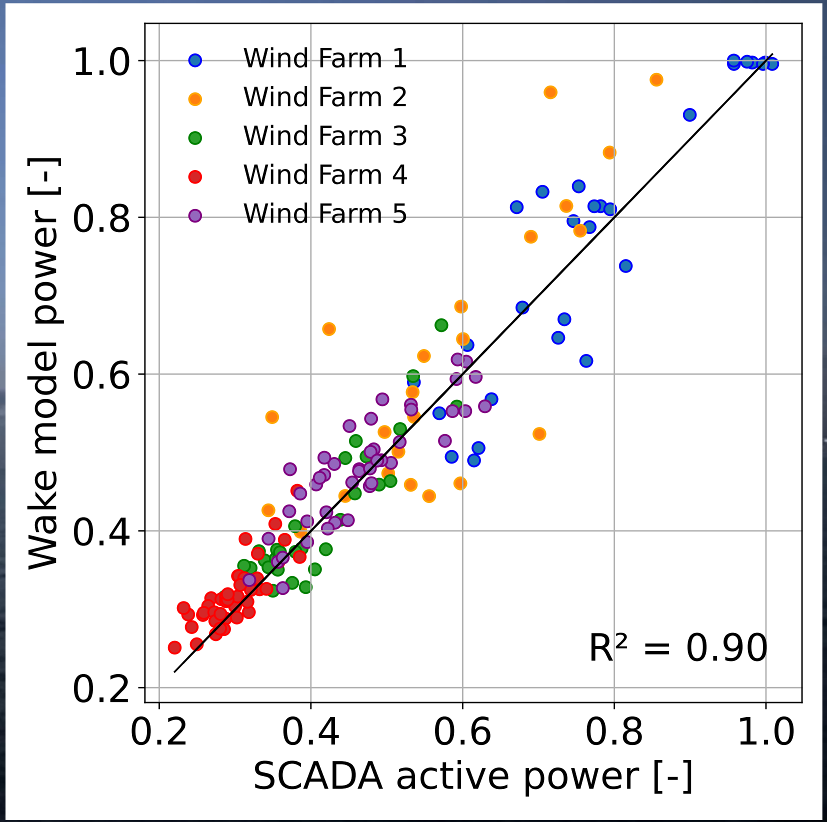
VUB VRIJE UNIVERSITEIT BRUSSEL

Step 2: Calibration at concession level

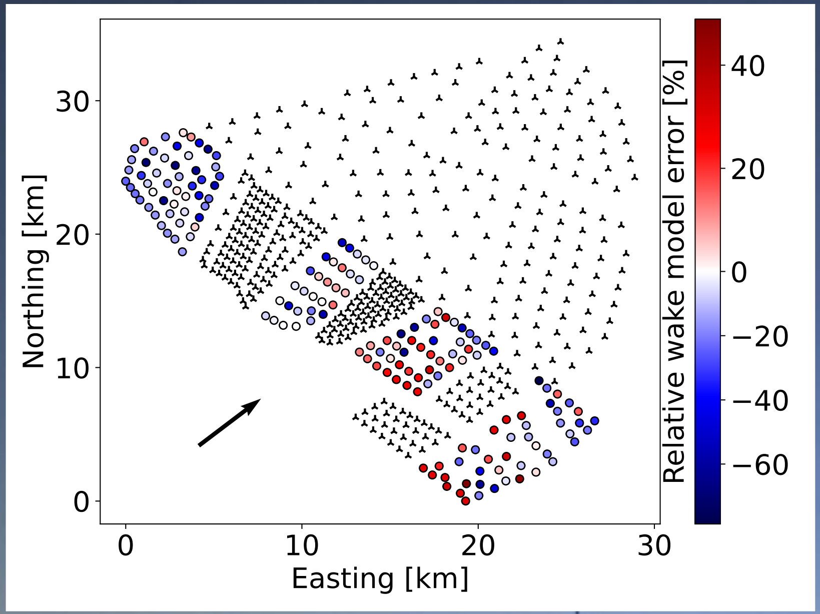


Comparison between simulated power and measured power production when **North-West** wind faced:

- High correlation between model and observations
- No major over- or underestimation of power production at a farm-wide level



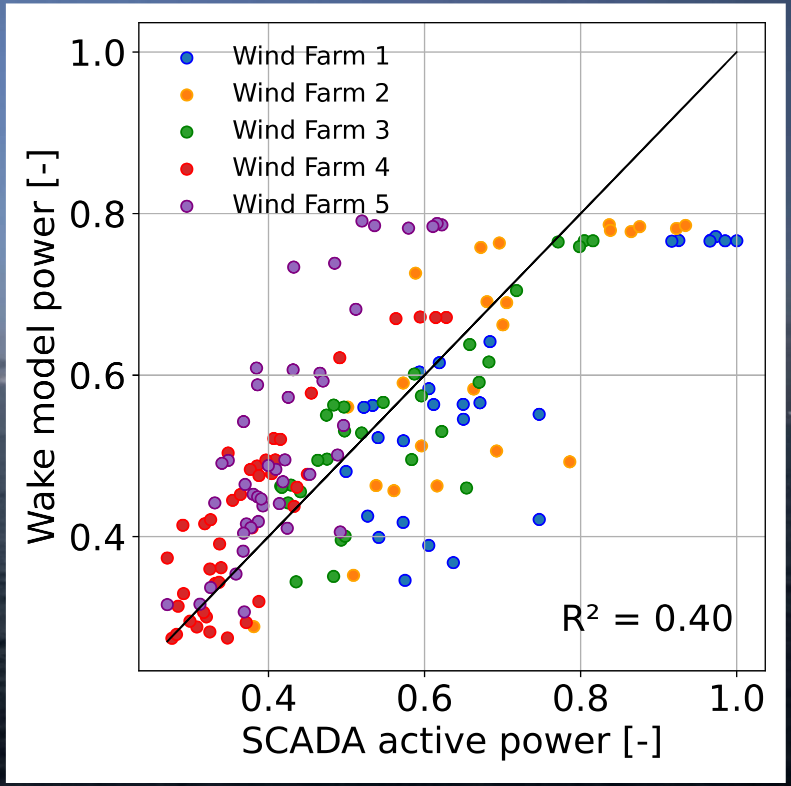
Step 2: Calibration at concession level



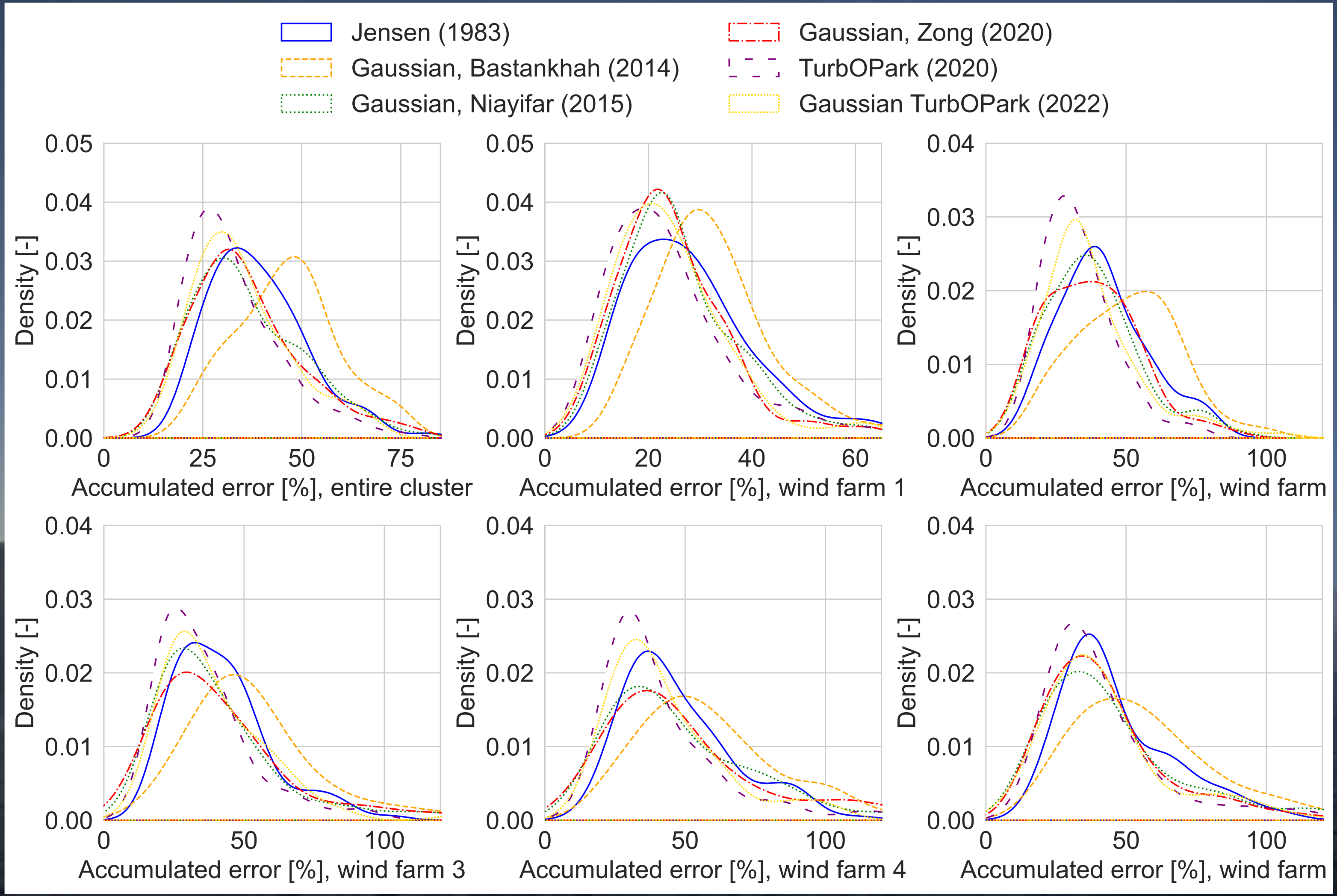
Comparison between simulated power and measured power production when **South-West** wind faced:

- Significantly lower correlation between model and observations
- Over- or underestimation of power production at a farm-wide level

Further investigation needed in these wind direction (e.g. implementing heterogeneous wind conditions)



Step 3: Comparison of different wake models



Models need to be tuned to ensure simulation matches reality

- Initially large discrepancy between internal wake losses of the different models
- Calibration procedure significantly reduces variability between the different models

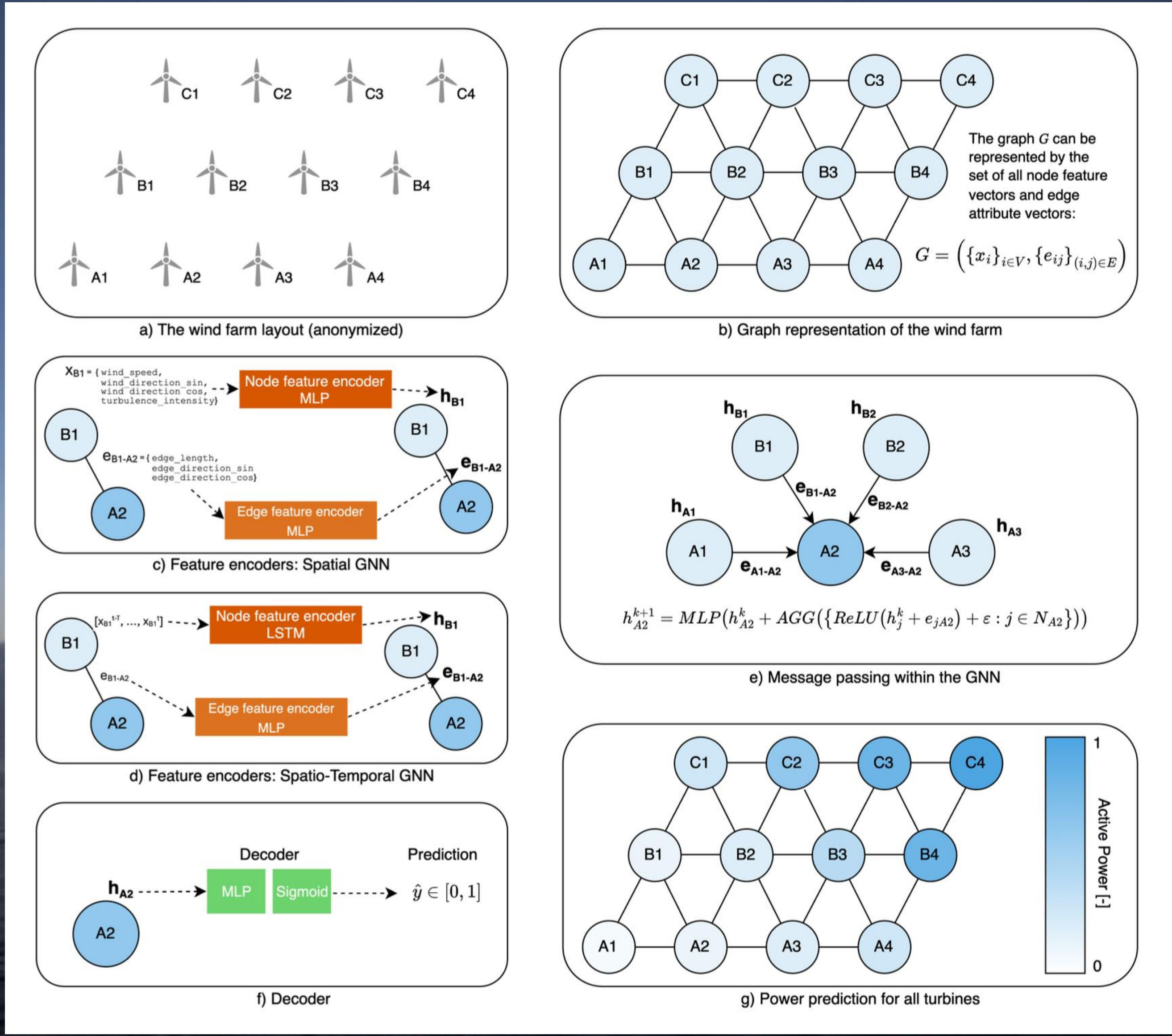
$$P_{acc,wt}^{cluster} = \frac{\sum_{j=1}^{N_{WF}} \sum_{j=1}^{N_{WT}} \left|P_{i,j}^{scada} - P_{i,j}^{model}\right|}{\sum_{i=1}^{N_{WF}} \sum_{j=1}^{N_{WT}} P_{i,j}^{scada}}$$

$$P_{acc,wt}^{farm} = \frac{\sum_{j=1}^{N_{WT}} \left|P_{j}^{scada} - P_{j}^{model}\right|}{\sum_{j=1}^{N_{WT}} P_{j}^{scada}}$$

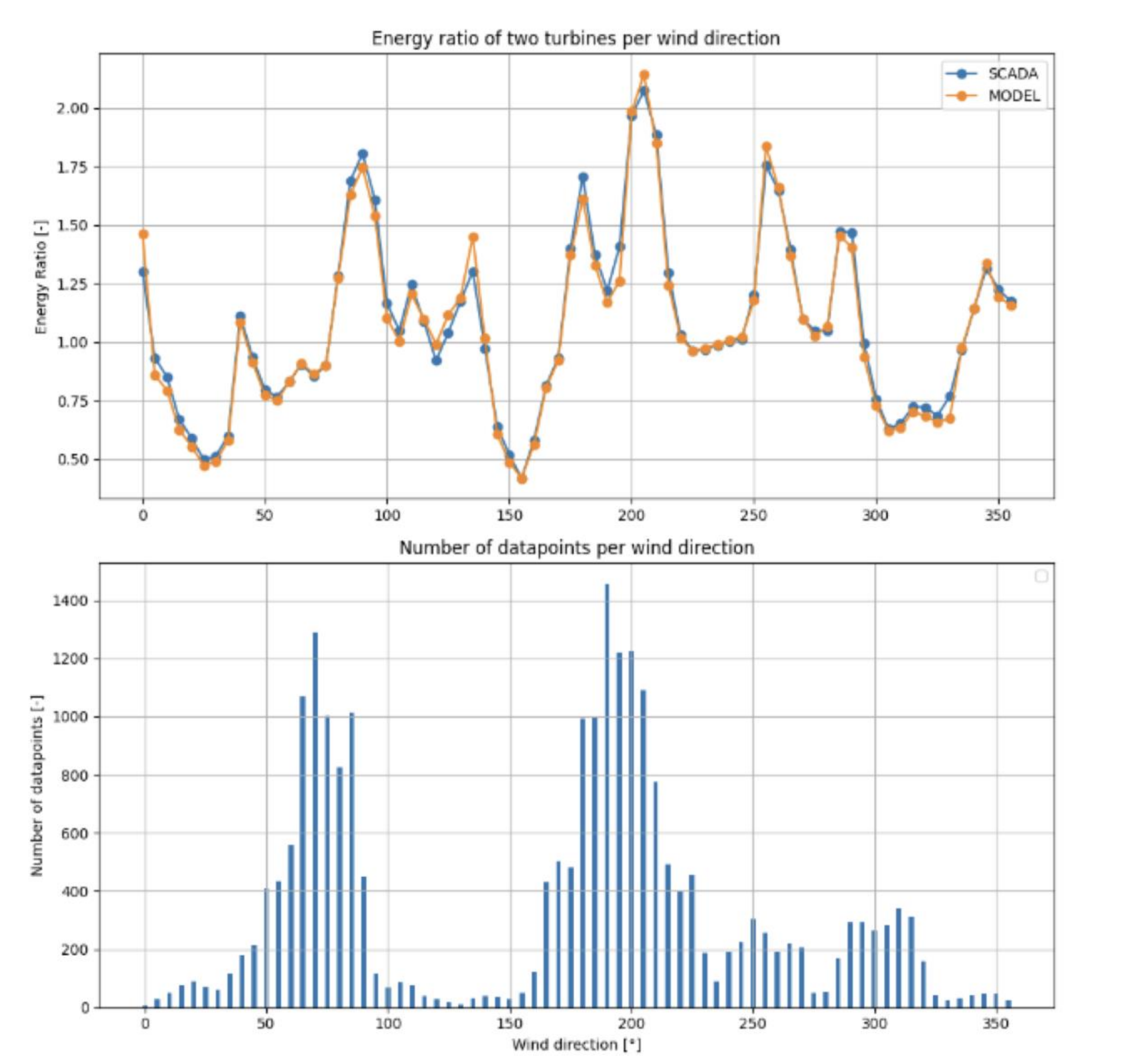
AI based wind farm modeling

VUB VRIJE UNIVERSITEIT BRUSSEL

Deep learning based power model



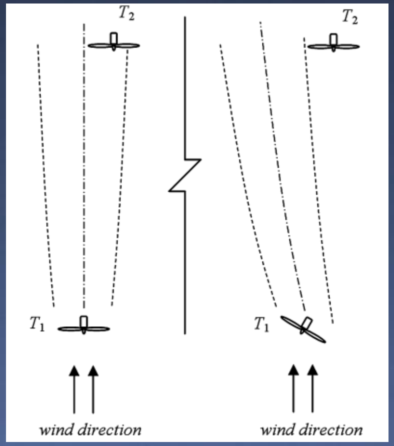
Deep learning based power model



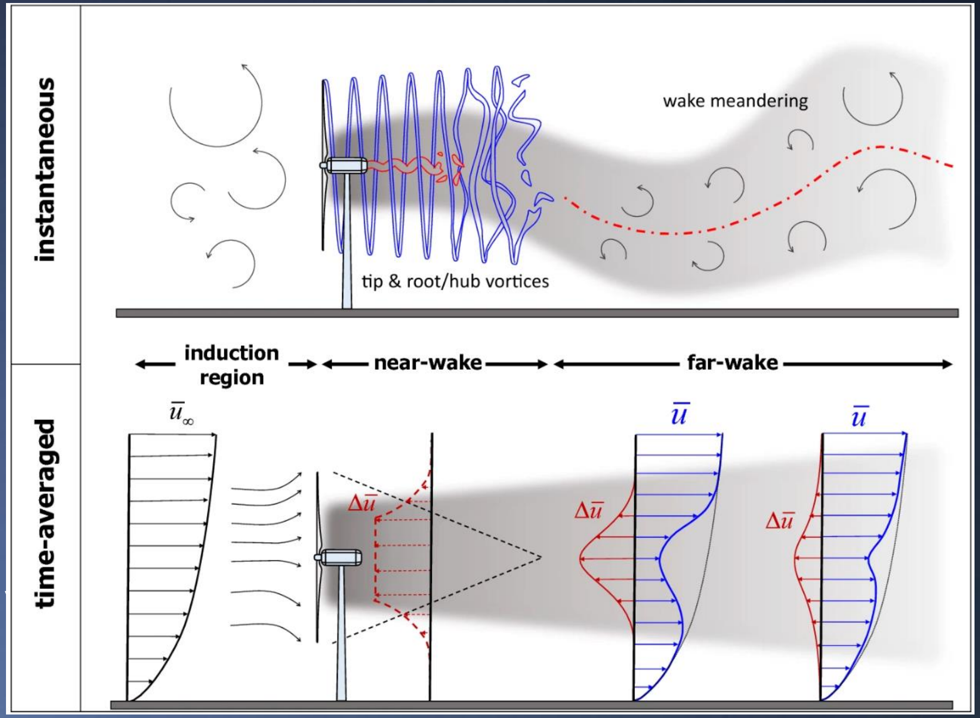
VRIJE
UNIVERSITEIT
BRUSSEL

Wind farm control

Introduction



Jimenez A, Crespo A, Migoya E, *Wind Energy* **13**:559-572 (2010)



Porté-Agel F, Bastankhah M, Shamsoddin S, *Boundary-layer Meteorol* **174**, 1-59 (2020)

• Why wake steering?

- Potential power gains on farm level

• Why don't we perform wake steering on large-scale

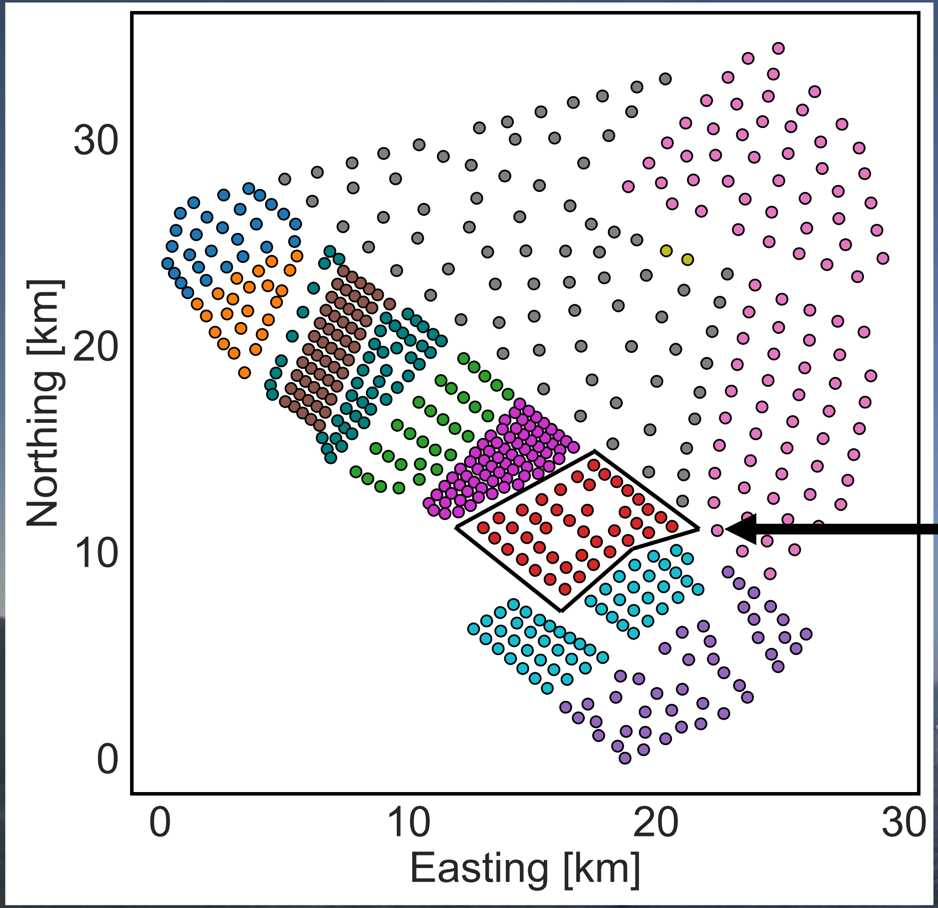
- Dependent on wind and atmospheric conditions (e.g. stability)
- Prone to inflow and sensor uncertainty

• How can we minimize uncertainty?

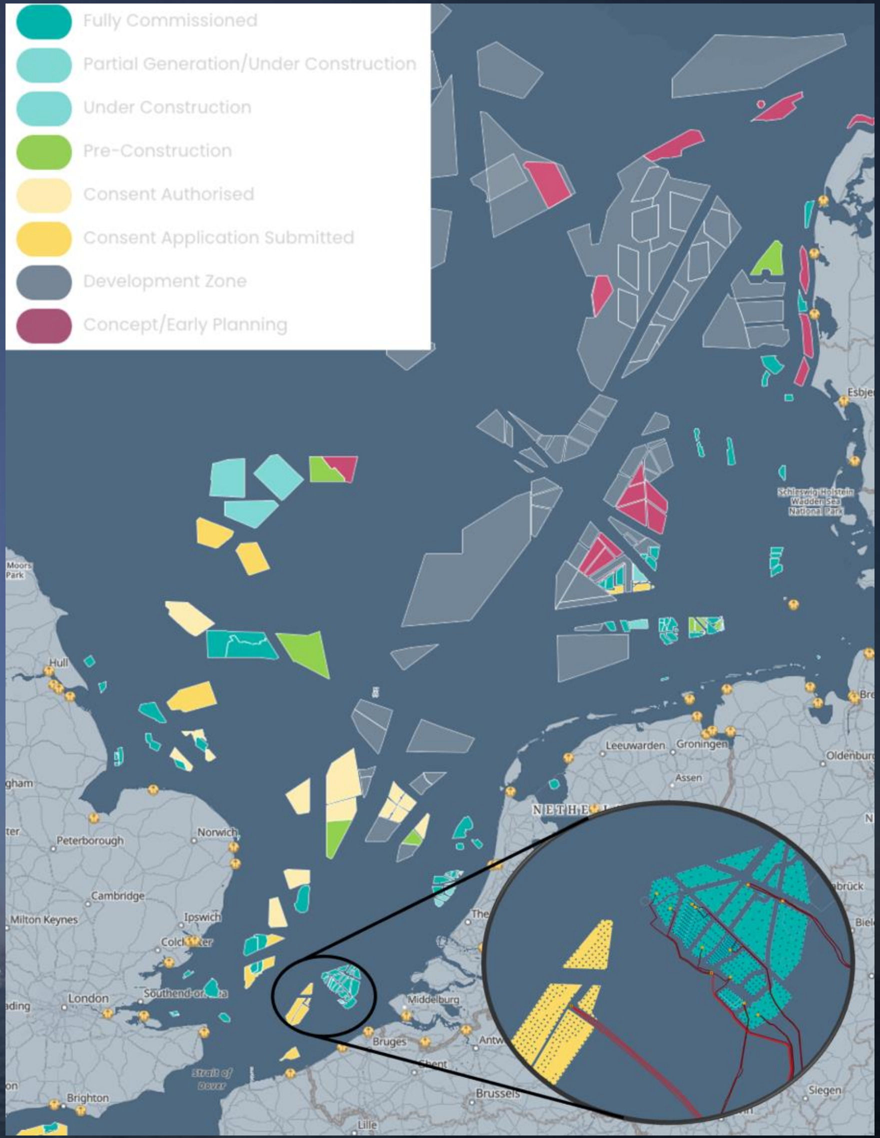
- Robust controller design (by including sources of uncertainty)
- Correlate atmospheric stability with wake properties (e.g. velocity deficit)

VRIJE UNIVERSITEIT BRUSSEL

Case study



Northing [km]
Easting [km]
0
10
20
30
0
10
20
30



Fully Commissioned
Partial Generation/Under Construction
Under Construction
Pre-Construction
Consent Authorised
Consent Application Submitted
Development Zone
Concept/Early Planning
Peterborough
Cambridge
Norwich
Ipswich
Milton Keynes
London
Brighton
Bruges
Middelburg
Leeuwarden
Groningen
Assen
Brussels
Siegen
Oldenburg

Methodology

Time-series based

- Calibrated wake model[1,2,3]
- Stability annotation

Calibration outcomes as function of stability

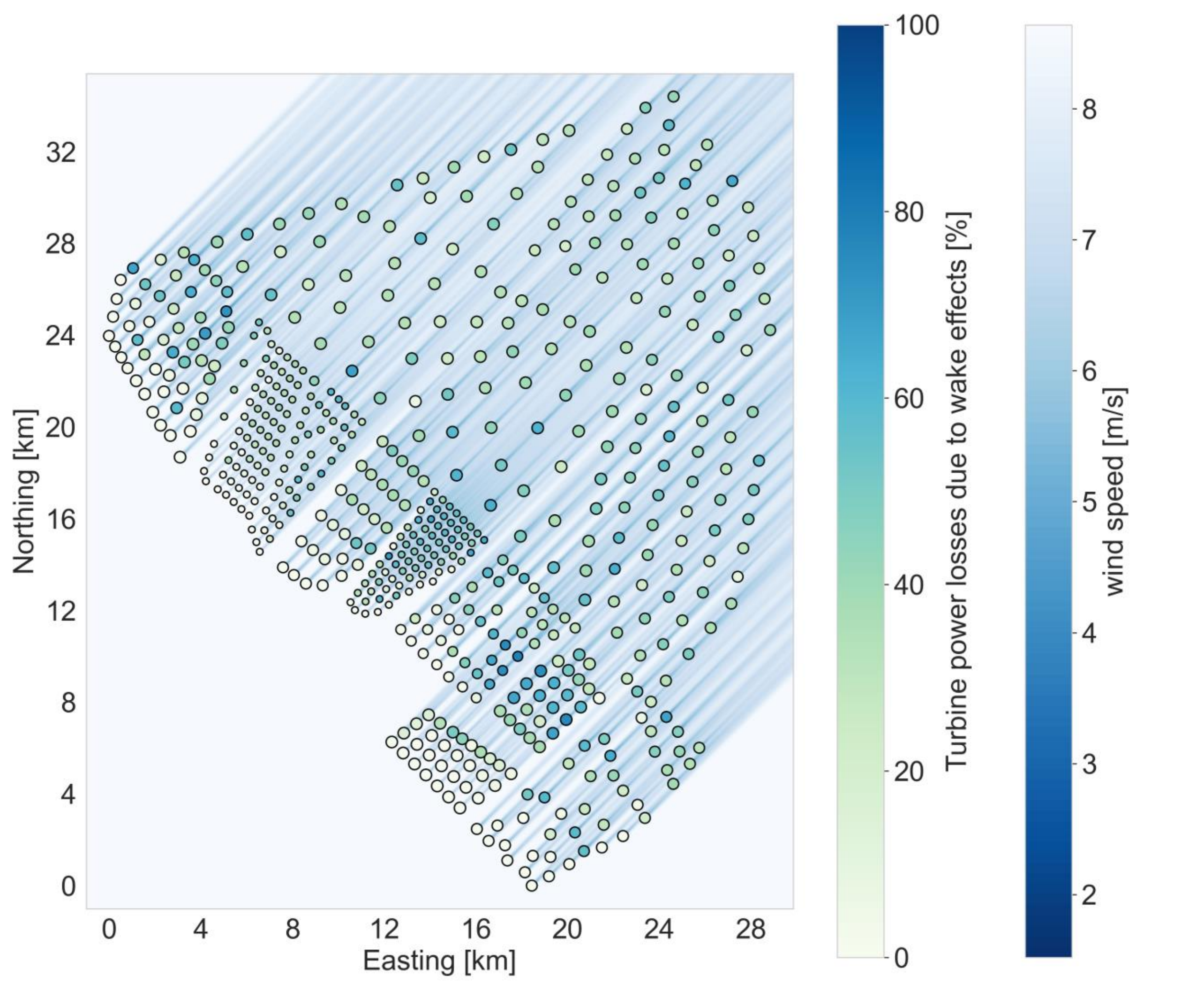
Yaw angle optimization for different calibration outcomes using Serial-refine method[4] and Jimenez wake deflection model[5]

Methodology

- Calibrated wake model:
- Time-series calibration on SCADA data (2 y

- Framework:
- Pywake[6]
- Homogeneous
- Time-invariant
  - No meandering

- Gaussian TurbOPark model[7]
  - Tuning parameter: A

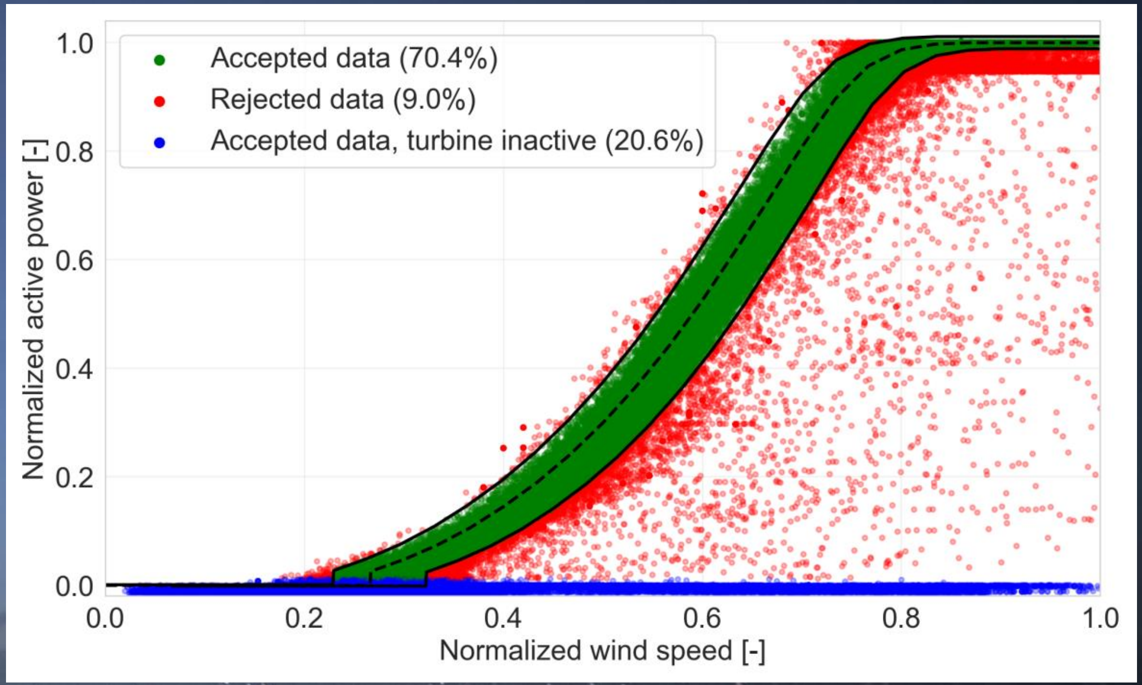


Van Binsbergen D, Verma A, Nejad A, Helsen J **2024** Journal of physics: conference series vol xxx [deepwind 2024]

Methodology

- **Determining wake properties using SCADA:**

- Calibrate wake model velocity deficit parameter(s)
  - Filtering:
    - Power-curve
    - Large misalignment
    - Curtailment
    - Status logs



Van Binsbergen D, Daems P J, Verstraeten T, Nejad A, Helsen J **2024** *wind energy science* Vol. 9, No. 7 p. 1507-1526

Methodology

- **Calculate atmospheric stability using:**
- Metetereological mast

→ Stability annotation

  - Bulk richardson number: $R_b = \frac{gz(T_a - T_s)}{(273.15+T_a)u^2}$
  - Unstable: $R_B < -0.02$
  - Stable: $R_B > 0.02$
  - Neutral: $-0.02 \leq R_B \leq 0.02$

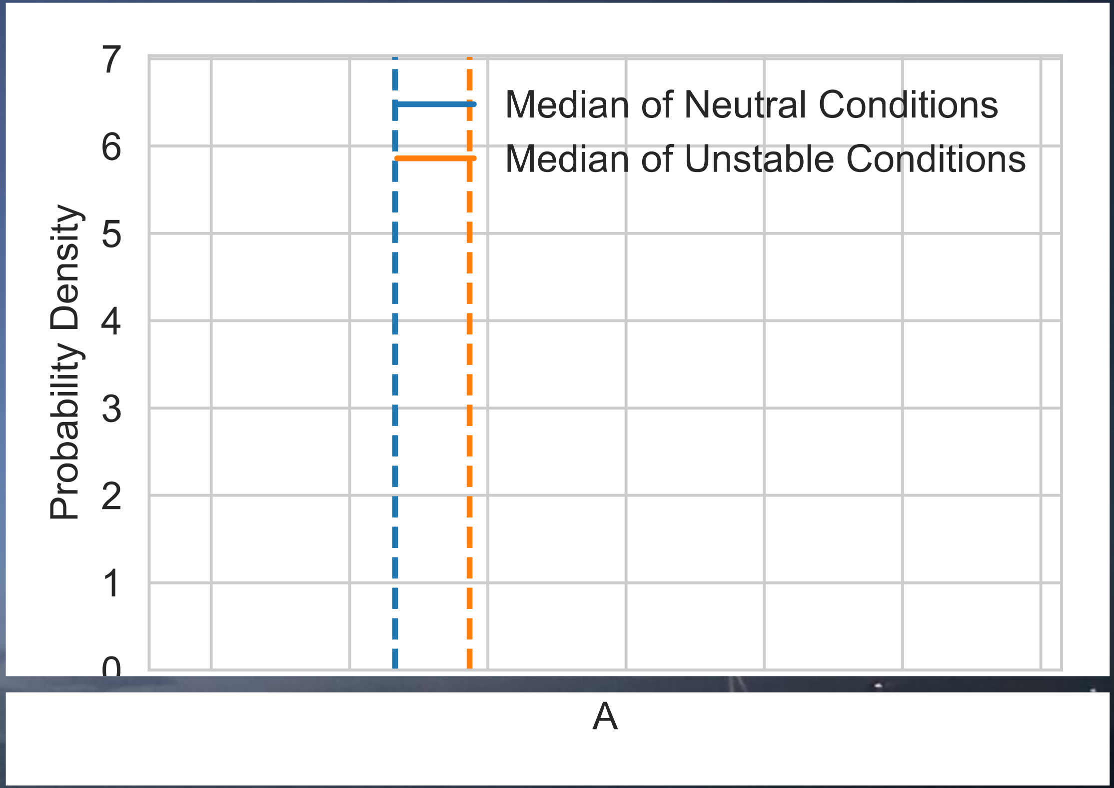
Westhinder met mast

VRIJE UNIVERSITEIT BRUSSEL

Results

Tuning parameter distributions:

- Stable conditions are relatively uncommon in the north sea
- Wake expansion parameter, A:
  - Larger for unstable conditions
  - Smaller for neutral conditions

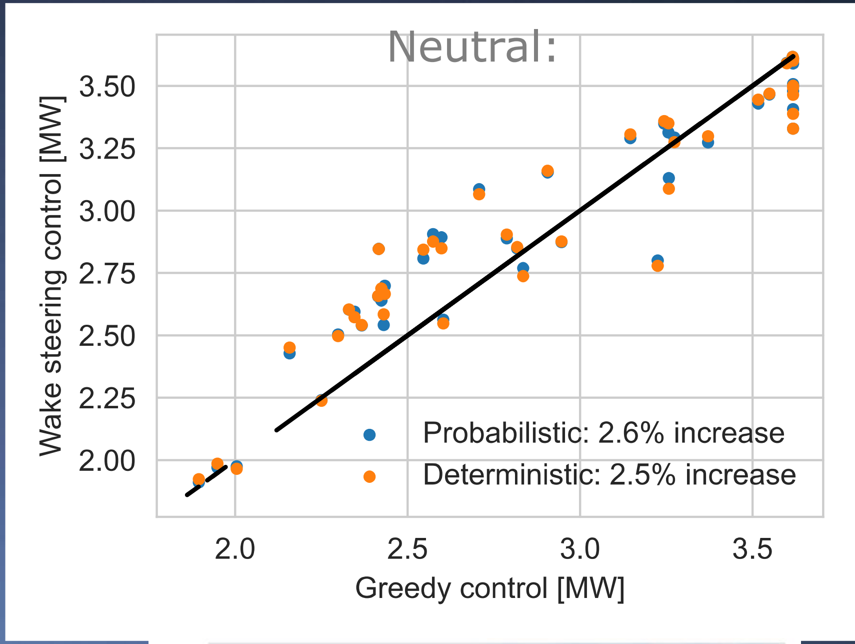


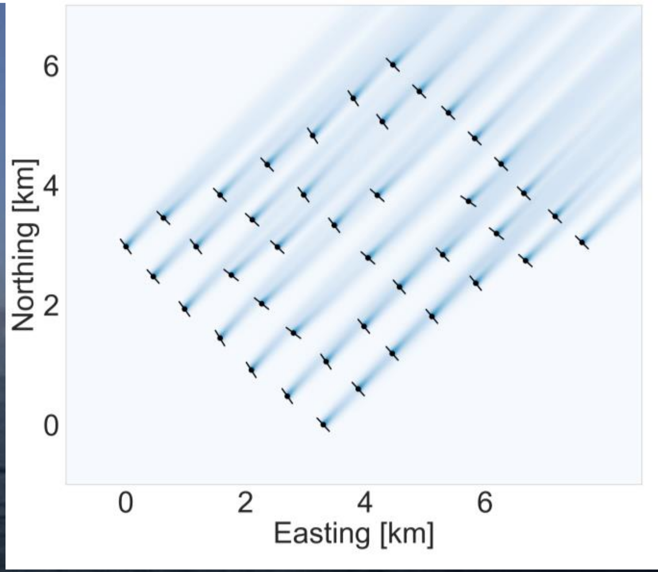
VRIJE UNIVERSITEIT BRUSSEL

Results

Deterministic and robust optimization:

- Deterministic optimization:
  - $\max_{\gamma}(P_{farm}(\boldsymbol{\gamma})) = P_{farm}(\boldsymbol{\gamma}, A)$
- Robust optimization:
  - $\max_{\gamma}(P_{farm}(\boldsymbol{\gamma})) = \sum_{A} P_{farm}(\boldsymbol{\gamma}, A) \cdot f(A) \cdot \Delta A$
- Wind speed: 9 m/s
- Wind direction: 225 degrees

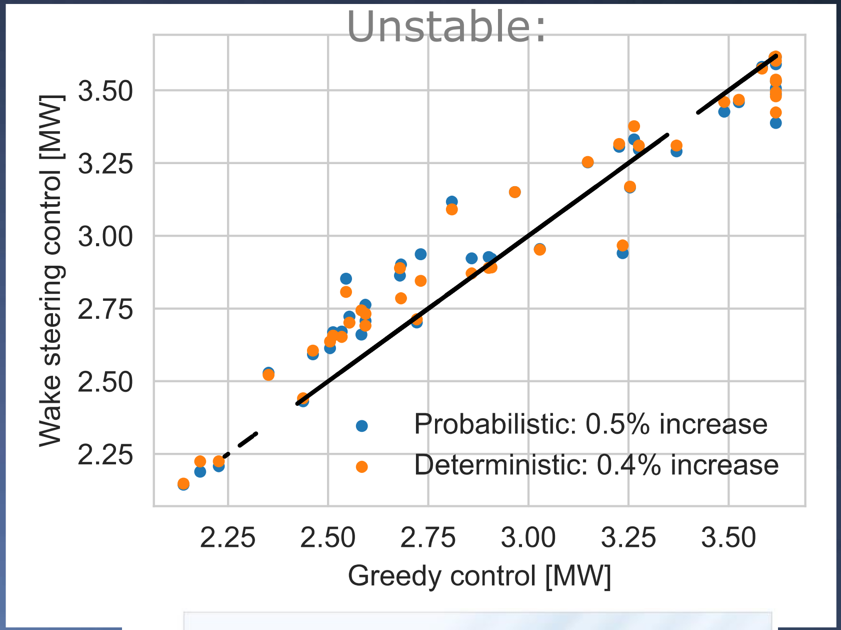


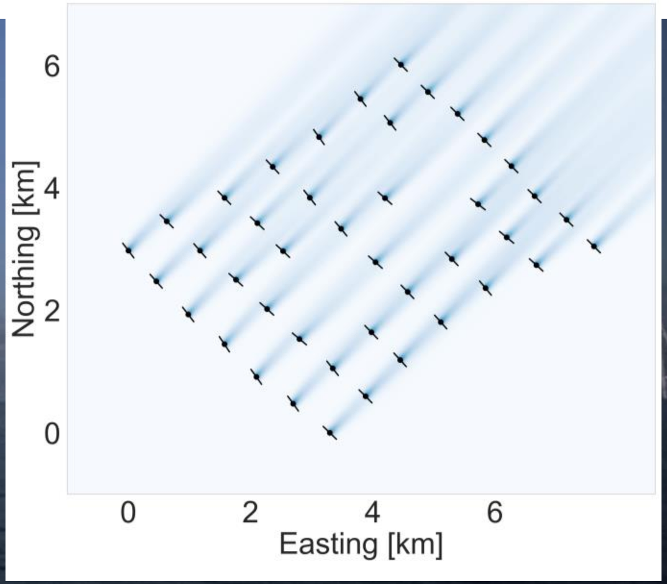


Results

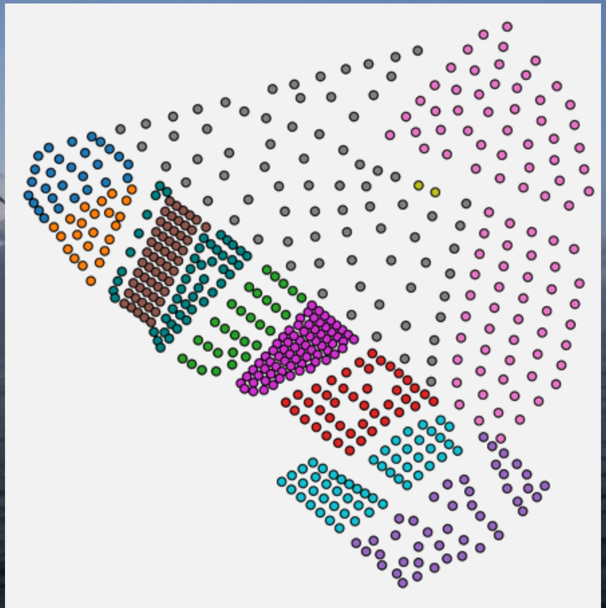
Deterministic and robust optimization:

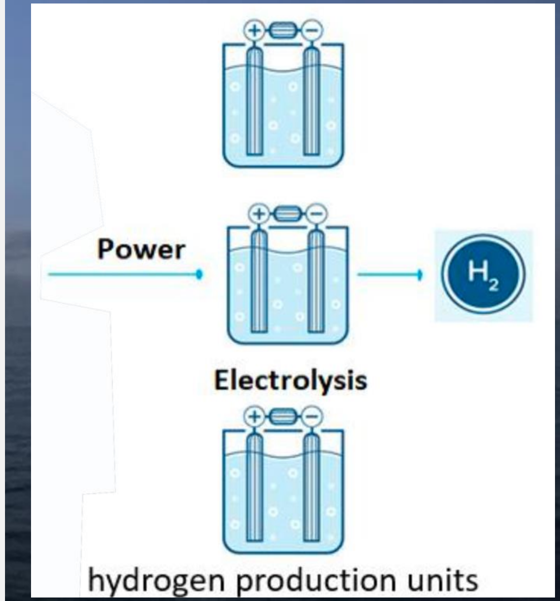
- Deterministic optimization:
  - $$\max_{\gamma}(P_{farm}(\boldsymbol{\gamma})) = P_{farm}(\boldsymbol{\gamma}, A)$$
- Robust optimization:
  - $$\max_{\gamma}(P_{farm}(\boldsymbol{\gamma})) = \sum_{A} P_{farm}(\boldsymbol{\gamma}, A) \cdot f(A) \cdot \Delta A$$
- Wind speed: 9 m/s
- Wind direction: 225 degrees





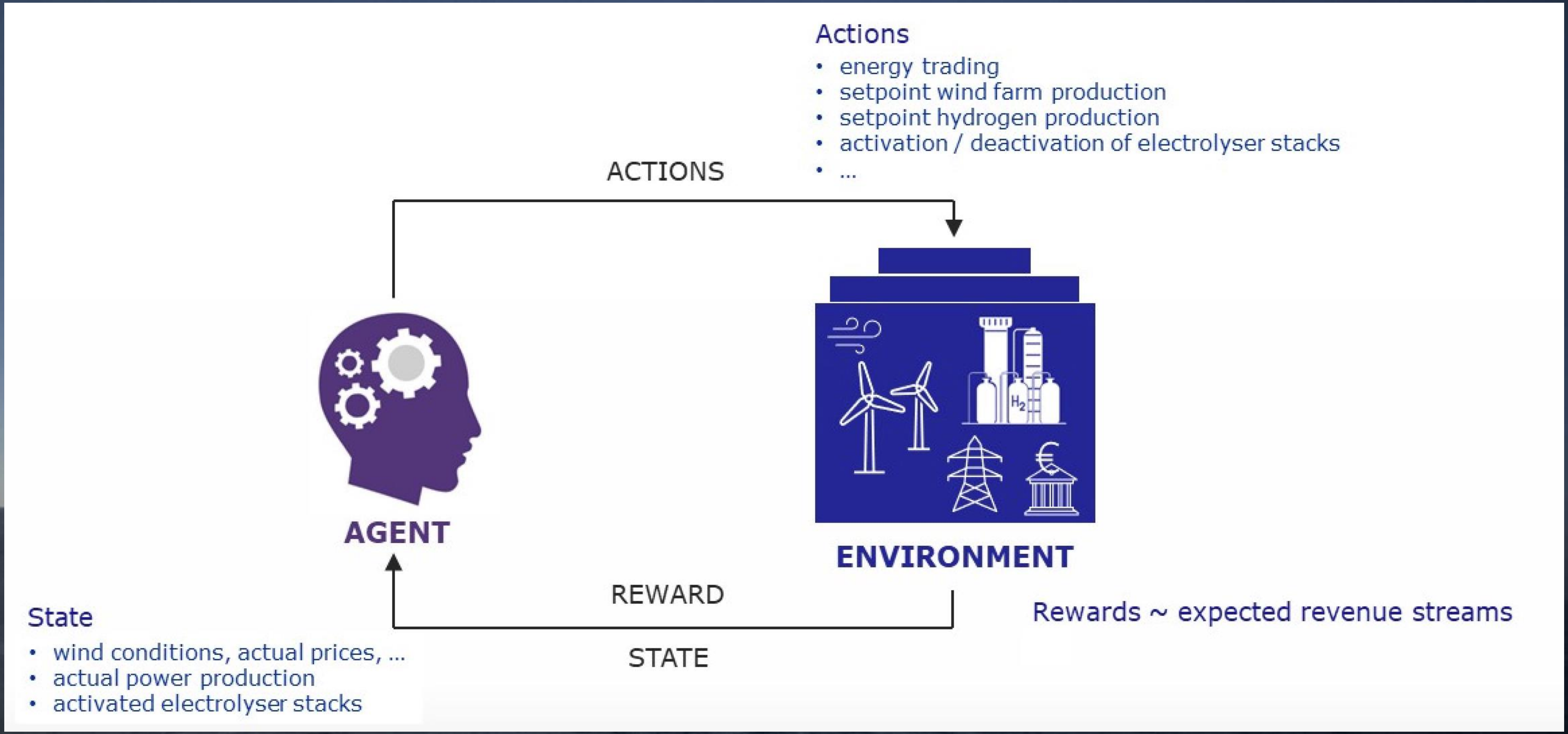
Wind farm control combined with storage



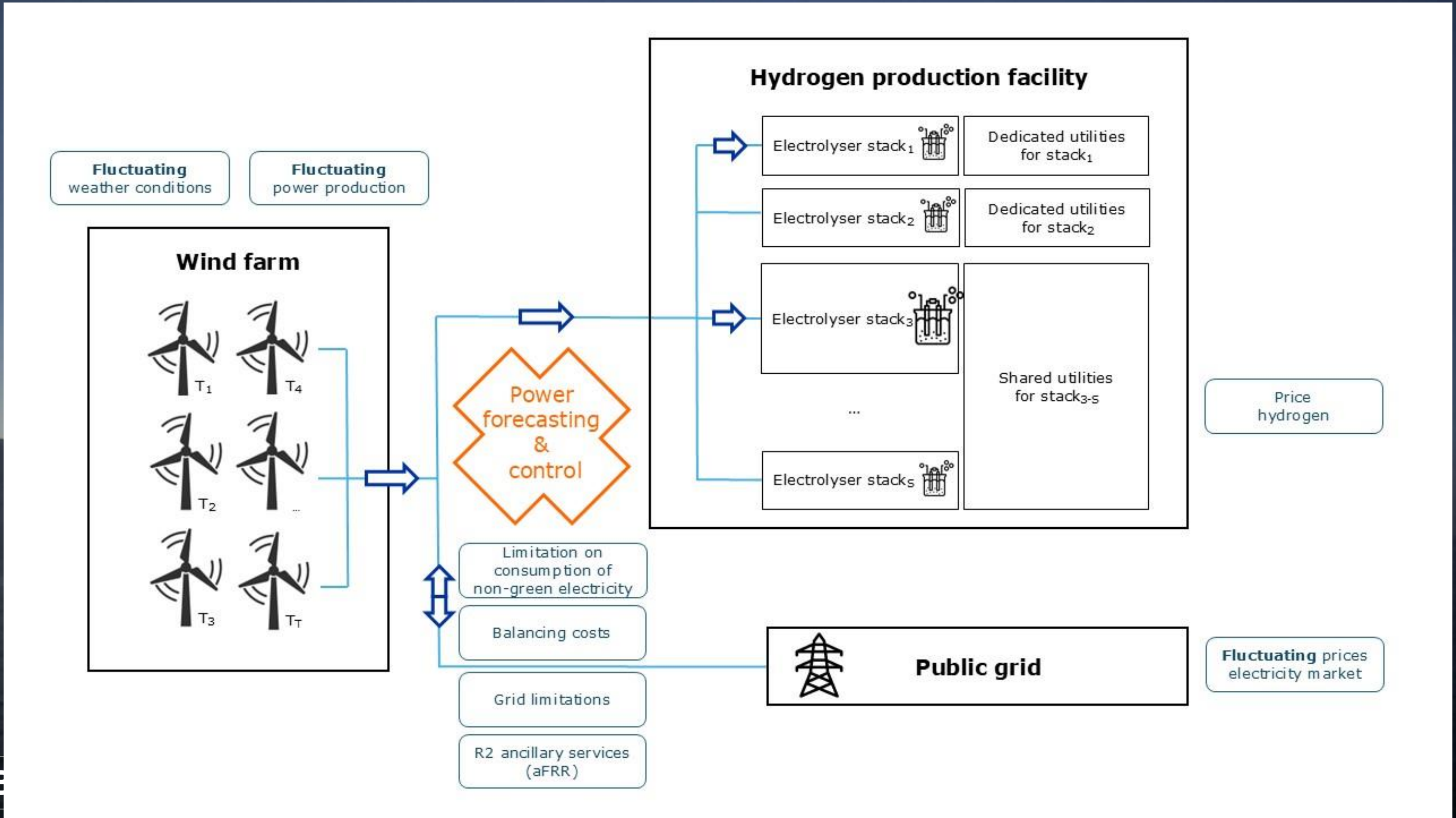


VUB VRIJE UNIVERSITEIT BRUSSEL

AI based approach for market driven control



AI based approach for market driven control in combination with H_2 production



Conclusions

- The energy ecosystem is changing drastically due to larger share of renewables
- Intermittency is playing a crucial role in guaranteeing a stable energy grid
- AI can contribute in different fields to this challenge

Thank you for your attention

@ jan.helsen@vub.be

Special acknowledgement to:

economie

Energietransitiefonds

AGENTSCHAP INNOVEREN & ONDERNEMEN

BLAUWE CLUSTER

samen voor #sterkgroeien

fwo Research Foundation Flanders
Opening new horizons