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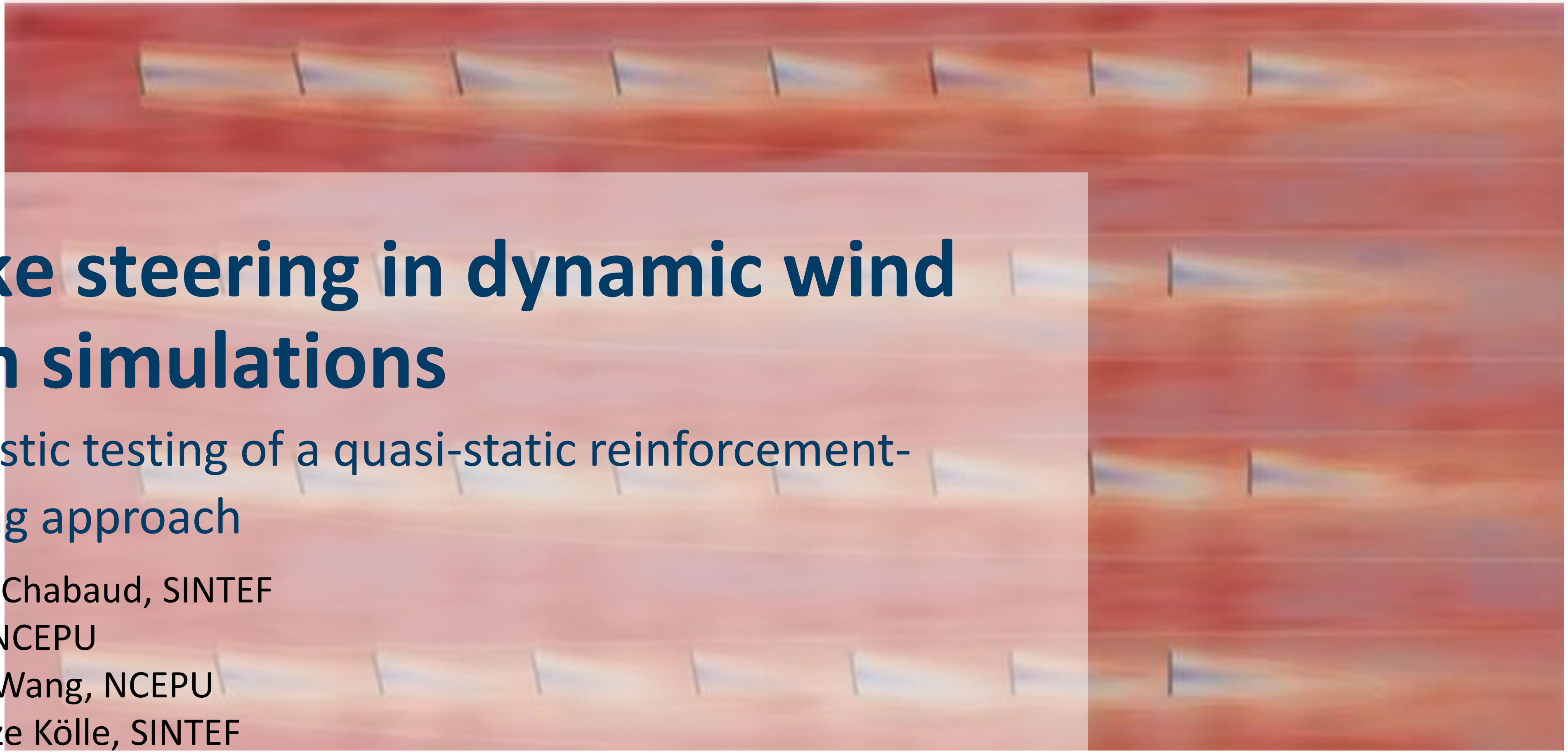


Wake steering in dynamic wind farm simulations

Stochastic testing of a quasi-static reinforcement-learning approach

Valentin Chabaud, SINTEF
Jie Yan, NCEPU
Hangyu Wang, NCEPU
Konstanze Kölle, SINTEF
Spyridon Chapaloglou, SINTEF

Outline

- Wake steering controller
- Dynamic simulation platform
- Case study
- Preliminary results and outlook

Wake steering controller

- CONWIND: Collaboration project between Norway and China
- NCEPU – Research group of Prof. Liu Yongqian, Assoc. Prof. Jie Yan, Phd student Hangyu Wang – among others.
- The algorithm is being tested in a real offshore wind farm
- Consists of two steps, both based on deep learning:

1. Prediction of wind speed and direction ahead of first row from LIDAR data
2. Determination of best yaw angle combination from quasi-static wake simulations depending on wind speed and direction

Minute/second-scale wind prediction and RL offshore wind farm control

Jie Yan

North China Electric Power University

Email: yanjie@ncepu.edu.cn

23 January 2023

Multi-task prediction of wind speed and direction

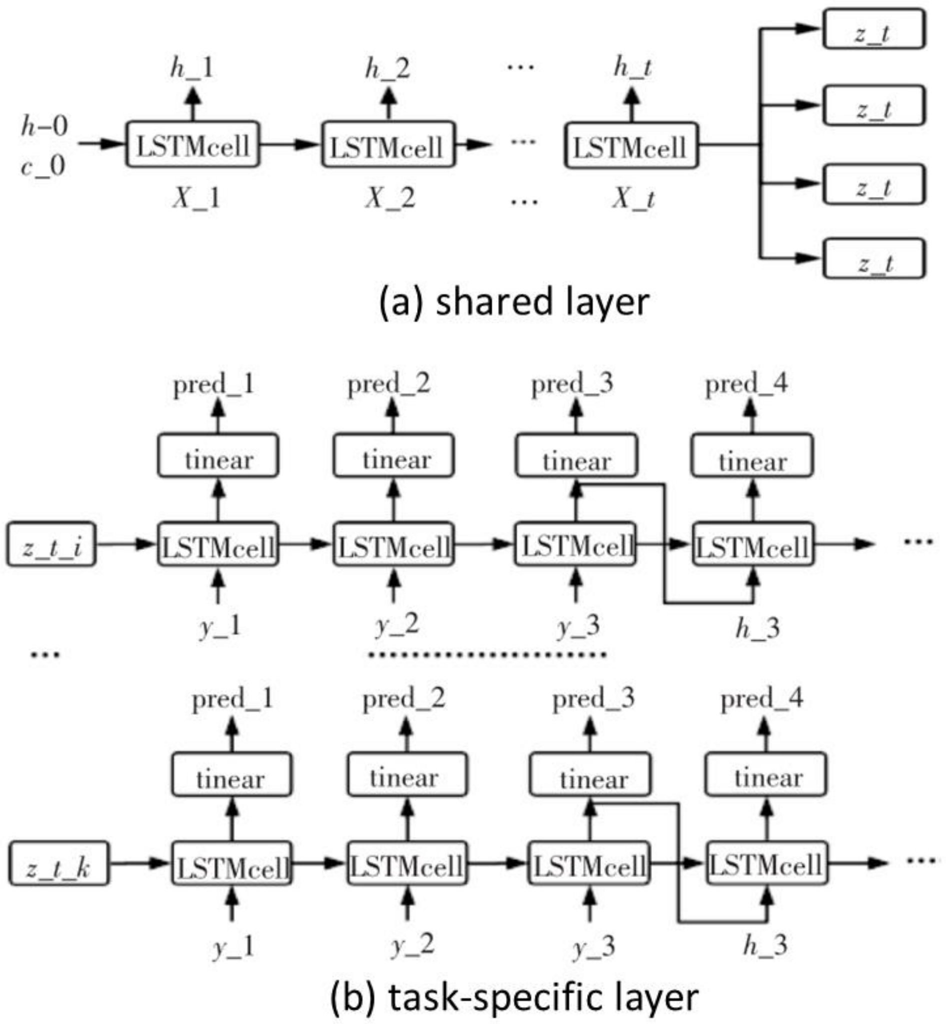


Figure12 Multi-task learning model framework

①Using multi-task learning based on parameter sharing to jointly predict wind speed and direction.

②Two tasks can provide additional information for each other, thereby improving both tasks.

③Using LSTM as basic learning unit.

④The MTL model includes two modules, a shared layer for extracting shared parameters and a specific task layer for forecasting each subsequence.

Multi-task prediction of wind speed and direction

- Based on the division of typical wind processes and multi-task learning model, the wind speed and direction of different types of wind processes are modeled and predicted respectively, with a time resolution of 1min and a time span of 15min.

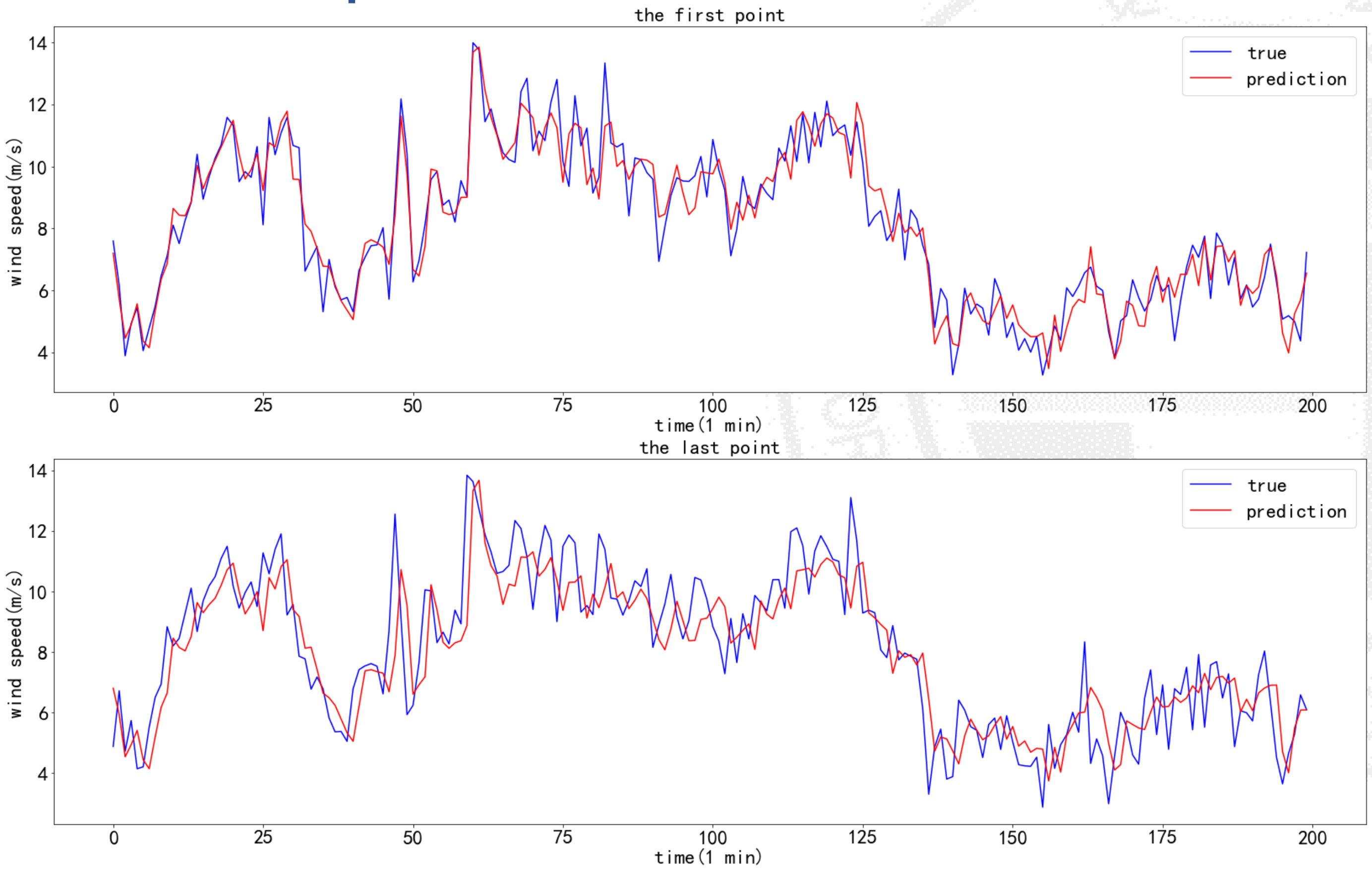


Figure13 The first and last step in wind speed forecasting

Table 3 Wind speed forecasting error statistics

Step	RMSE(m/s)	Step	RMSE(m/s)
1	0.20	9	0.41
2	0.25	10	0.43
3	0.28	11	0.45
4	0.31	12	0.46
5	0.33	13	0.47
6	0.36	14	0.48
7	0.38	15	0.50
8	0.40		

Multi-task prediction of wind speed and direction

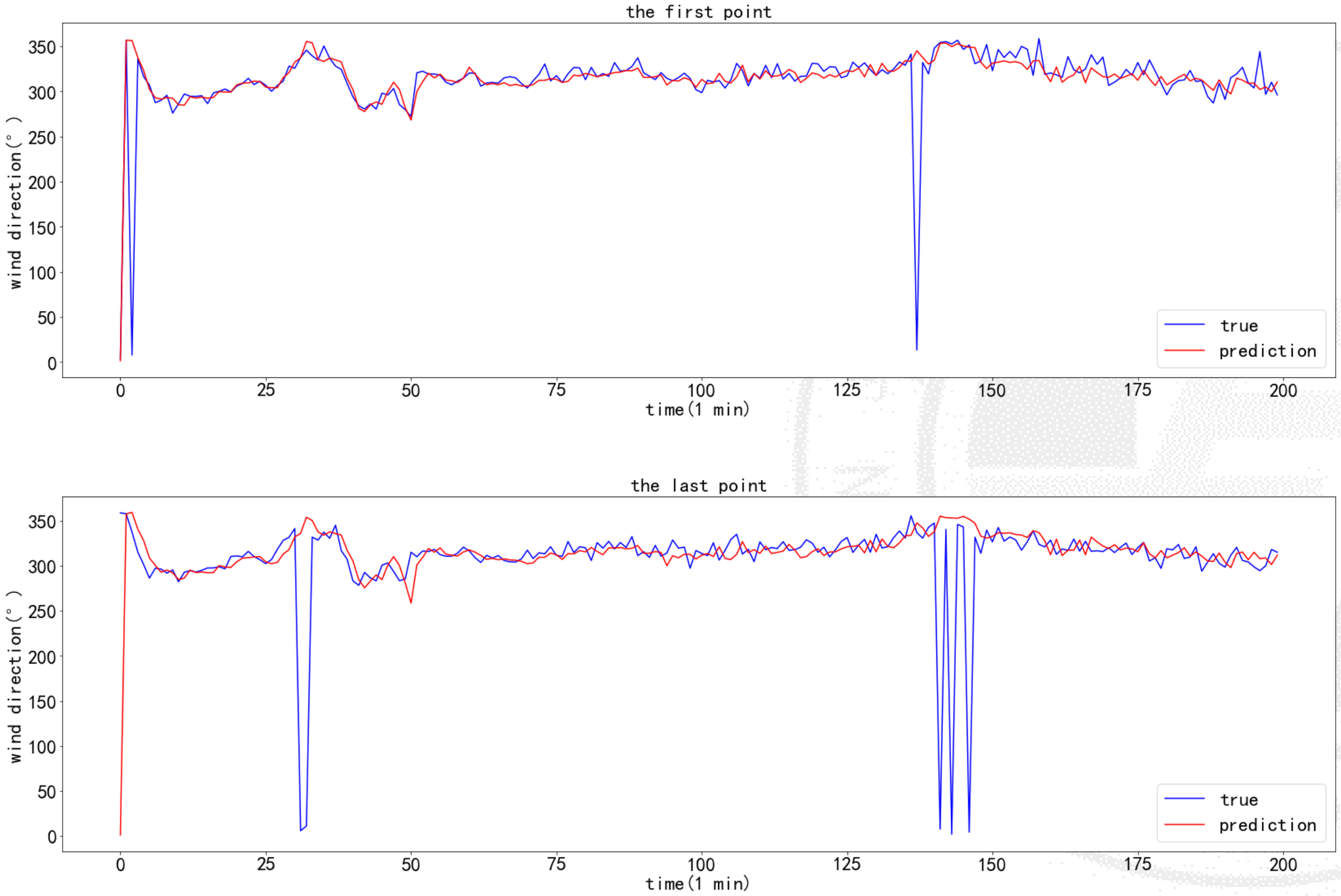
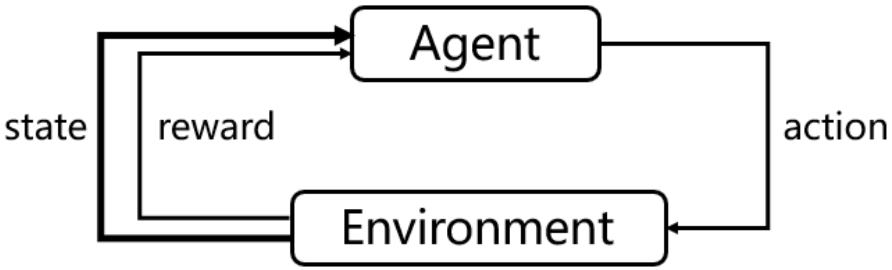


Figure14 The first and last step in wind direction forecasting

Table 4 Wind direction forecasting error statistics

step	RMSE(°)	step	RMSE(°)
1	5.36	9	7.41
2	5.86	10	7.69
3	6.23	11	7.83
4	6.49	12	7.92
5	6.77	13	7.91
6	6.94	14	8.03
7	7.01	15	8.22
8	7.19		

Offline training and online learning with DRL



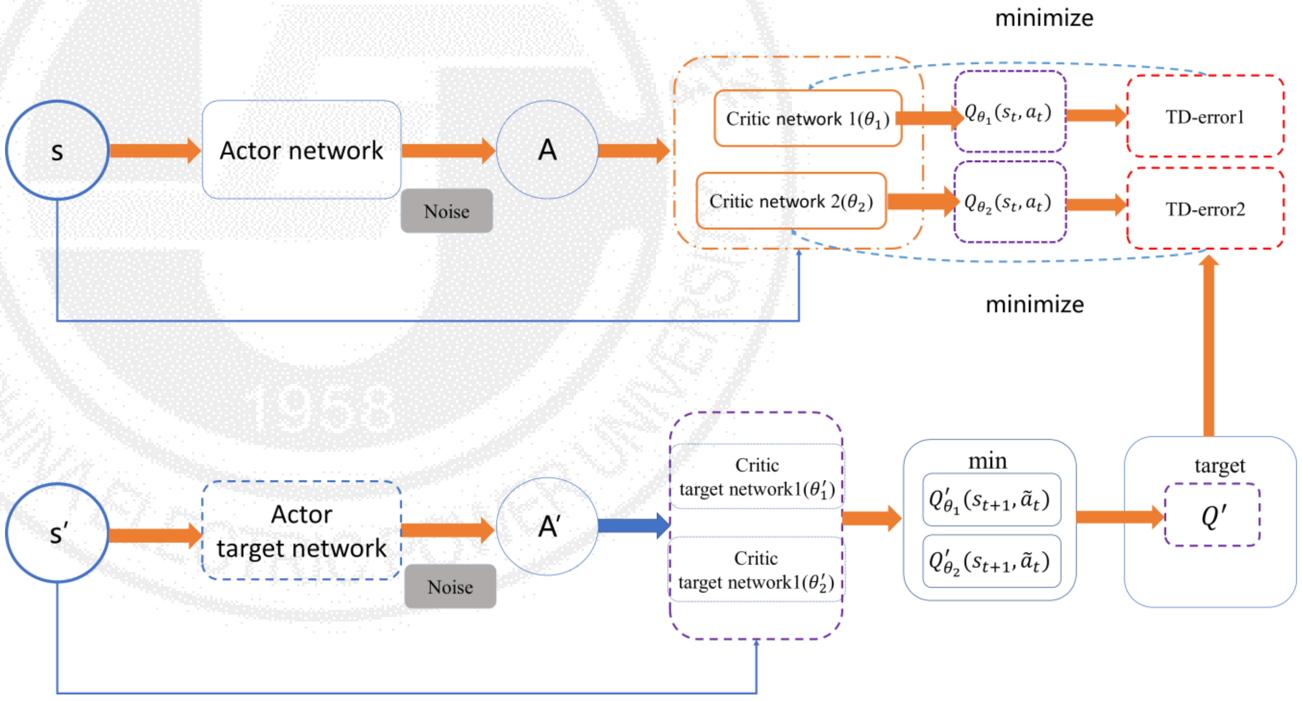
Agents act in complex and uncertain **environments** to maximize **rewards**

Perception of Deep Learning
Decision-Making of Reinforcement Learning

Twin Delayed Deep Deterministic Policy Gradient

Sequential actions space-oriented

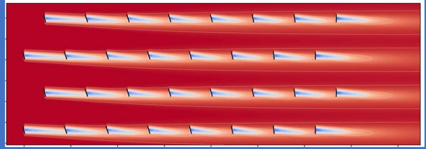
Actor-Critic network structure



Offline training and online learning with DRL

- 1. **O** tain
  netw
  actio

FLORIS simulations



- 2. **Generalization** towards "unknown" samples

- 3. Inv SCADA
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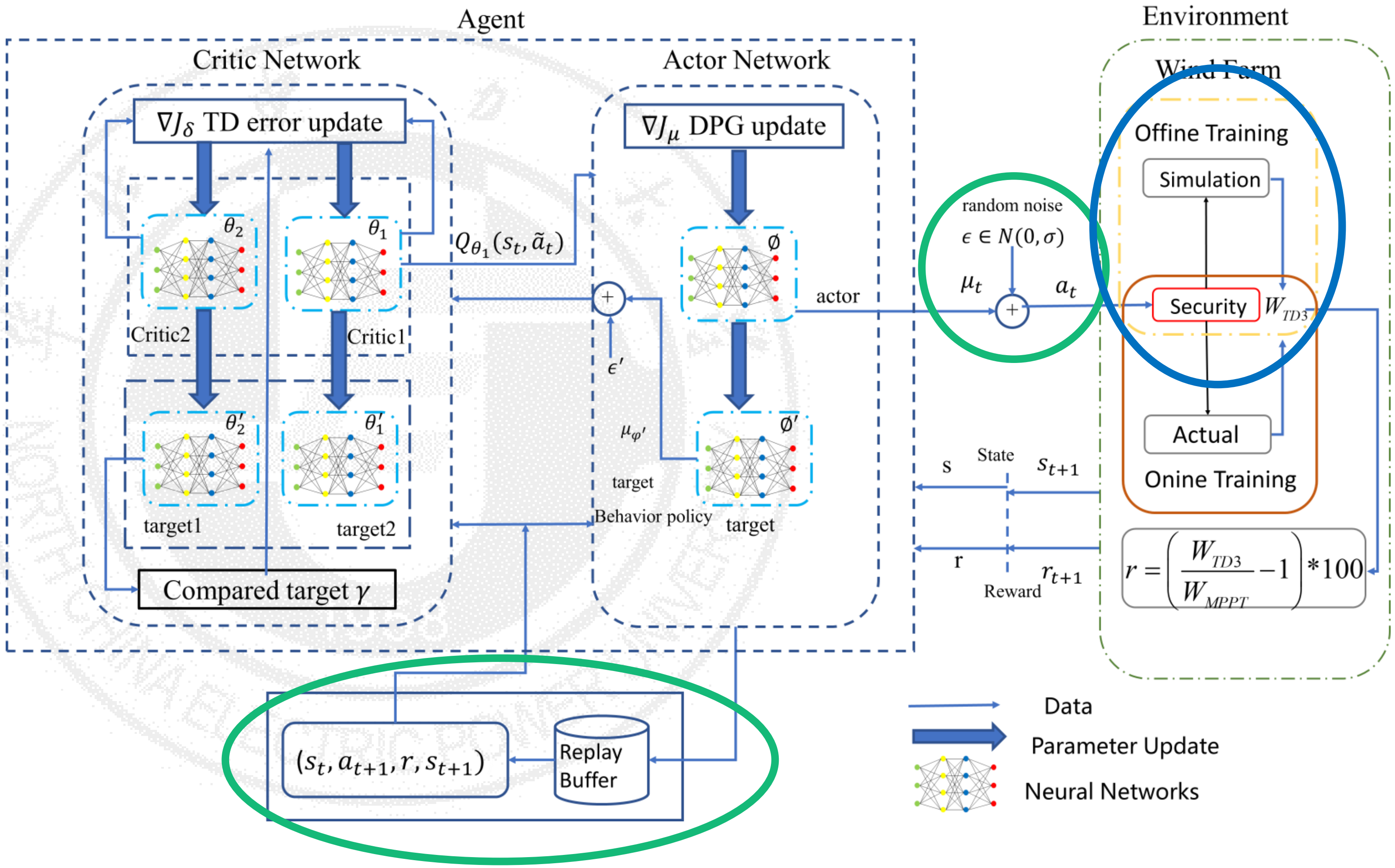
Compensation for wind fluctuations



Offline training and online learning with DRL

Results (ws=8 m/s; wd=270°)

WS Variance	WD Variance	Average Optimization(SLSQP)	Sequence Optimization(SLSQP)	Sequence Optimization(TD3)
0-0.3	0-20	0.892%	2.649%	2.193%
0-0.3	20-60	-4.19%	1.471%	1.277%
0-0.3	60-140	-3.311%	1.104%	0.841%
0.3-0.6	0-20	-0.605%	2.854%	2.214%
0.3-0.6	20-60	-4.931%	1.945%	1.694%
0.3-0.6	60-140	-4.294%	0.724%	0.545%
0.6-1.2	0-20	0.584%	3.406%	2.082%
0.6-1.2	20-60	-2.563%	0.571%	0.264%
0.6-1.2	60-140	-1.557%	0.913%	0.756%
Other		-3.38%	0.79%	0.67%
Weighted Lift Rate		-1.43%	2.02%	1.67%

Research question

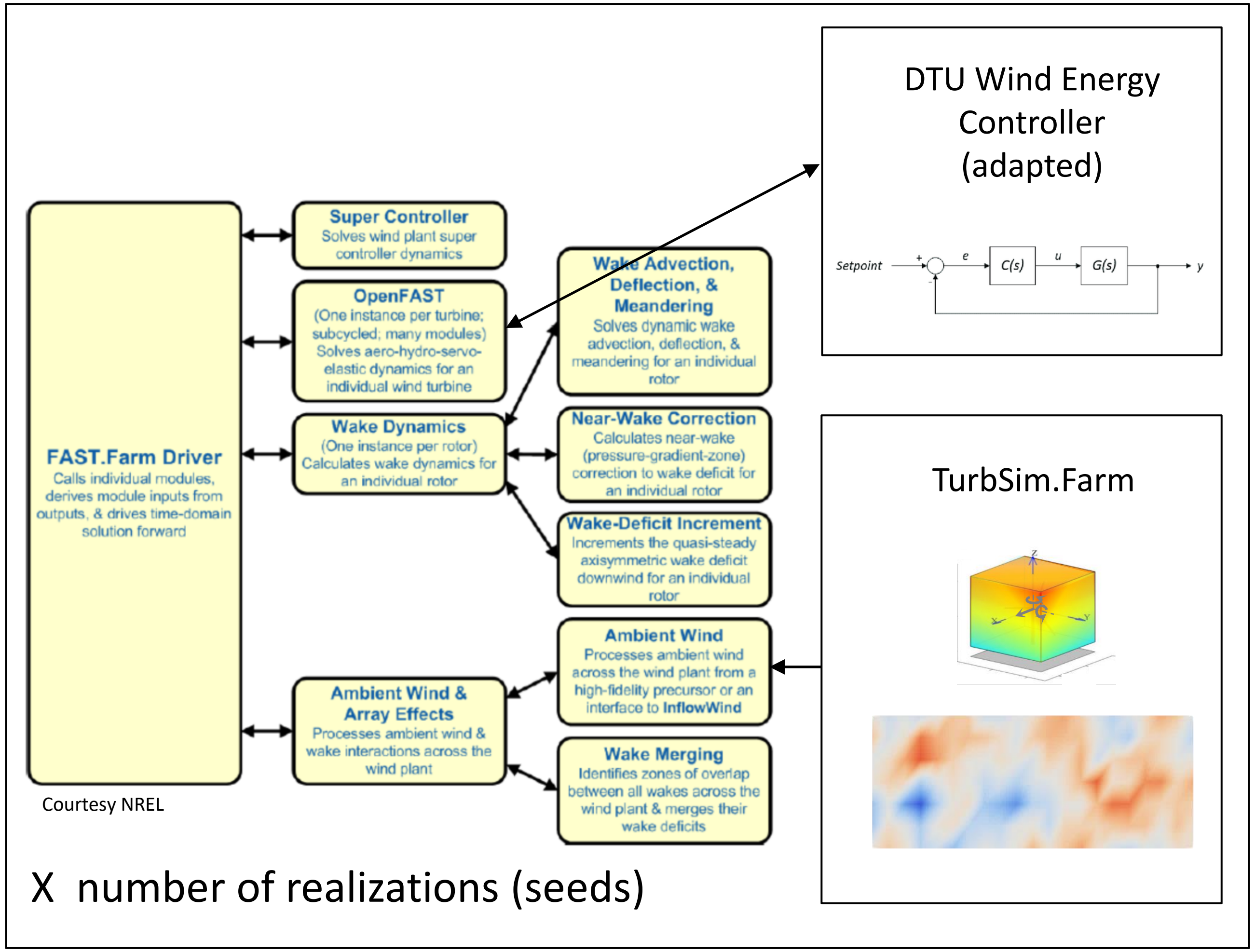
The wake steering algorithm is learned from quasi-static simulations

- time variations are represented through speed and direction variances
- no distinction between low- and high-frequency variations

→ How is its performance affected by a more comprehensive representation of farm-wide turbulent fluctuations and wake dynamics, especially at low frequencies?

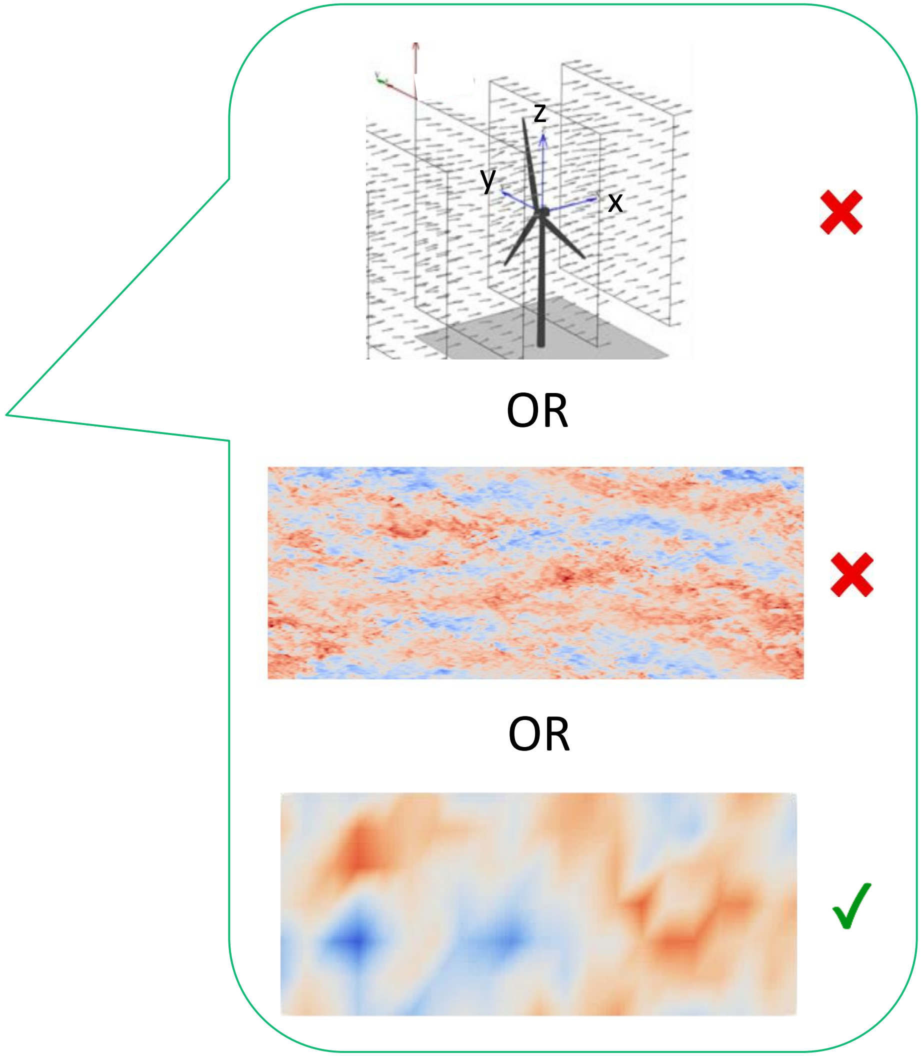
Dynamic simulation platform

- Medium fidelity!
- NREL's FAST.Farm
  - aero-servoelastic farm simulations
  - running OpenFAST for each turbine
  - solving for wake dynamics
- Ambient wind field input from TurbSim.Farm (courtesy NREL)
  - at turbines
  - in between for wake dynamics
- DTUWEC with yaw control
- Parallel computing -Multiple seeds



Mid-fidelity ambient flow modeling
Limitations in synthetic turbulence generation

- Option 1: Point-based Gaussian process generation
  - Frozen-wake turbulence: longitudinal coherence mixed with temporal coherence = time shift, not appropriate for large farms
  - Curse of dimensionality
- Option 2: LES simulations of ambient wind
  - Overkill and inconvenient
- **New option: Aggregated Gaussian process generation**



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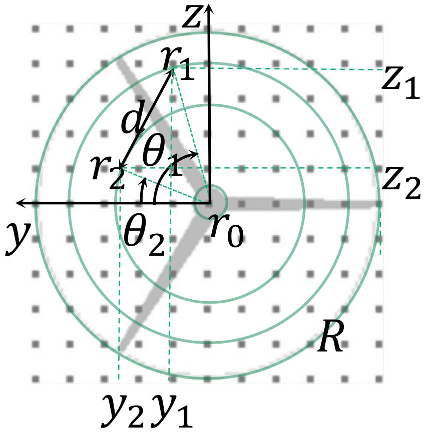
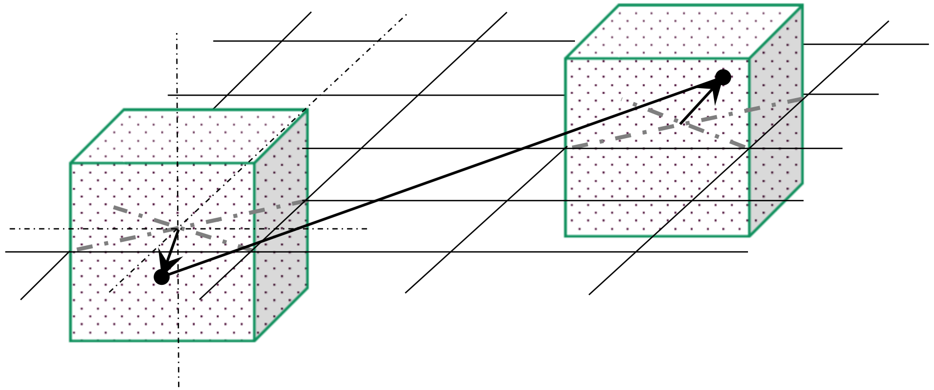
Aggregated Gaussian process generation

- From Poul Sørensen et al., 2000s
- Based on spectral representation of turbulence
- Frequency-domain transfer functions obtained by spatial averaging of the coherence function
- Reduction of DOFs by ~20^3,
- Reduction of timestep by ~20
- Temporal coherence from phase delay due to advection: no frozen turbulence assumption



$$H^2(f) = 4\frac{\int_{r0}^{R}\int_{r0}^{R}\int_{0}^{2\pi}\int_{0}^{2\pi} C(d,f)\ r_1 r_2 d\theta_1 d\theta_2 dr_1 dr_2}{(R^2 - r_0^2)^2}$$

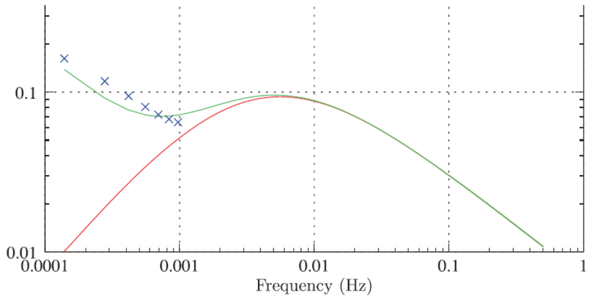
$$S_{agg}(f) = H^2(f)\ S_{point}\ (f)$$



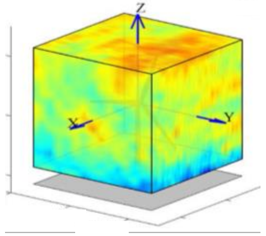
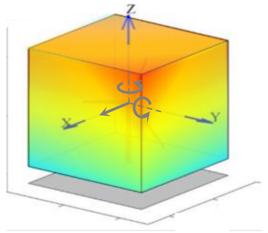
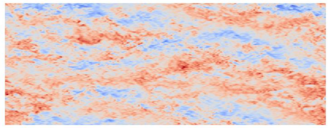
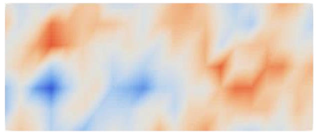
TurbSim.Farm

- Farm-wide: microscale + mesoscale
  - Farm-level spectrum & coherence models
  - Correlated, aggregated (rotor-averaged) wind field
    - At each turbine
    - Between turbines for wake dynamics
  - No frozen turbulence assumption
- Constrained turbulence: reconstruction of correlated wind fields given prior knowledge without loss of information
  - Rest of the farm based on wind speed observation at some turbines
  - Full resolution wind field for specific turbine(s) based on aggregated field
- Multiple realizations
  - Stochastic (Monte Carlo) simulations

Turbine	Farm
$S_{IEC}(f)$	$S_{H\o v,fitted}(f)$



Turbine	Farm
10 min	3 h

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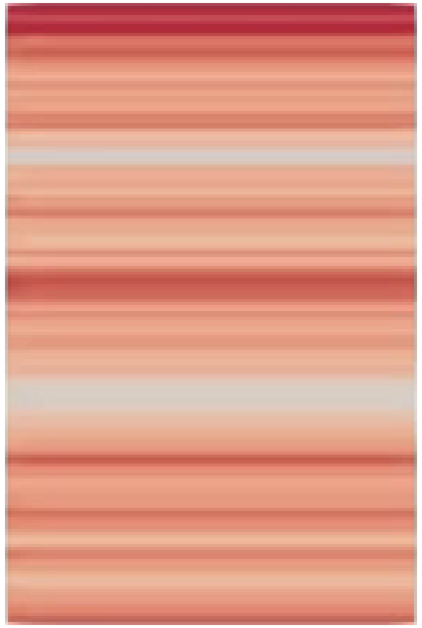
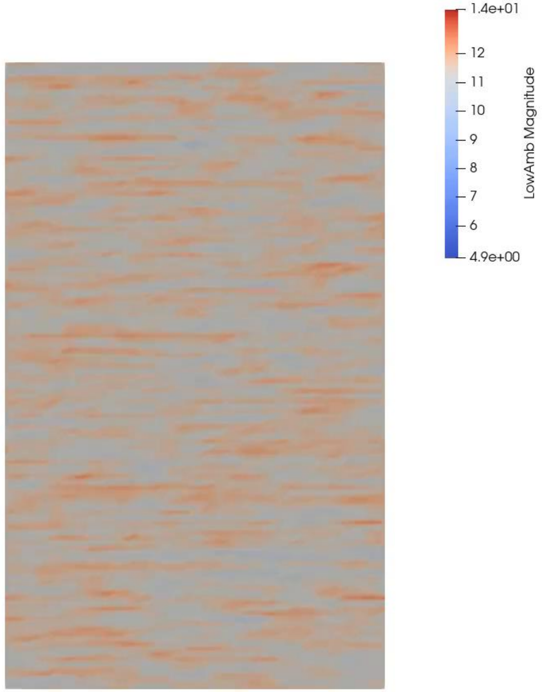
Aggregated ambient wind fields



Quasi-static turbulence
based on first row
(as in wake steering
algorithm / FLORIS)

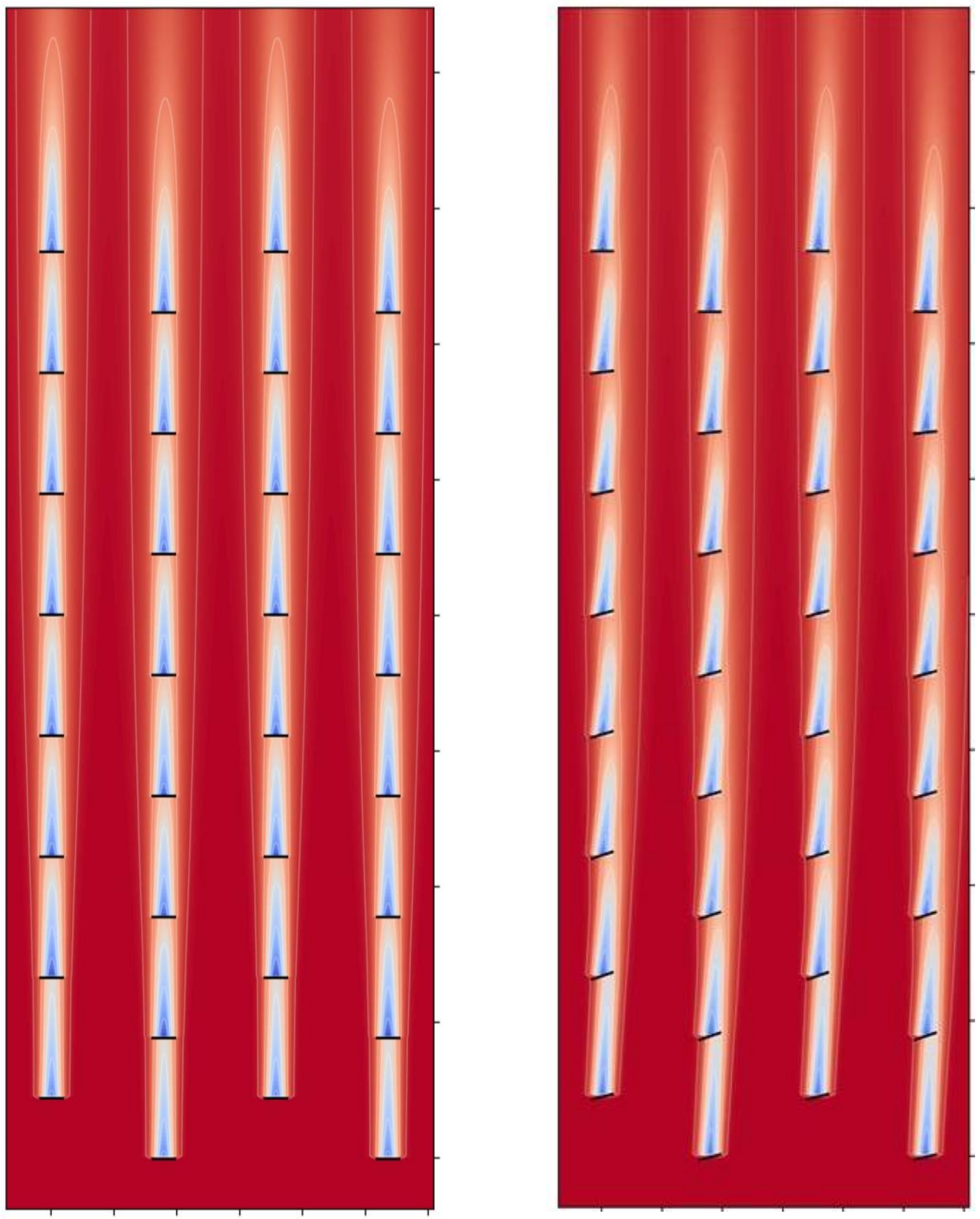


Frozen turbulence
(as in TurbSim)

Farm scale turbulence

Case study

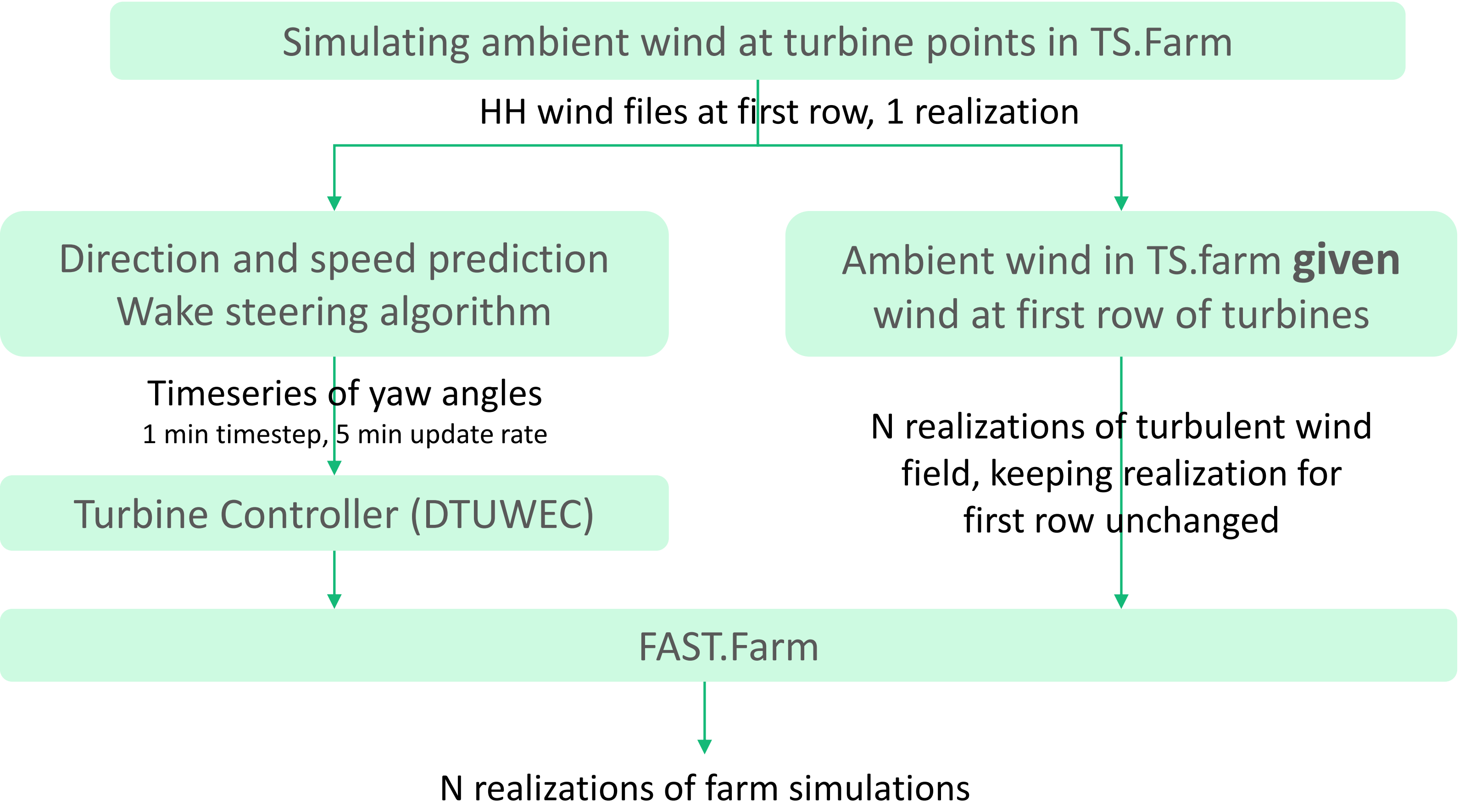
- TotalControl reference wind power plant
  - 32 x DTU10MW turbines, staggered layout 5D spacing
- 10 m/s, 90 degrees (South)
  - ➔ Most unfavourable conditions (7 wake superpositions, 5D spacing)
- Standard turbulence model
  - IEC Kaimal, Class B
  - Farm-scale spectrum and coherence function from Vigueras-Rodriguez et al.
- 1h, 5 seeds
- Limitations: Rotor-averaged, rigid, 3 wake superpositions



Procedure

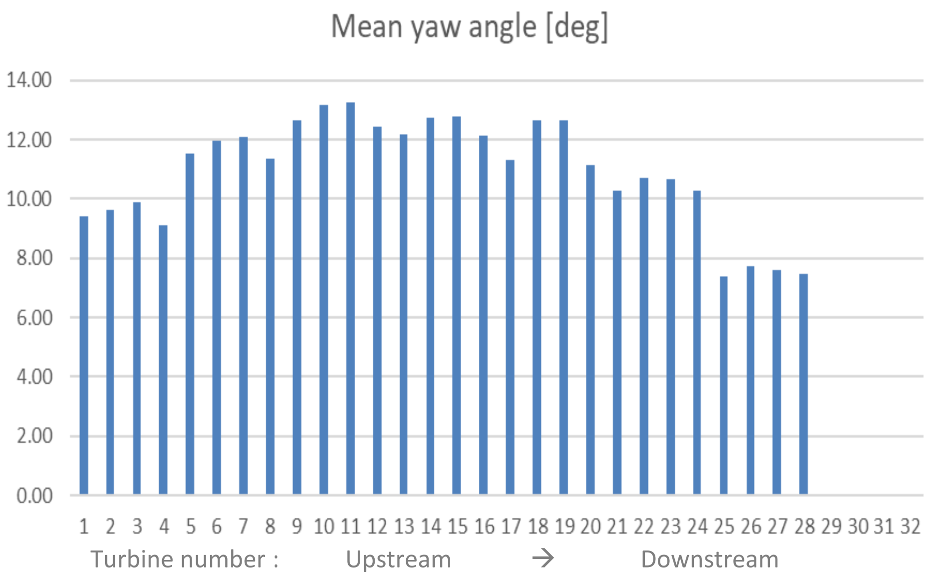
Test matrix (4 cases):

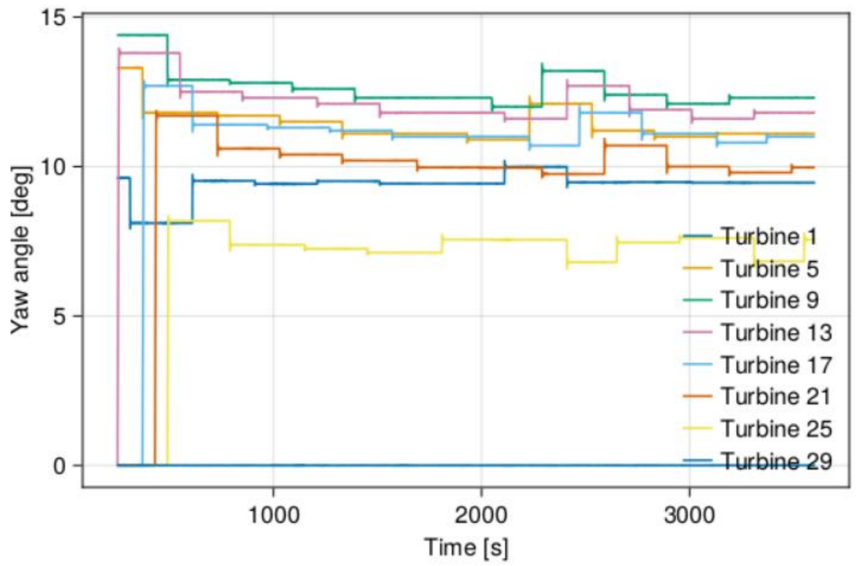
- With and without wake steering
- Quasi-static vs farm-wide turbulence



Preliminary results

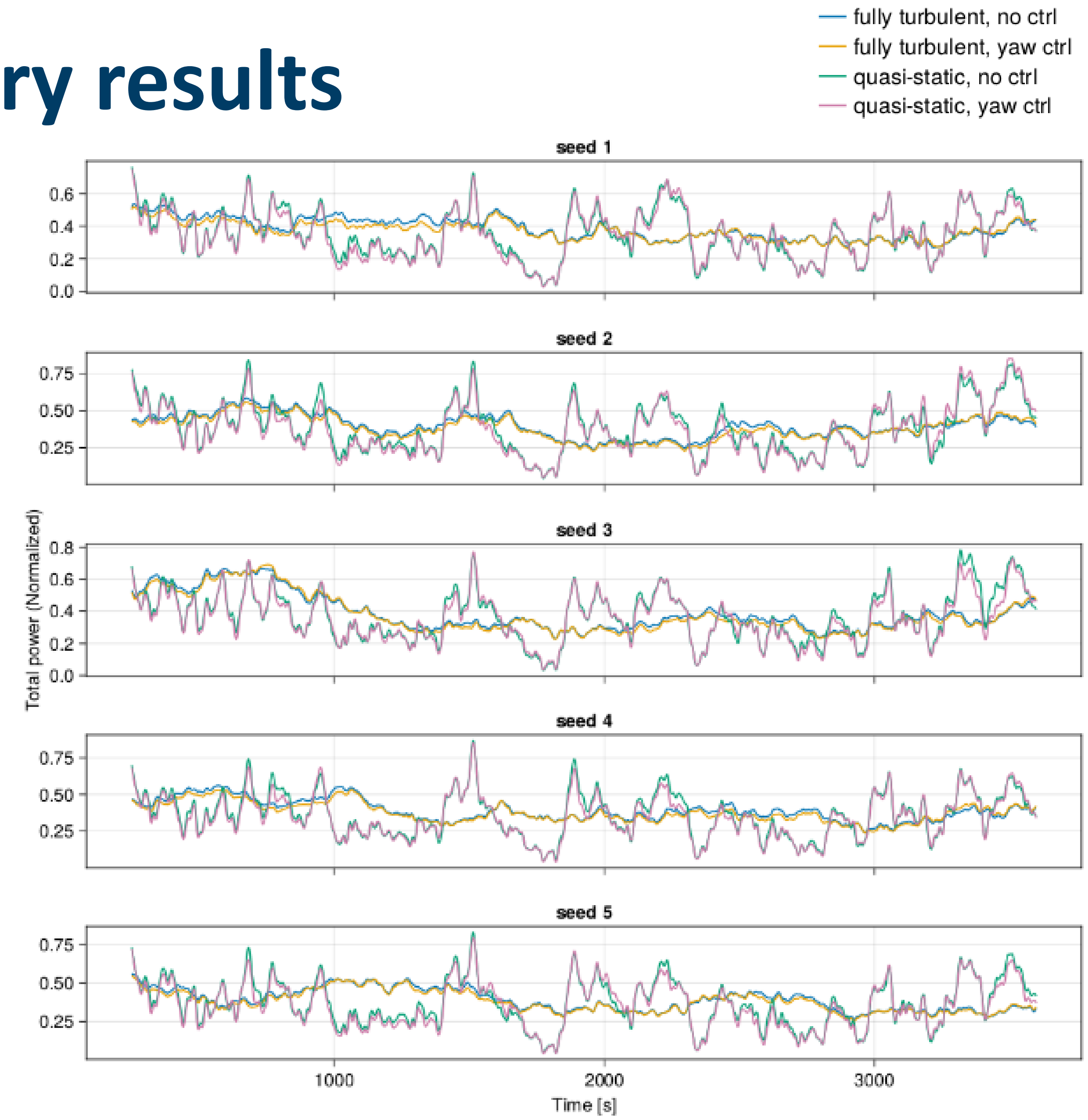
- Computational speed on 64-core workstation, all realizations in parallel
  - TurbSim.farm ~ 2 * realtime
  - FAST.Farm: ~ realtime
- Yaw angle varying in time as function of direction





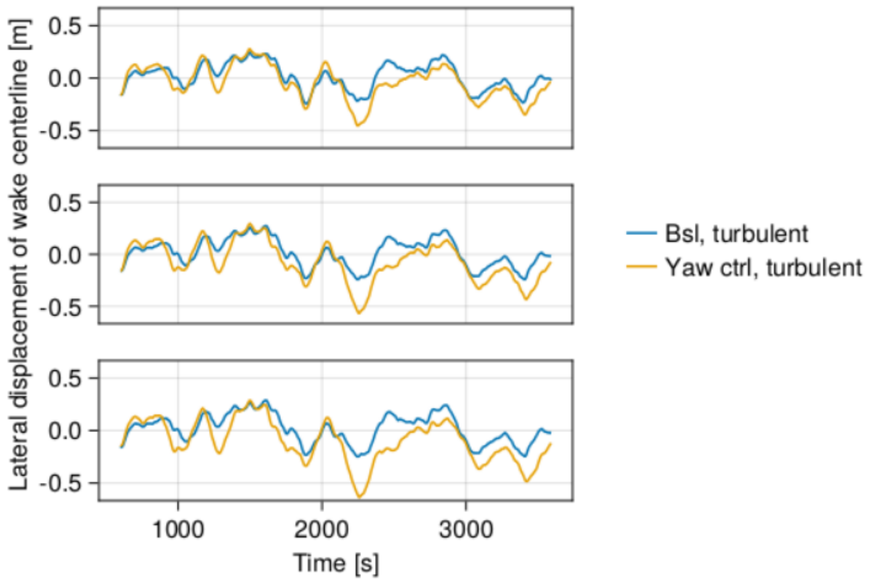
Preliminary results

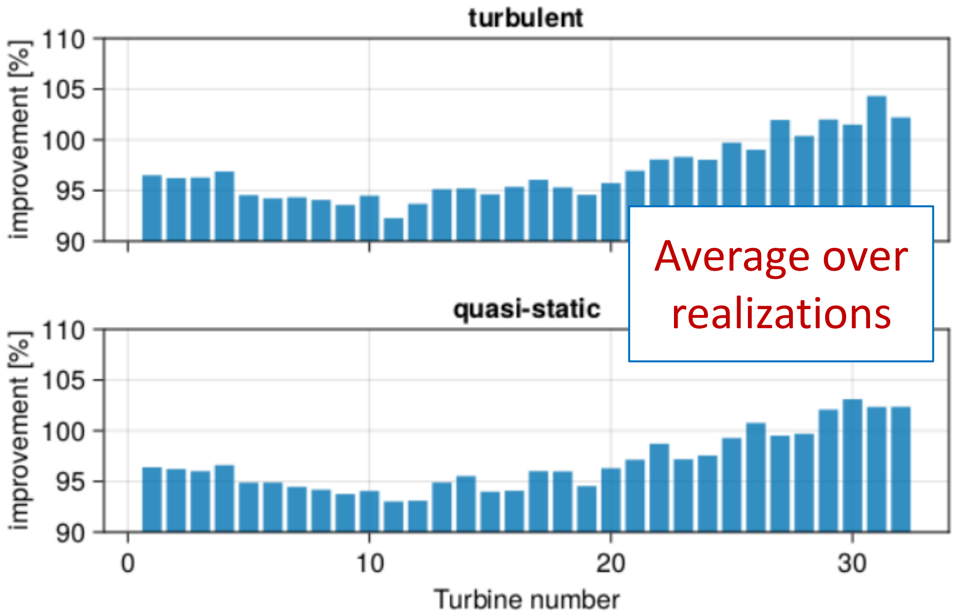
- Yaw control decreases power production
  - Not only in the turbulent, but also in the quasi-static case



Preliminary results

- Yaw control decreases power production
  - Not only in the turbulent, but also in the quasi-static case
  - Power losses due to yaw misalignment are larger than gains by wake deflection
  - Meandering >> Deflection





Conclusions and outlook

- Fruitful collaboration – development and testing of an advanced control algorithm
  - Deep learning can cope with the large number of variables in wake steering
  - Medium fidelity enables efficient testing for various load cases
- The efficiency of wake steering is fragile
  - Dependent on calibration of TurbSim.Farm/FAST.Farm and control tuning
  - Open-loop testing approach without online training for feedback correction is questionable
- Next steps
  - Closed-loop control embedding the controller in FAST.Farm instead of using a pre-calculated set of yaw angles
  - Calibration and tuning

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Technology for a better society