Hybrid Modeling for Wind Farm Simulation and Control

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Wind Farm Simulation

Definitions:

- Boundary layer (BL): thin layer of fluid near a surface
- Wake: region of low-speed wind downstream of turbine

Key characteristics of wind farms:

- Wake; influenced by blade BL
- ABL, including Coriolis effect and buoyancy
- Wake-ABL interaction
- Turbine-turbine interactions

Modeling options

Reynolds-Averaged Navier Stokes (RANS): $k - \varepsilon$, $k - \omega$, Shear stress transport (SST)

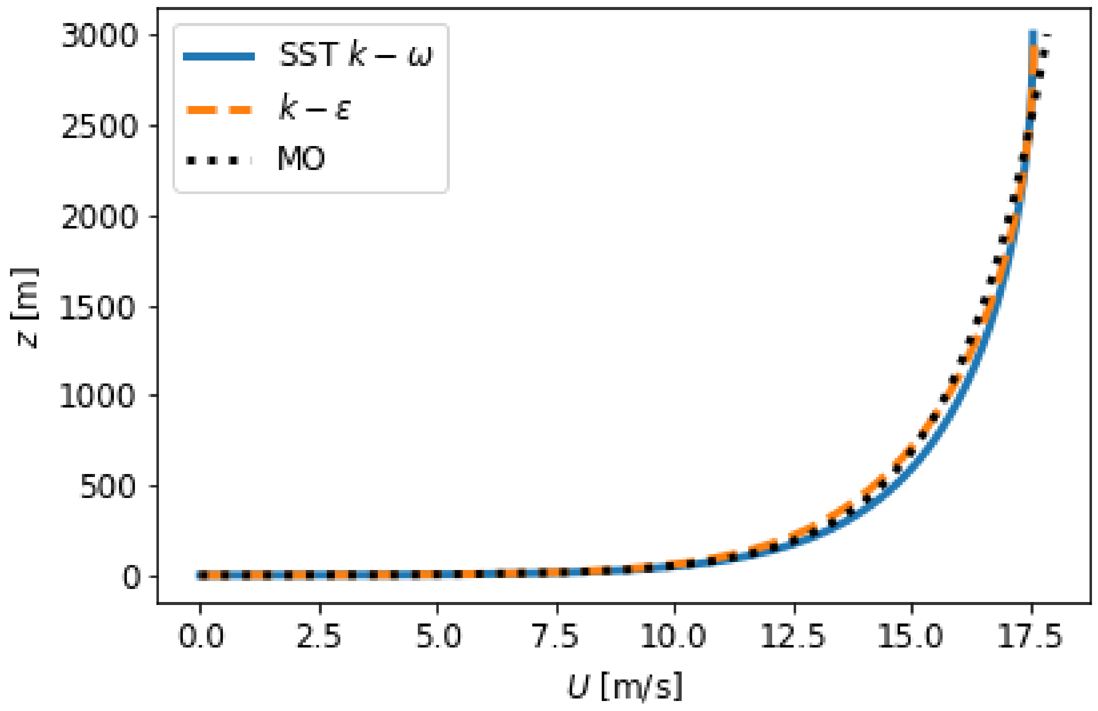
Large eddy simulations (LES)

Active Model Split (AMS): hybrid between RANS and LES; non-zonal

	RANS ($k - \varepsilon$)	RANS ($k - \omega$)	RANS (SST)	LES	AMS [6] w/ SST
Blade BL		x	x	x	x
ABL	x		x	x	x
Wake-ABL				x	x
Turbine-turbine				~	x

[1] 2020 Porté-Agel et al., BL Meteorol.
[2] 2011 Sanderse et al., Wind Energ.
[3] 2019 Sprague et. al, NAWEA WindT.
[4] 1992 Menter, NASA Tech. Mem.
[5] 2006 Wilcox, Turb. modeling for CFD
[6] 2022 Haering et al., Phys. Rev. Fluids

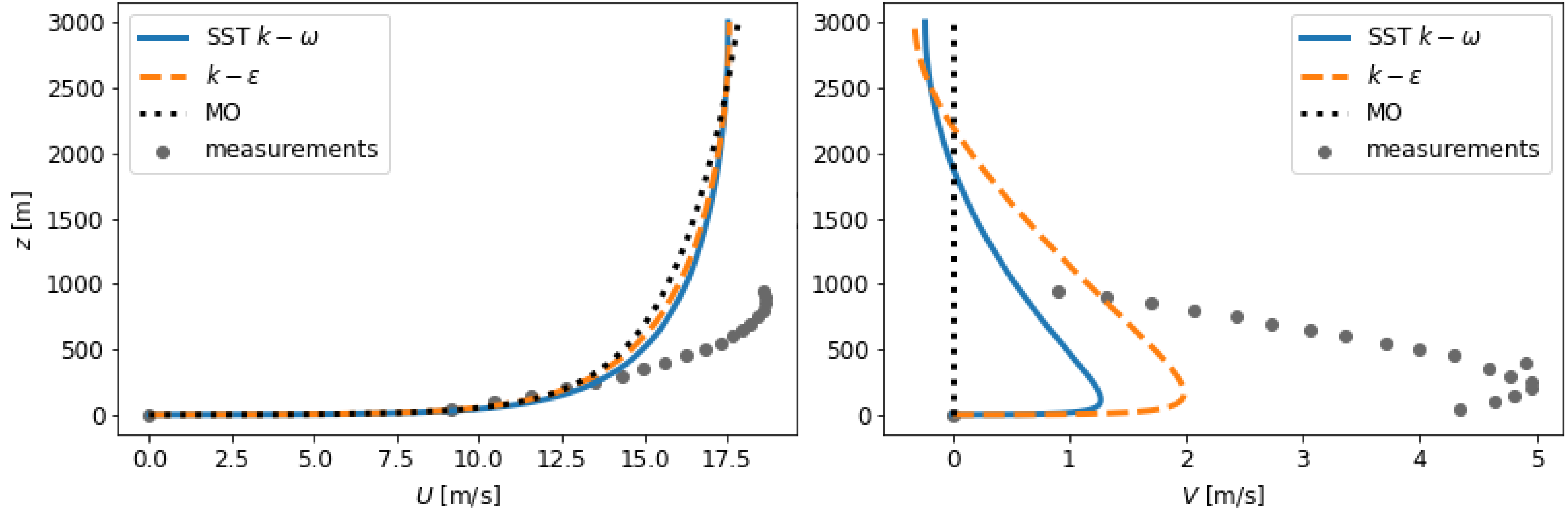
Baseline SST $k-\omega$ and $k-\varepsilon$ w/out Coriolis [7]



- Match Monin-Obukhov (MO) similarity theory
- MO log wind profile:
- $u = \frac{u_\tau}{\kappa} \ln\left(\frac{z-z_0}{z_0}\right)$

[7] 2021 Adcock et al., APS DFD

Baseline SST $k-\omega$ and $k-\varepsilon$ w/ Coriolis



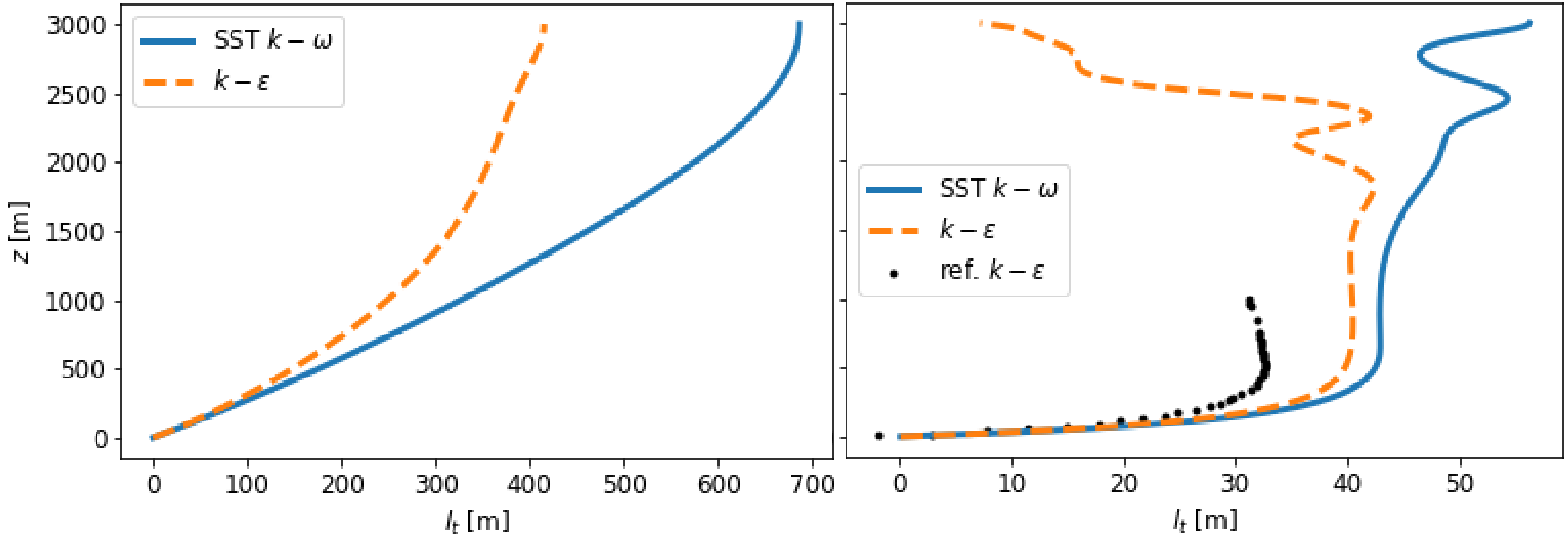
Measurements from Leipzig Field test [8]

Don’t fully capture Coriolis effect

[8] 1950 Lettau, Tellus

SST $k-\omega$ and $k-\varepsilon$: mixing length [7]

Baselines: excessively large mixing length | W/ mixing length limiter: constrain limiter



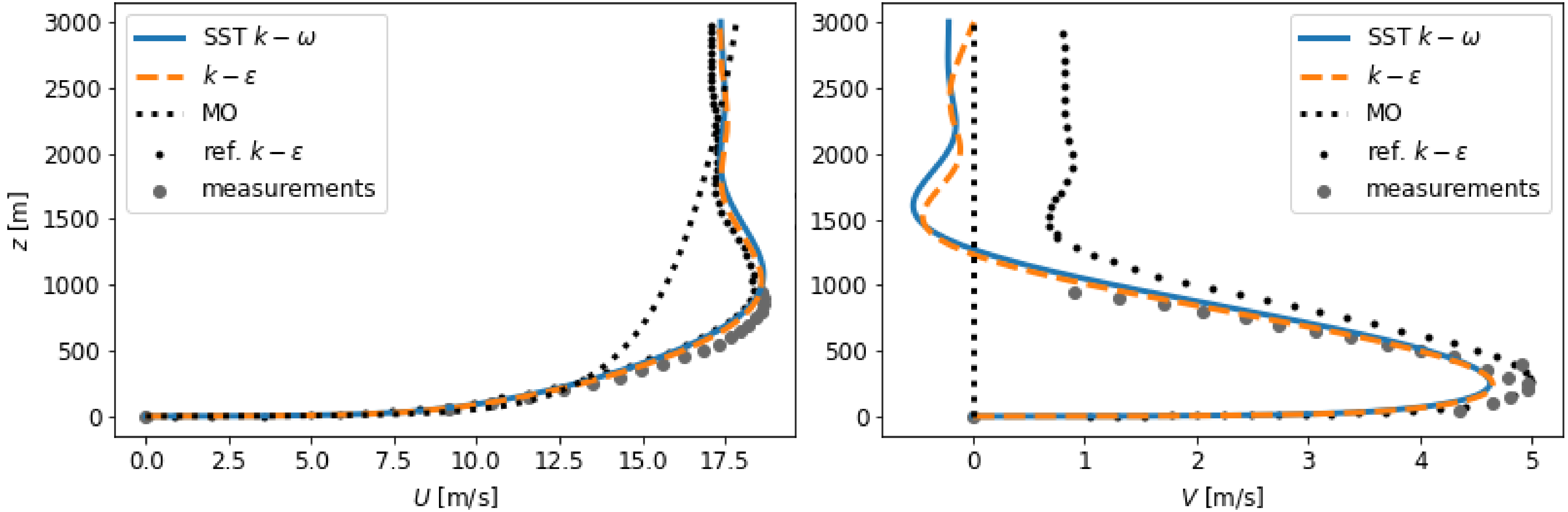
$$\frac{\partial \varepsilon}{\partial t} + \frac{\partial (U_j \varepsilon)}{\partial x_j} = \frac{\varepsilon}{k} C_{\varepsilon 1} P + \cdots ;\ C_{\varepsilon 1} \rightarrow C_{\varepsilon 1}{}^*$$

$$\frac{\partial \omega}{\partial t} + \frac{\partial (U_j \omega)}{\partial x_j} = \frac{\gamma}{\mu_t} P + \cdots ;\ \gamma \rightarrow \gamma^*$$

Reference $k-\varepsilon$ w/ limiter from [9] 2013 Koblitz, Ph.D. thesis, DTU (also uses wall function & extra diffusion)

[7] 2021 Adcock et al., APS DFD

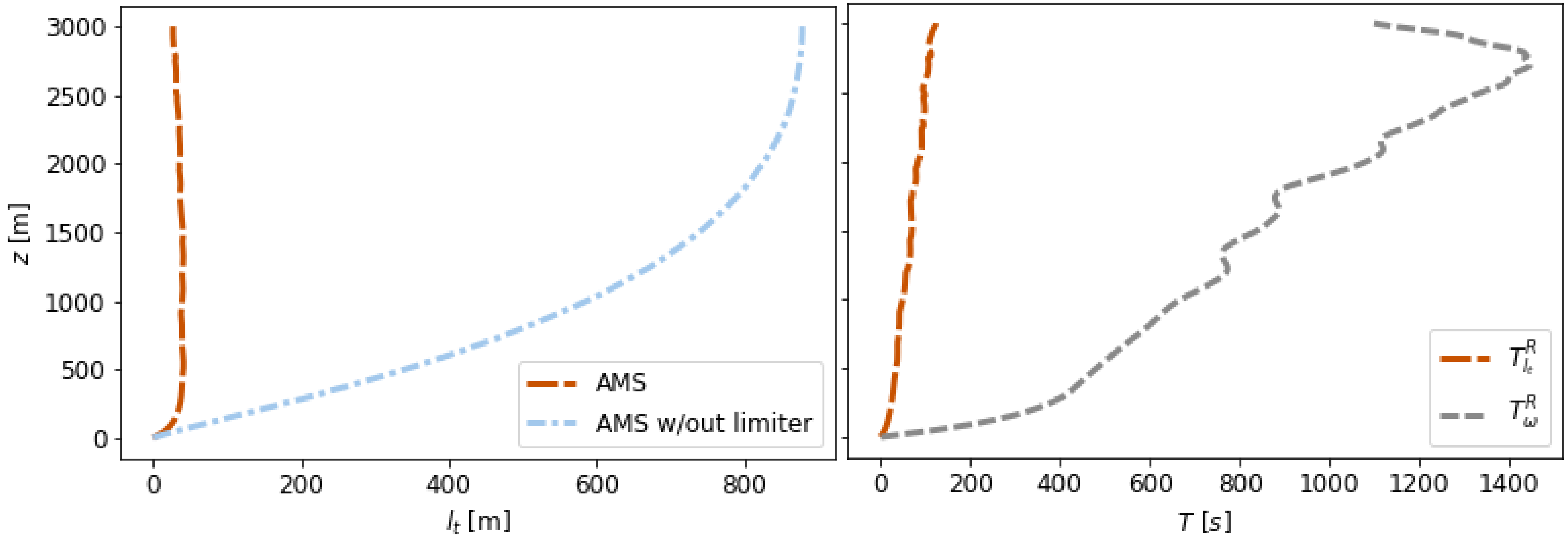
SST $k-\omega$ and $k-\varepsilon$ w/ limiter [7]



W/ limiter capture Coriolis effect

[7] 2021 Adcock et al., APS DFD
[9] 2013 Koblitz, Ph.D. thesis, DTU

AMS: limiter; time scale for averaging [10]

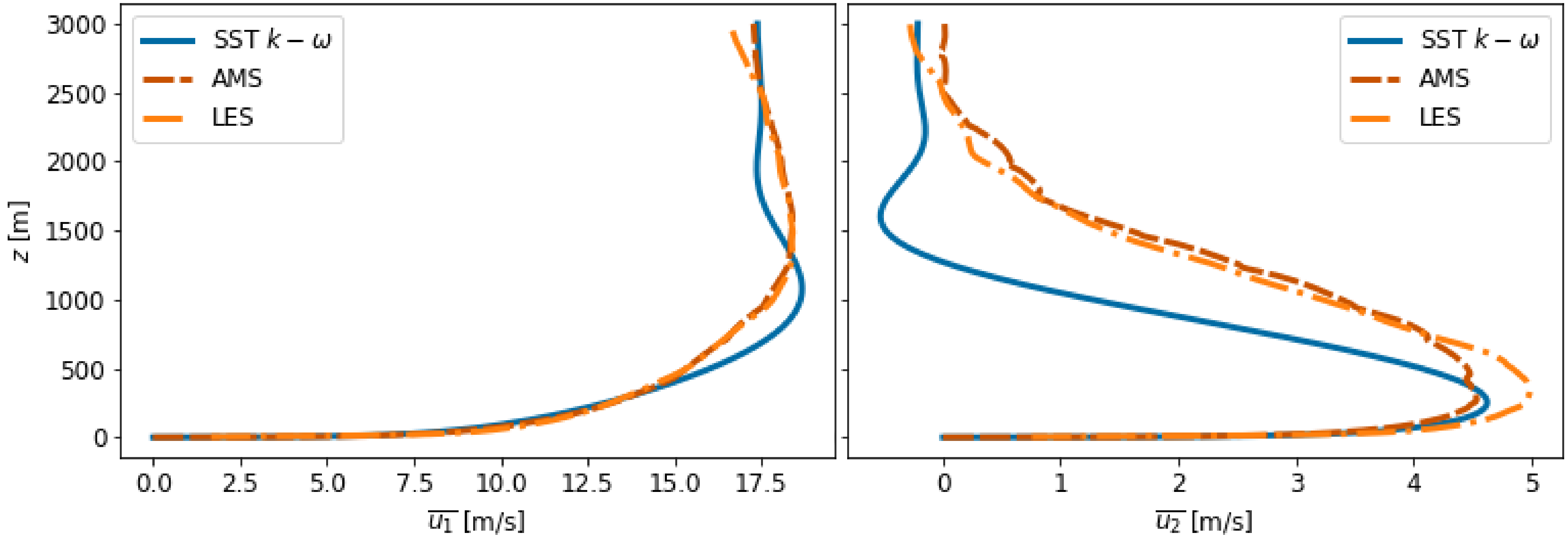


Limiter important not just for SST but also for AMS

Important to use time scale consistent w/ limiter: $T^R_{l_t}$ (not T^R_ω)

[10] 2022 Adcock et al., AIAA SciTech

SST with l_t [7] and AMS with l_t and $T^R_{l_t}$ [10]

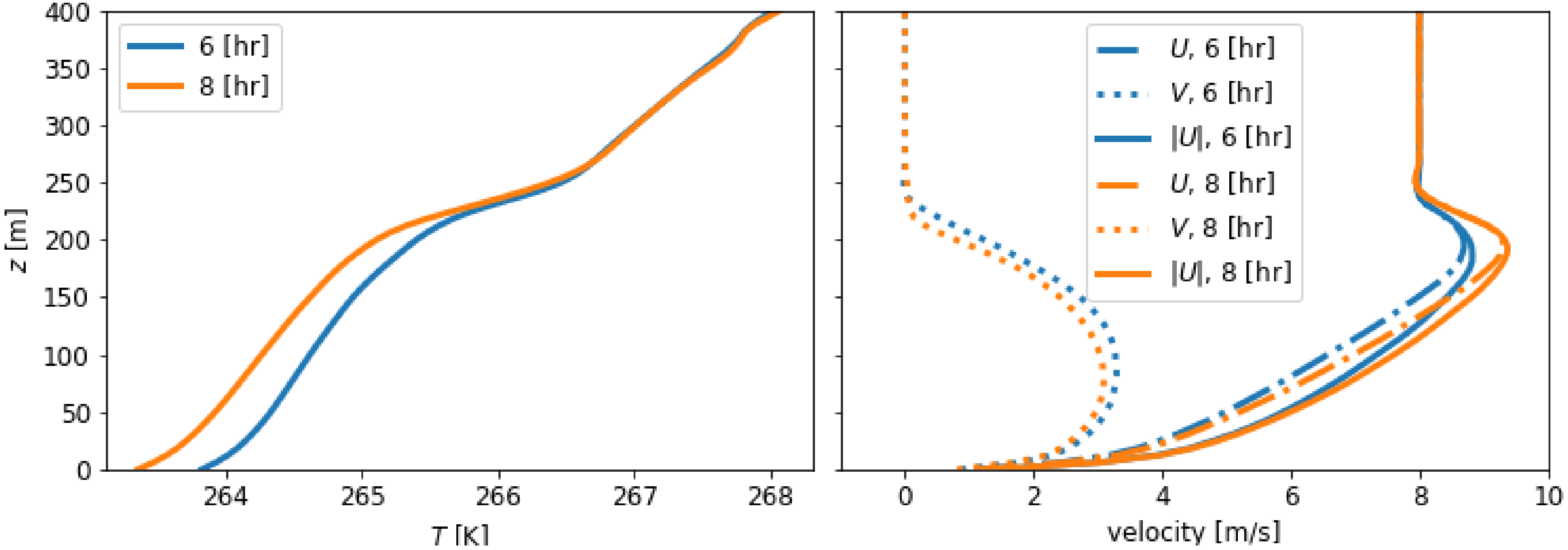


AMS with l_t and $T^R_{l_t}$ matches LES well; better than SST does

[7] 2021 Adcock et al., APS DFD
[10] 2022 Adcock et al., AIAA SciTech

Ongoing work

- Adding buoyancy to SST $k-\omega$ and AMS
  - LES of GABLS test case [11]:



- Add turbines [3]

[3] 2019 Sprague et al, NAWEA WindTech
[11] 2006 Beare et al., BL Meteor.

High Performance Computing

Contributed to **Nalu-Wind** [3]:

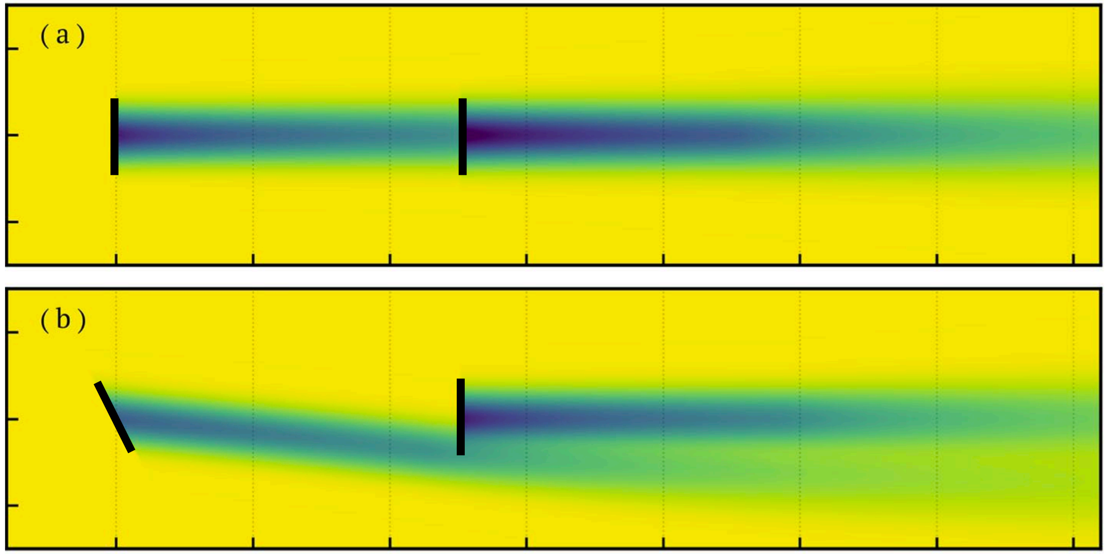
- Incompressible flow solver for simulations of wind turbines in wind farm
- Open-source: https://github.com/Exawind/nalu-wind
- Massively parallel; uses Trilinos [9] and MPI
- Developed by NREL, Sandia, UT Austin; my work in main branch

Run on Eagle [10], HPC system at NREL

- ABL simulation w/ 8 nodes, 18 processors/node takes hrs (RANS)-days (LES)

[3] 2019 Sprague e al, NAWEA WindTech
[12] 2022 Trilinos
[13] 2021 NREL, www.nrel.gov/hpc/eagle-system-configuration.html

Wind Farm (Yaw) Control



Find yaw angle for each turbine to maximize total power that wind farm produces

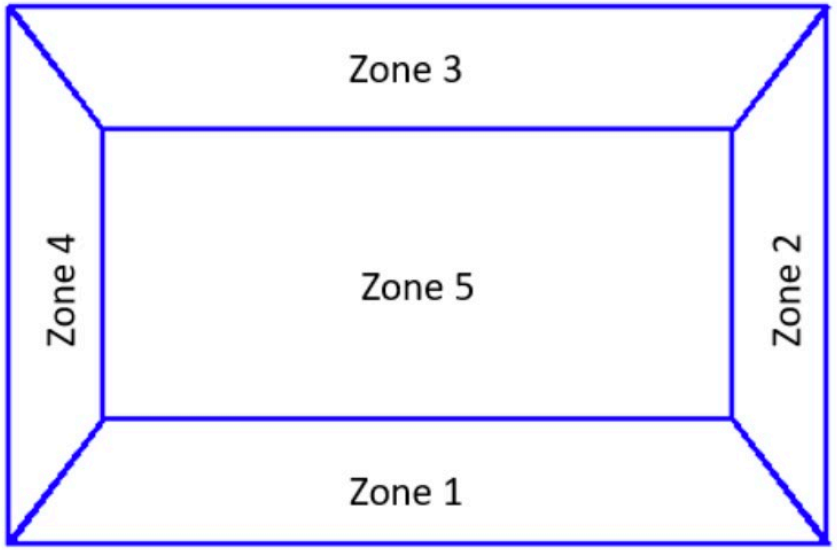
Control methods

Model-based	Learning-based	E.g.	Online (method)	Offline (model)	Ease of implementation
x		MPC	slow (opt.)	n/a	medium
	x	RL	fast (policy)	slow (no model)	easy
x	x	DPC	fast (policy)	fast (model)	hard

Online
- Opt: solve online optimization problem
- Policy: evaluate policy, π_θ, which is an analytic function, e.g. a neural network

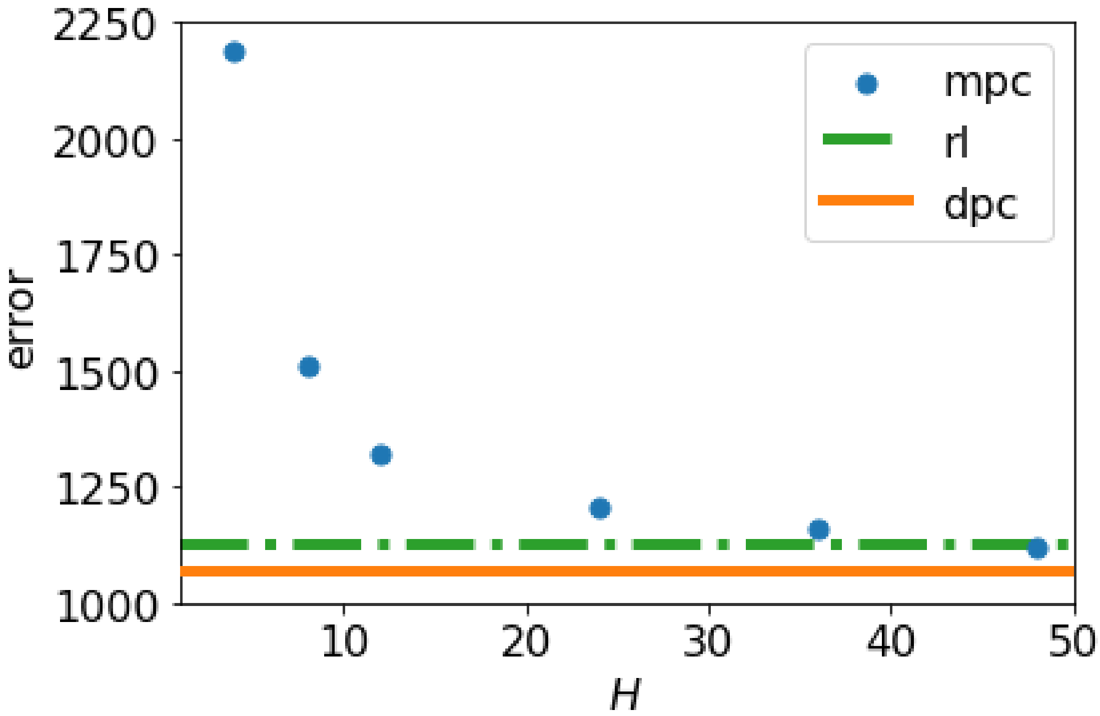
Offline: training; update θ based on results of applying π_θ to data

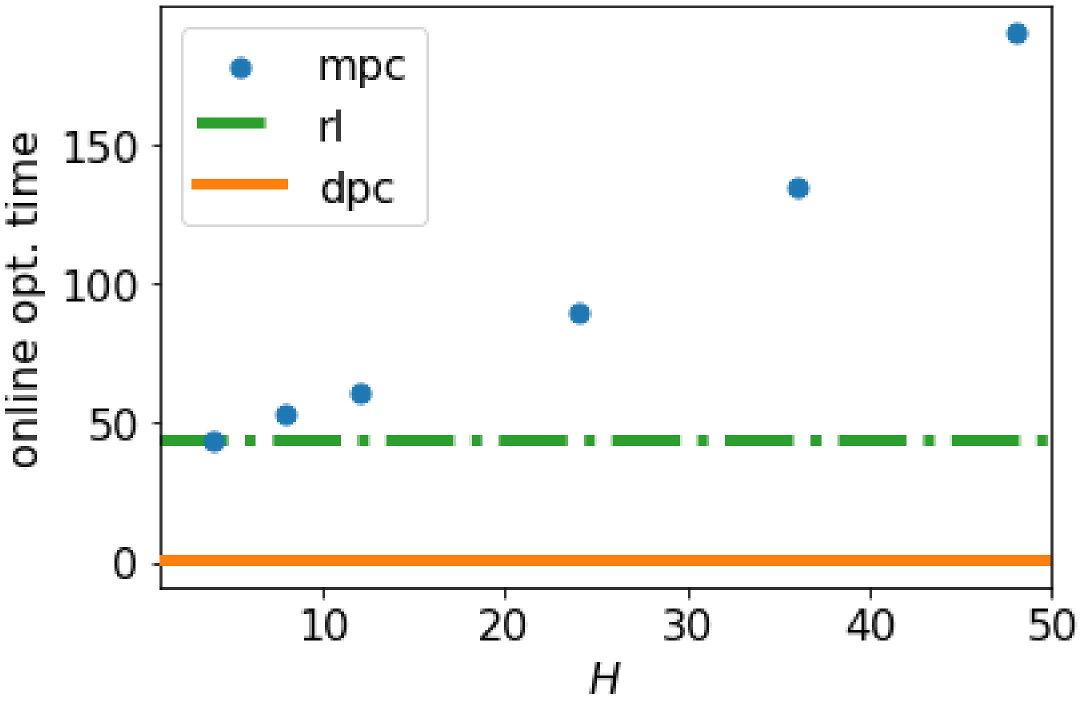
Building Control



Keep temperature in each zone comfortable while minimizing cost by setting central cooling and fan power for each zone

DPC, MPC, RL for Building Control





DPC training time = 28% x [RL training time]

Collaboration w/ Dave Biagioni and Xiangyu Zhang at NREL

Ongoing Work

Apply DPC to dynamic wind farm control

Downside of DPC: hard to implement

- Need to reimplement wind farm wake model in learning package (e.g. pytorch)

Computing

Models fast (ran run in seconds on laptop) for small farm

For large farm need to parallelize simulation (requires e.g. distributed control) or use faster control method (e.g. DPC)

Require HPC to evaluate method using e.g. RANS, LES, or AMS

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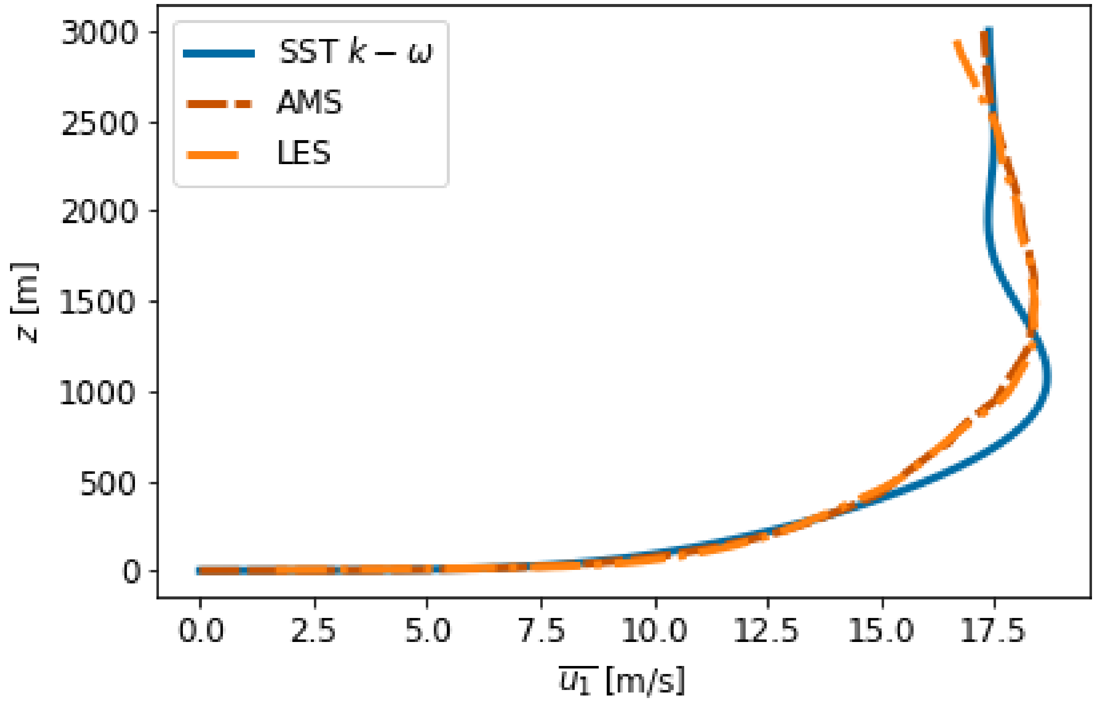
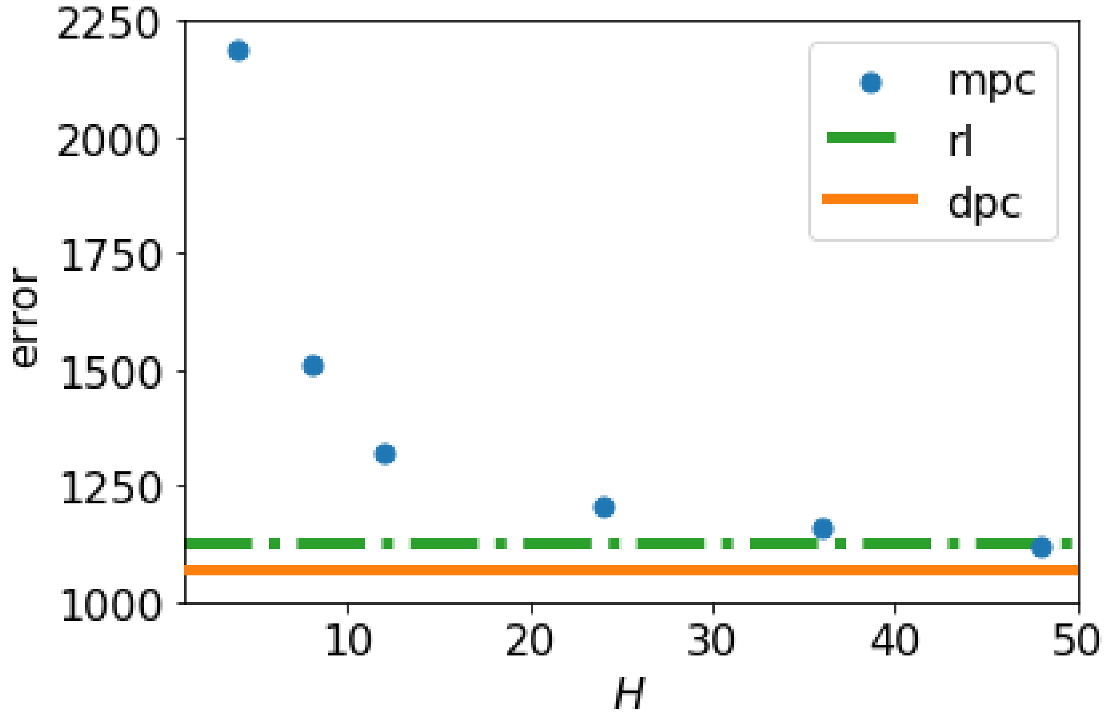
Questions


SST $k-\omega$
AMS
LES
3000
2500
2000
1500
1000
500
0
z [m]
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
$\overline{u_1}$ [m/s]


mpc
rl
dpc
2250
2000
1750
1500
1250
1000
error
10
20
30
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50
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