THE UNIVERSITY OF WARWICK

Intelligent Control & Smart Energy

Machine Learning Based Modelling and Control of Wind Turbine Structures and Wind Farm Wakes

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  - Farm level
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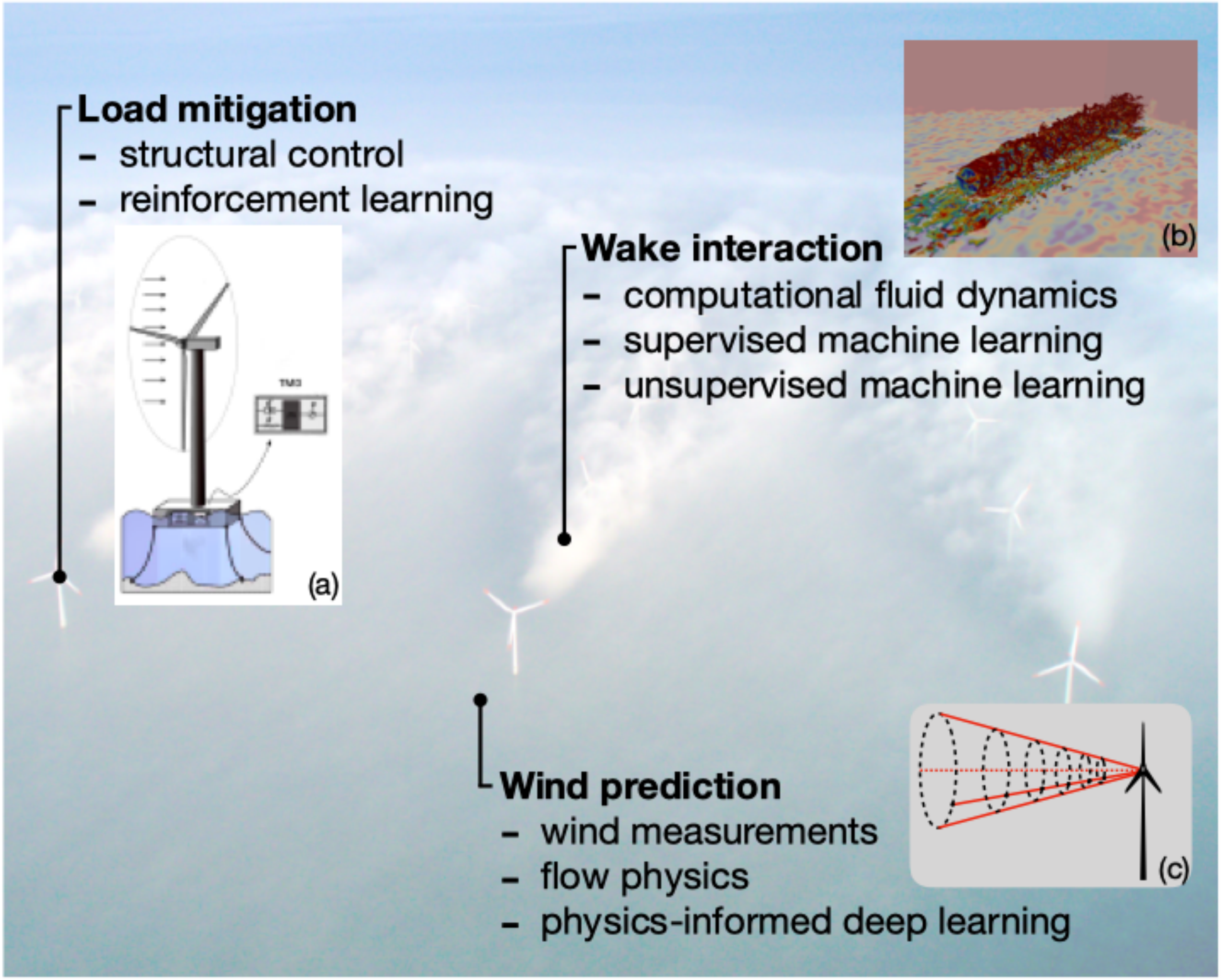
- Machine learning (ML) approaches
  - Reinforcement learning
  - Supervised
  - Unsupervised
  - Physics-informed



Background: the Horns Rev Offshore Wind Farm (photo by Christian Steiness); (a) the illustration of a floating turbine structural system (figure adapted from [9]); (b) the illustration of wind turbine wake flows, generated by CFD simulations; (c) the illustration of wind measurements by turbine-mounted LIDAR.

Publications

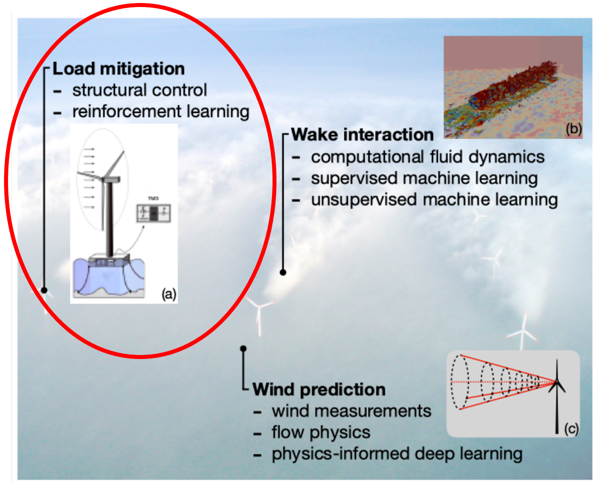
- Control of wind turbine structures
  - Monopile wind turbines

    [C-1] **J. Zhang**, X. Zhao, and X. Wei, Data-driven structural control of monopile wind turbine towers based on machine learning, **Proceedings of the 21st IFAC World Congress**, Berlin, Germany, July 2020.

  - Floating wind turbines

    [J-1] **J. Zhang**, X. Zhao and X. Wei, Reinforcement learning-based structural control of floating wind turbines, **IEEE Transactions on Systems, Man, and Cybernetics: Systems** (2020), DOI: 10.1109/TSMC.2020.3032622.

    [J-2] H. Dong, X. Zhao, B. Luo, and **J. Zhang**, Robust Deep Reinforcement Learning with Application in Structural Control of Floating Wind Turbines, journal paper draft (2021).



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Publications

- Wind farm wake modeling
  - Uncertainty quantification of traditional wake model

[J-3] **J. Zhang** and X. Zhao, Quantification of parameter uncertainty in wind farm wake modeling, **Energy** 196 (2020) 117065.

  - ML-based wind farm wake modeling

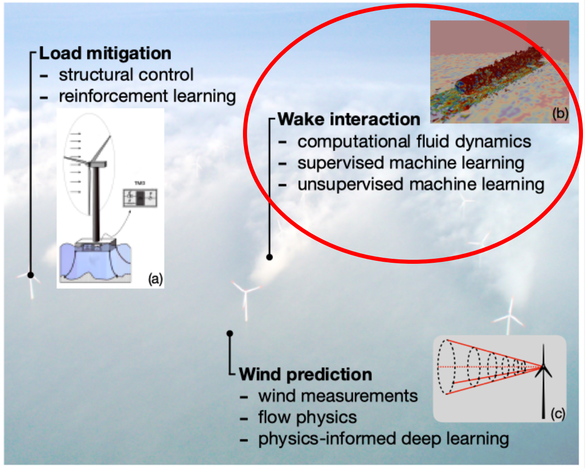
[J-4] **J. Zhang** and X. Zhao, A novel dynamic wind farm wake model based on deep learning, **Applied Energy**, 277 (2020) 115552.

[J-5] **J. Zhang** and X. Zhao, Machine-learning-based surrogate modeling of aerodynamic flow around distributed structures, **AIAA Journal** 59 (3) (2021) 868–879.

[J-6] **J. Zhang** and X. Zhao, Wind farm wake modeling based on deep convolutional conditional generative adversarial network, **Energy** (2021), to appear.

  - RL-based wind farm control

[J-7] H. Dong, **J. Zhang**, and X. Zhao, Intelligent Wind Farm Control via Deep Reinforcement Learning and High-Fidelity Simulations, **Applied Energy** 292 (2021) 116928.



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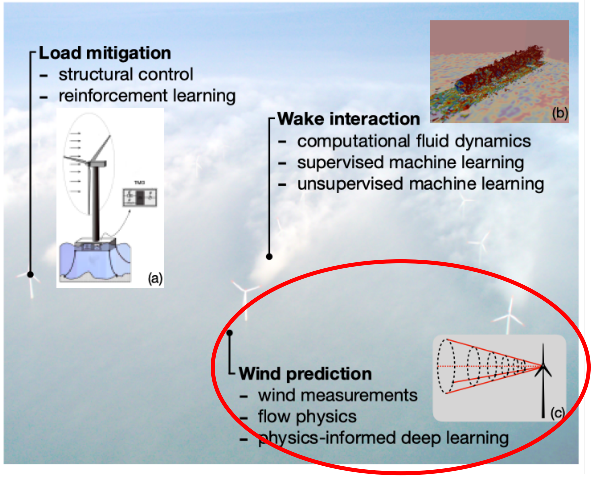
Publications

- Wind field predictions
  - Two-dimensional

    [J-8] **J. Zhang** and X. Zhao, Spatiotemporal wind field prediction based on physics-informed deep learning and LIDAR measurements, **Applied Energy** 288 (2021) 116641.

  - Three-dimensional

    [J-9] **J. Zhang** and X. Zhao, Three-dimensional spatiotemporal wind field reconstruction based on physics-informed deep learning, **Applied Energy** 300 (2021) 117390.



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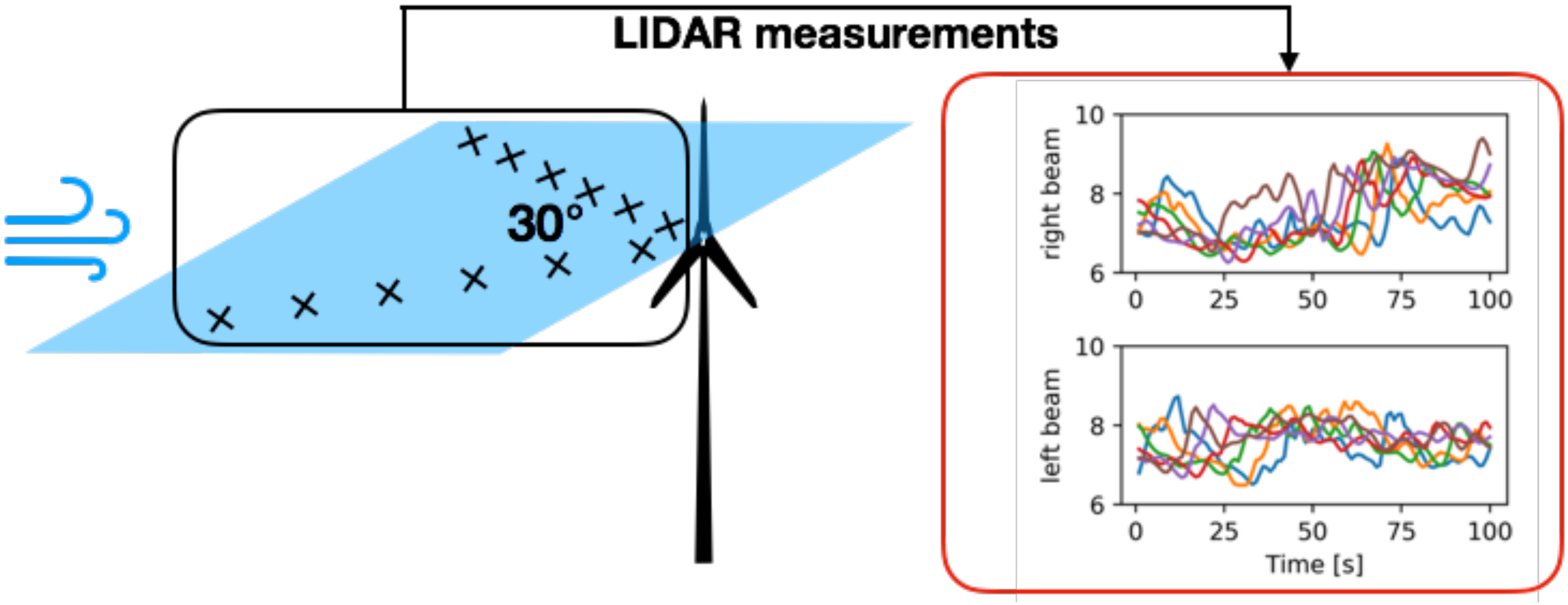
Summary of the ConFlex fellowship

- Publications
  - 7 high-impact journal papers as first author
  - 1 conference paper as first author
  - 1 high-impact journal paper as co-author
  - 1 journal paper draft under review as co-author

- PhD status
  - PhD degree awarded on 28 July 2021

- Career plan
  - Currently working as research fellow at University of Warwick
  - Plan to continue working in renewable energy research in academia, while actively seeking to collaborate with industry.

Spatiotemporal wind field prediction based on LIDAR measurements

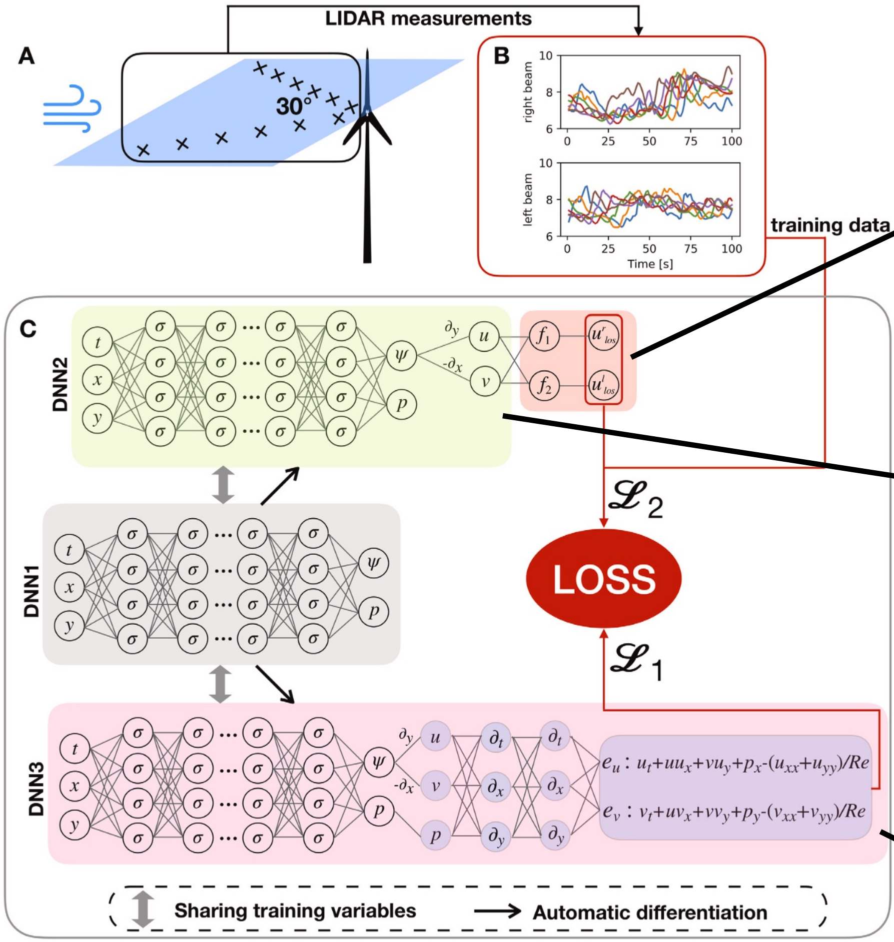


- line-of-sight wind speed measurements
- sparse spatial measurement locations

⇨

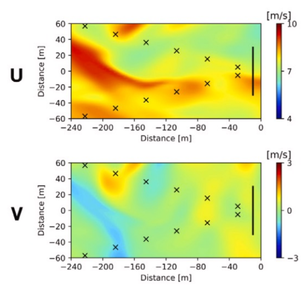
- wind direction?
- the spatiotemporal wind field?

Deep learning incorporating flow physics with LIDAR measurements



Training data: LIDAR measurements

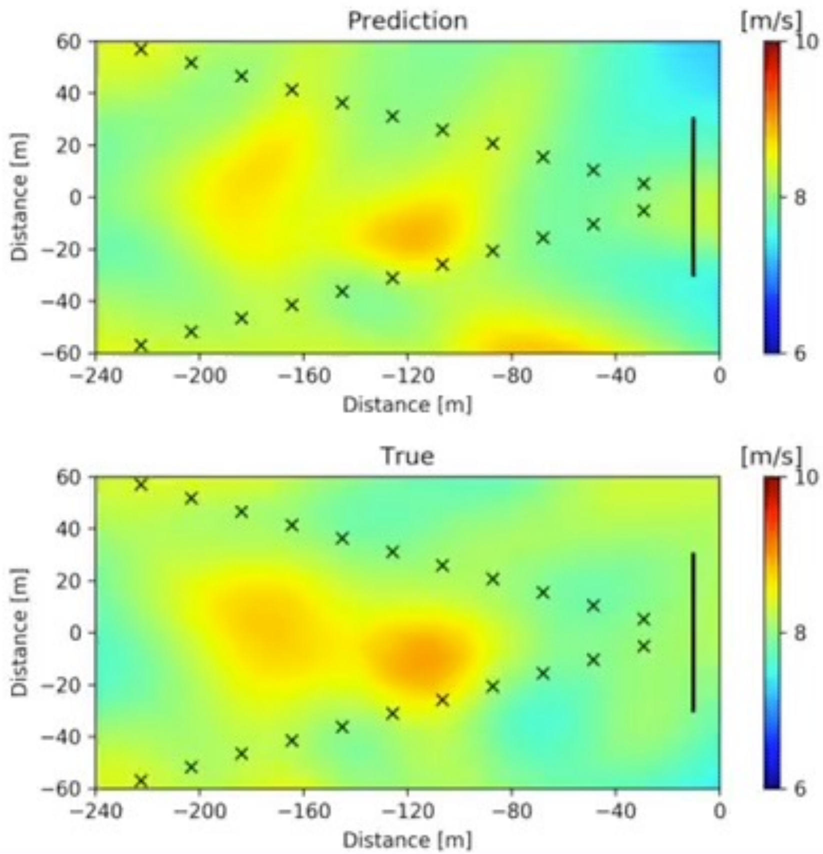
Prediction: spatiotemporal wind velocity field (including wind speed in x an y directions)

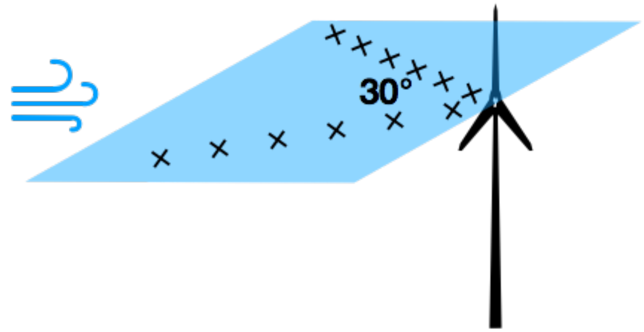


Physical model

2D wind field prediction – a baseline case

- Wind coming from turbine yaw direction



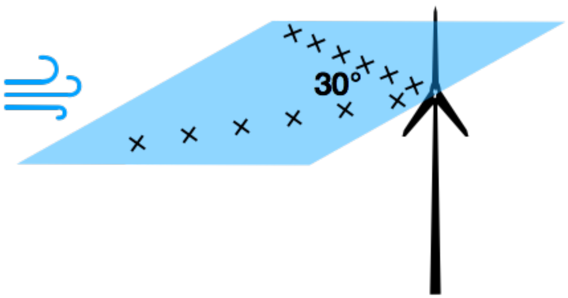


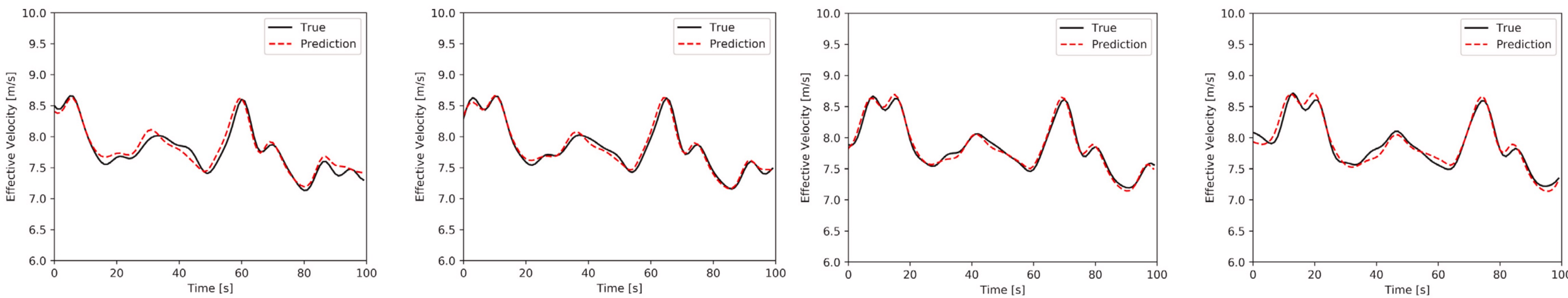
Lidar with fixed beam directions

2D wind field prediction – a baseline case

- Effective wind speed

$$\bar{U}_{x,t} = \frac{1}{N_y} \sum_{i=1}^{N_y} \hat{u}_{x,y_i,t}$$

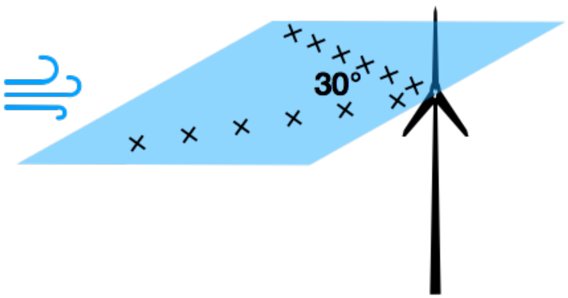


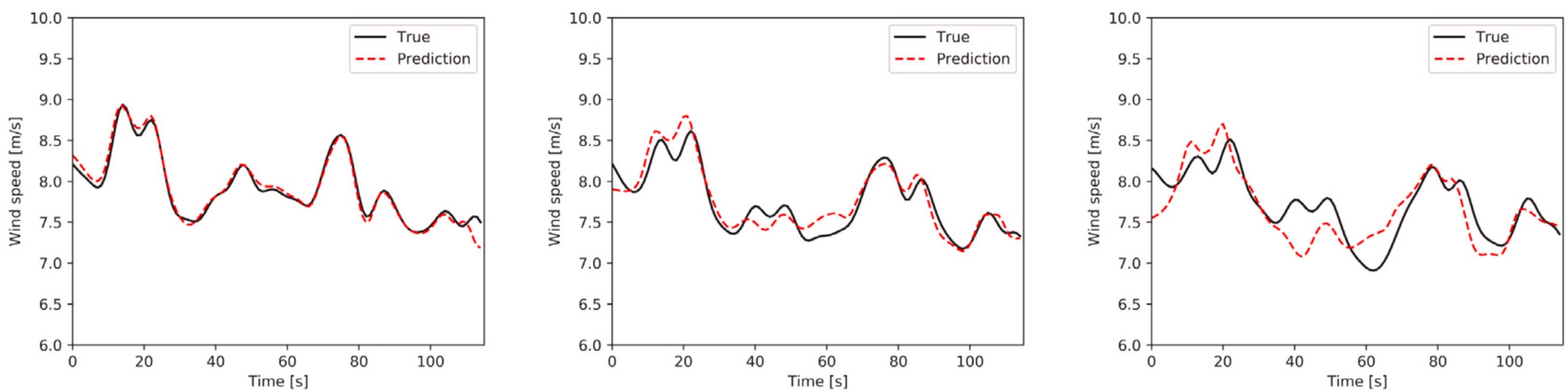


(a) x = -130m (b) x = -90m (c) x = -50m (d) x = -10m

2D wind field prediction – a baseline case

- Instantaneous wind speed
  - Reconstruction (0-100s)
  - Forecasting (100-115s)





(a) y = 0m (b) y = 15m (c) y = 30m

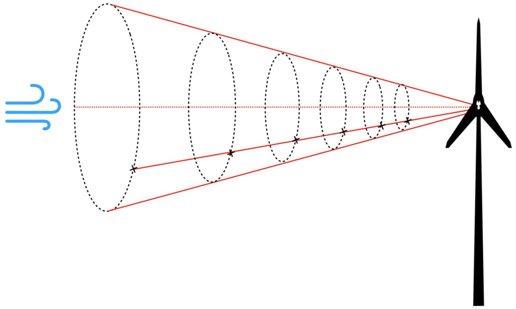
2D wind field prediction – a set of cases

- (A) the baseline case
- (B1-B4) with various levels of measurement noise
- (C) half spatial resolution
- (D) half temporal resolution
- (E) 20° LIDAR look direction
- (F) freestream turbulence level of 1%

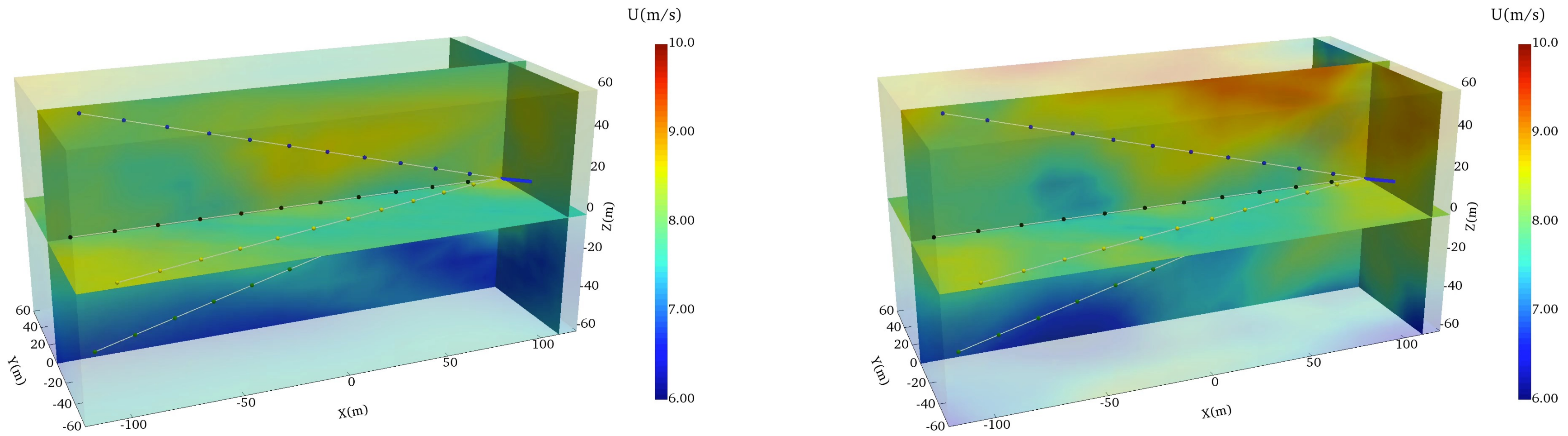
Case	Quantity (units)	Range	MRMSE
(A)	Magnitude (m/s) Direction (°)	[6.71, 9.52] [−6.03, 8.28]	0.198 2.77
(B1)	Magnitude (m/s) Direction (°)	[6.71, 9.52] [−6.03, 8.28]	0.208 2.75
(B2)	Magnitude (m/s) Direction (°)	[6.71, 9.52] [−6.03, 8.28]	0.236 3.32
(B3)	Magnitude (m/s) Direction (°)	[6.71, 9.52] [−6.03, 8.28]	0.387 3.73
(B4)	Magnitude (m/s) Direction (°)	[6.71, 9.52] [−6.03, 8.28]	0.523 4.35
(C)	Magnitude (m/s) Direction (°)	[6.71, 9.52] [−6.03, 8.28]	0.212 2.85
(D)	Magnitude (m/s) Direction (°)	[6.71, 9.52] [−6.03, 8.28]	0.222 2.66
(E)	Magnitude (m/s) Direction (°)	[6.70, 9.73] [11.4, 27.8]	0.281 2.46
(F)	Magnitude (m/s) Direction (°)	[6.71, 8.96] [−6.37, 6.13]	0.204 2.69

3D wind field prediction – a baseline case

- Wind coming from turbine yaw direction



Lidar with azimuth scanning



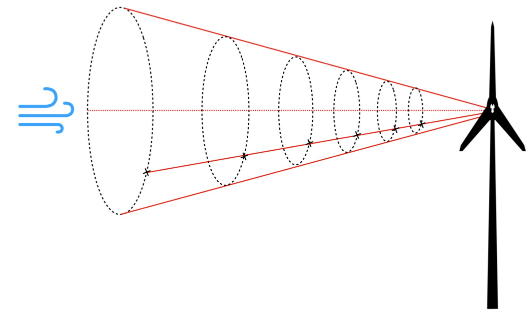
Predicted Flowfield

Ground Truth

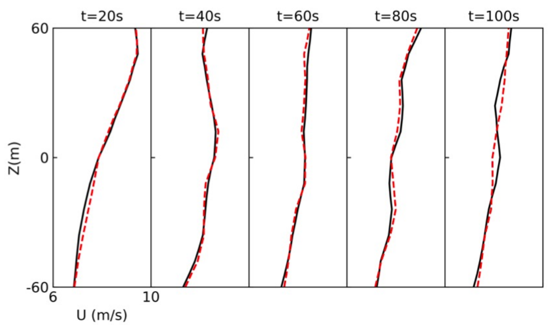
3D wind field prediction – a baseline case

- Effective wind speed

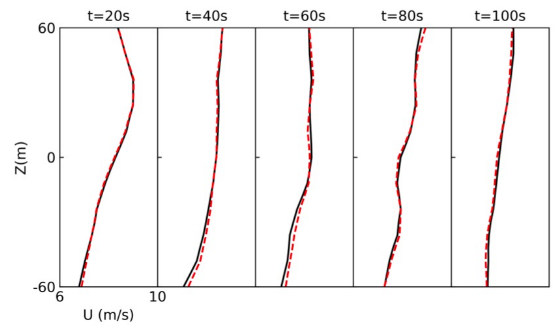
$$\bar{U}_{x_0,t}(z) = \frac{1}{N_y}\sum_{i=1}^{N_y} \hat{u}_{x_0,y_i,z,t}$$



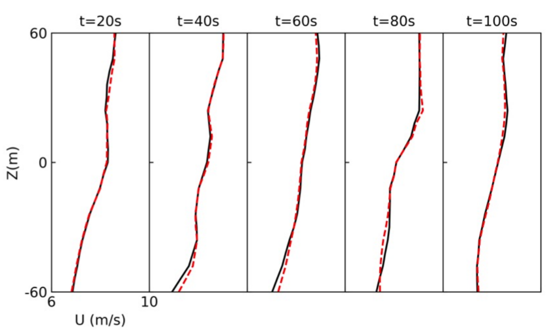
Lidar with azimuth scanning



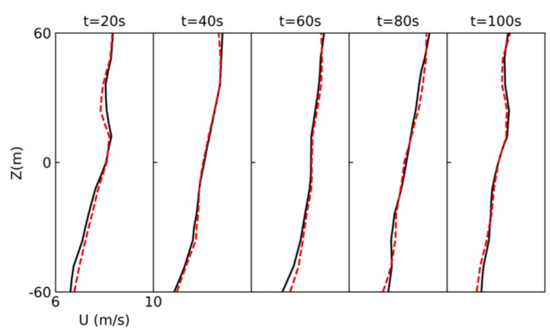
(a) x_0 = -50m



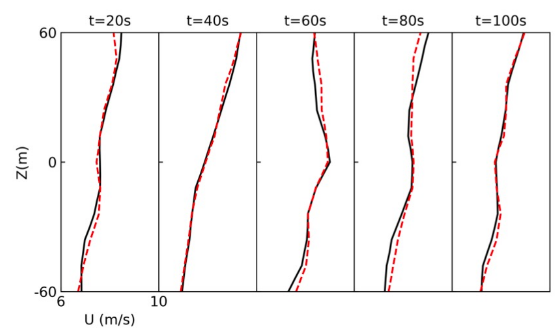
(b) x_0 = -10m



(c) x_0 = 30m



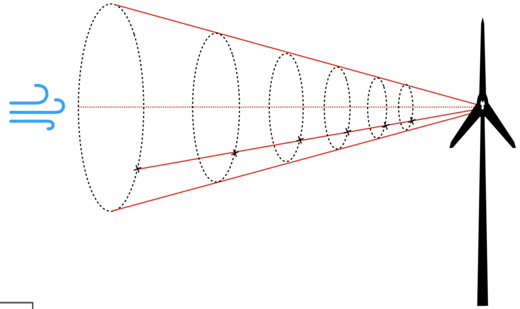
(d) x_0 = 70m



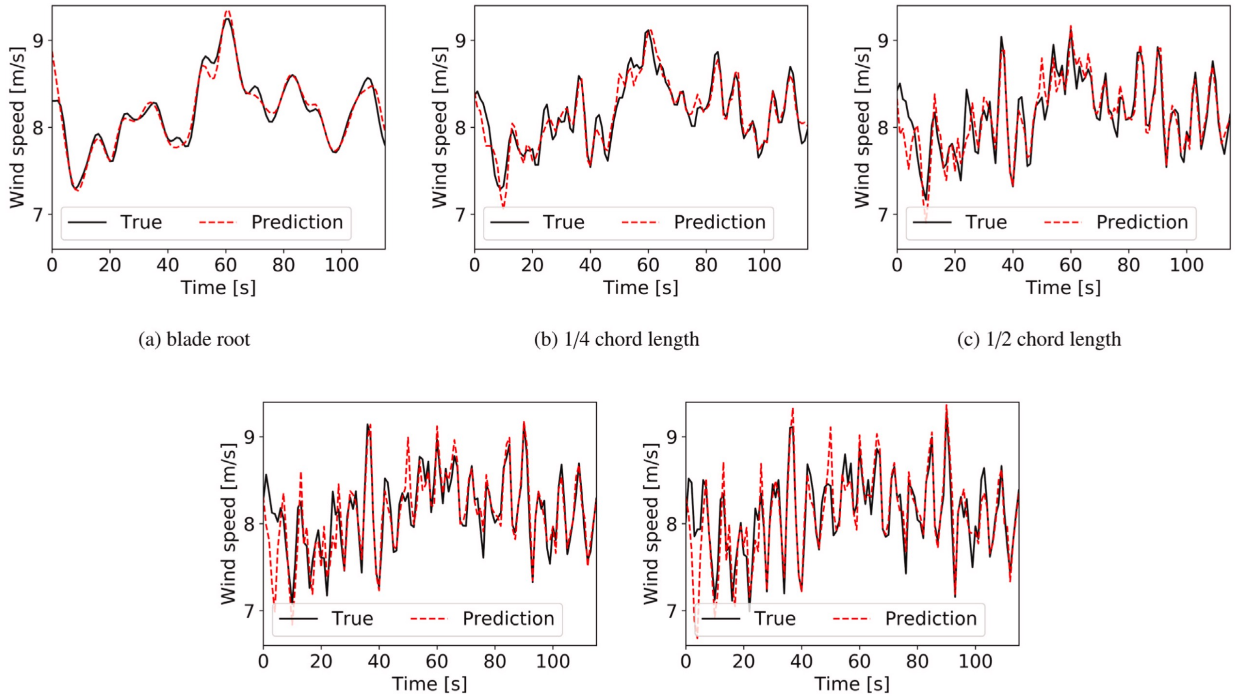
(e) x_0 = 110m

3D wind field prediction – a baseline case

- Instantaneous wind speed
  - Reconstruction (0-100s)
  - Forecasting (100-115s)



Lidar with azimuth scanning



(a) blade root
(b) 1/4 chord length
(c) 1/2 chord length
(d) 3/4 chord length
(e) blade tip

3D wind field prediction – a set of cases

Case	Quantity	Value range	RMSE (% of range)
8 m/s	u (m/s)	[6.08, 10.11]	0.263 (6.5%)
	v (m/s)	[−1.82, 1.53]	0.397 (11.9%)
	w (m/s)	[−1.48, 1.36]	0.361 (12.7%)
	γ_y (°)	[−11.4, 11.8]	2.84 (12.2%)
	γ_z (°)	[−10.1, 9.77]	2.58 (13.0%)
13 m/s	u (m/s)	[9.53, 16.07]	0.592 (9.1%)
	v (m/s)	[−2.89, 2.90]	0.625 (10.8%)
	w (m/s)	[−2.53, 2.56]	0.590 (11.6%)
	γ_y (°)	[−12.6, 12.4]	2.76 (11.0%)
	γ_z (°)	[−10.3, 10.9]	2.60 (12.3%)
18 m/s	u (m/s)	[13.14, 21.62]	0.958 (11.3%)
	v (m/s)	[−4.18, 4.47]	0.837 (9.7%)
	w (m/s)	[−4.04, 3.50]	0.774 (10.3%)
	γ_y (°)	[−11.9, 14.9]	2.73 (10.2%)
	γ_z (°)	[−12.1, 12.1]	2.52 (10.4%)
23 m/s	u (m/s)	[16.53, 28.44]	1.296 (10.9%)
	v (m/s)	[−4.57, 5.79]	1.098 (10.6%)
	w (m/s)	[−4.82, 5.12]	1.036 (10.4%)
	γ_y (°)	[−11.2, 12.8]	2.72 (11.3%)
	γ_z (°)	[−11.7, 13.1]	2.57 (10.4%)

Summary and perspective

Summary:

- A deep learning model: limited data + physics
- Spatiotemporal prediction of wind field: LIDAR + NS equations
- Combination of LIDAR and physics without model reduction
- 3D wind field reconstruction and forecasting for the first time
- Wind forecasting without using Taylor's frozen turbulence hypothesis

Perspective:

- wind resource assessment
- wind turbine control/monitoring
- load/power forecasting

Thanks for your attention !