

Yaw augmented frequency regulation

Dennice F. Gayme
Department of Mechanical Engineering
Johns Hopkins University
dennice@jhu.edu




Floating
Offshore Wind™



Ralph O'Connor Sustainable Energy Institute (ROSEI)

- ▶ **Vision:** We see a world fueled by carbon-free energy abundance where no individual or community lacks access to these resources.
- ▶ **Mission:** Research, Education and Translation for the Energy Transition.
- ▶ **Values:** Innovation, Education, Equity, Community
- ▶ **Founded:** Earth Day 2021



HUB JOHNS HOPKINS UNIVERSITY

JOHNS HOPKINS LAUNCHES NEW INSTITUTE FOCUSED ON CREATING CLEAN, RENEWABLE ENERGY TECHNOLOGIES

The establishment of the Ralph S. O'Connor Sustainable Energy Institute is part of a 10-year, \$75M investment by the university in energy-related research and education

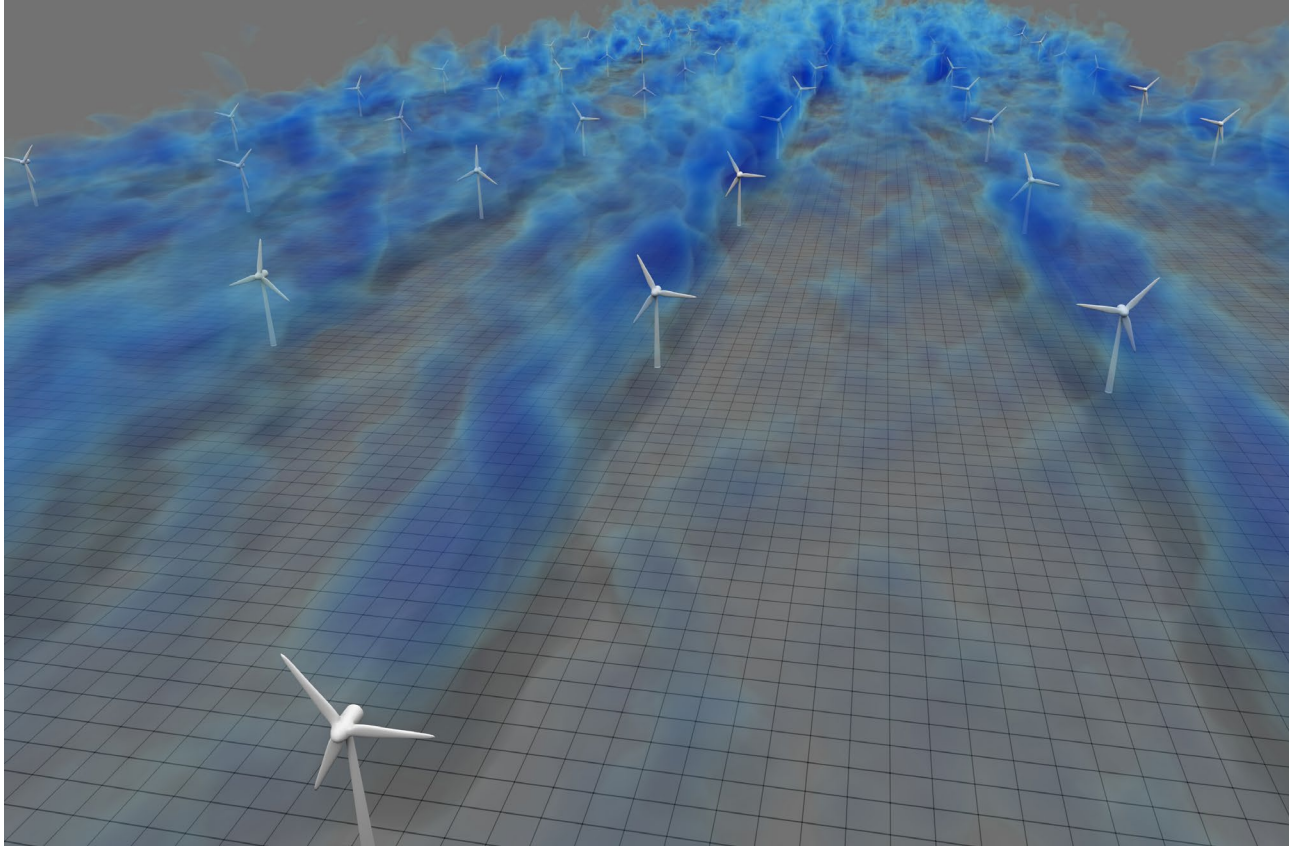
Hub staff report / Apr 22, 2021

With a \$20 million gift from the estate of trustee emeritus and alumnus Ralph S. O'Connor, the Johns Hopkins University and its Whiting School of Engineering today announced the establishment of the Ralph S. O'Connor Sustainable Energy Institute (ROSEI) to serve as the university's interdisciplinary home for ongoing research and education aimed at creating clean, renewable, and sustainable energy technologies.

[MEDIA INQUIRIES](#)

[Twitter](#)
[Pinterest](#)
[Email](#)
[+](#)

ROSEI team: wind energy



In-silico wind farm Large-Eddy-Simulations using the JHU-LES code

Simulation details: [Stevens, R. J., Gayme, D. F., & Meneveau, C. \(2016\).](#)

Wind Energy, **19**, 359-370. Visualization: D. Brock (Extended Services, XSEDE)

Related Expertise	ROSEI Faculty
Wind power grid integration, markets, systems modeling	Yury Dvorkin , Elec Eng Civil & Systems Eng.
Wind farm modeling and control, grid integration	Dennice Gayme , Mech. Eng.
Wind power grid integration, markets	Ben Hobbs , Env. Eng.
Wind farm simulation, wake modeling	Charles Meneveau , Mech. Eng.
Atmospheric modeling, metocean modeling	Julie Lundquist Earth & Planetary Sci./MechE
Wind harvesting, flow physics, fluid-structure interaction	Rajat Mittal , Mech. Eng.
Wind tower structures, design and optimization	Ben Schafer , Civil & Systems Eng.
Wind tower reliability, uncertainty quantification ML	Michael Shields , Civil & Systems Eng.
Wind policy, social acceptance, int'l markets	Johannes Urpelainen , Political Science

ARROW

ACADEMIC CENTER FOR RELIABILITY
& RESILIENCE OF OFFSHORE WIND



Empower, Engage, Innovate



U.S. DEPARTMENT OF
ENERGY



MASSACHUSETTS
**CLEAN ENERGY
CENTER**



Maryland
Energy
Administration



+ Affiliate universities, funders, and broad suite of stakeholder/engagement partners

Empower, Engage, Innovate



Broad view of ROSEI Faculty Expertise:

Engineers

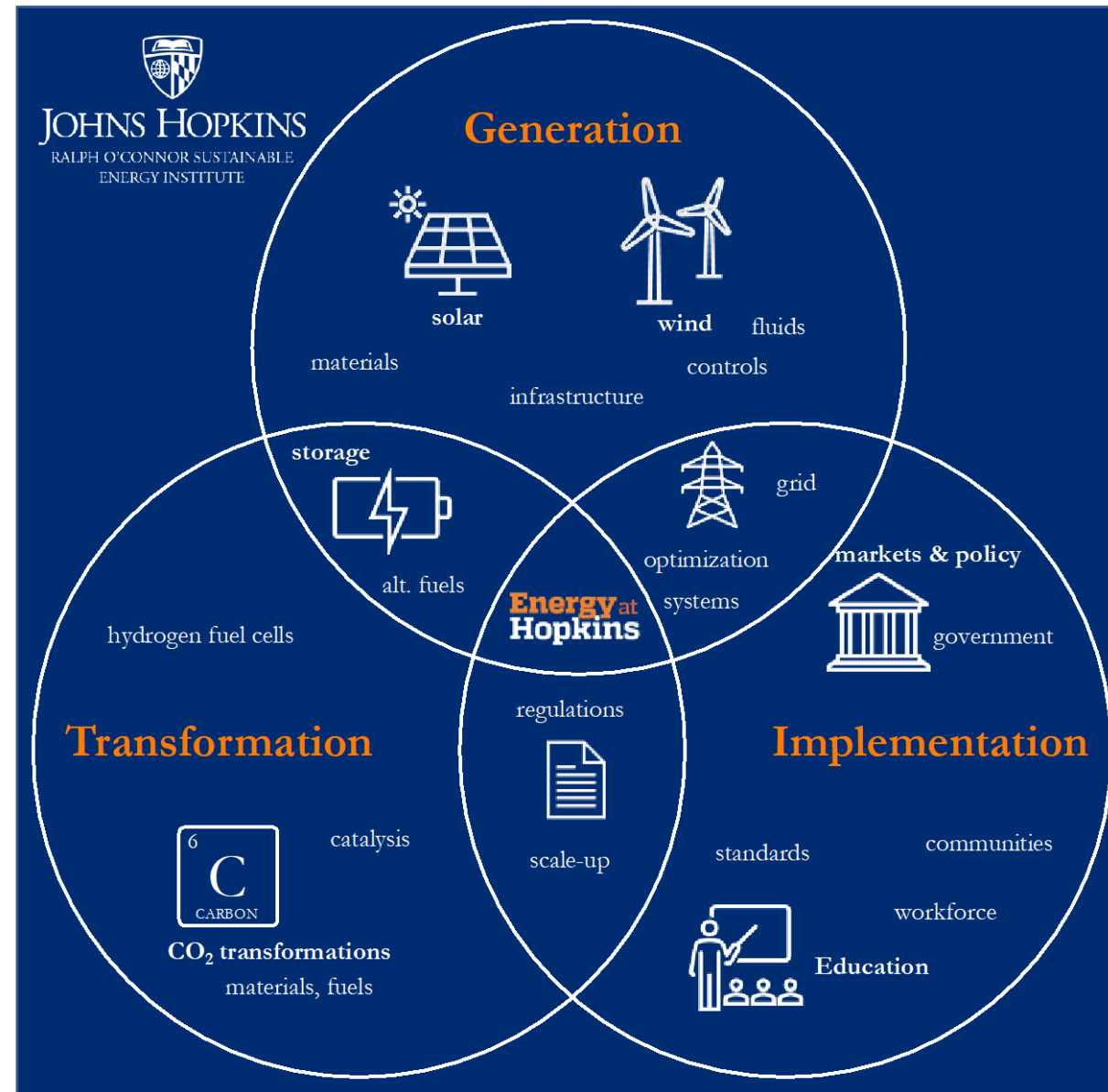
Chemical Eng, Materials Science, Electrical Eng., Mechanical Eng., Civil Eng., Systems Eng., Env. Eng., App. Math

Scientists

Chemistry, Earth Sciences, Physics

Social Scientists

Economics, Political Science,
Sociology, Anthropology



ROSEI Research Pillars and Cross-Cutting Areas

captured, upcycled
repurposed

Carbon



Community

integrated,
sustainable, safe

Storage



Education

efficient, scaled,
reliable

Wind



Policy



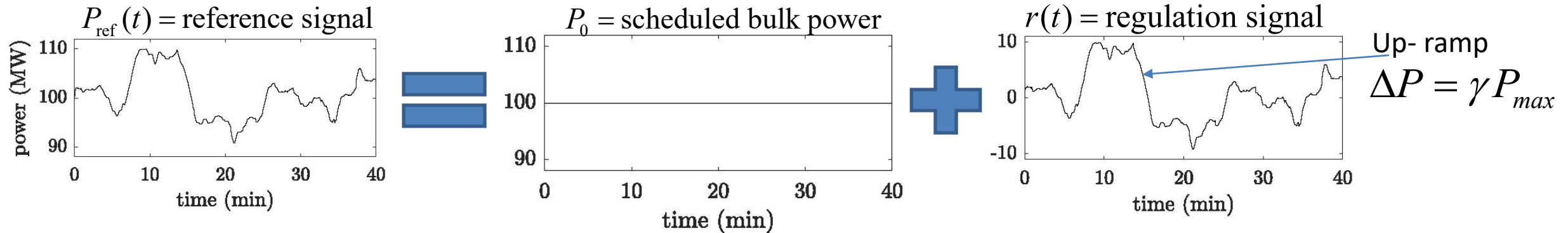
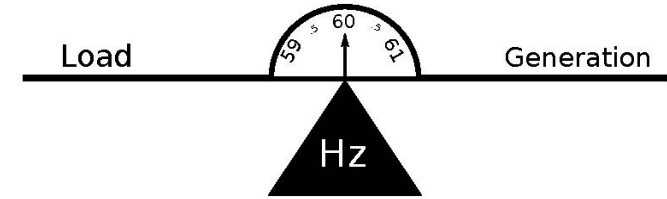
Translation

economic, equitable,
transformed

Grid

Wind farm power tracking

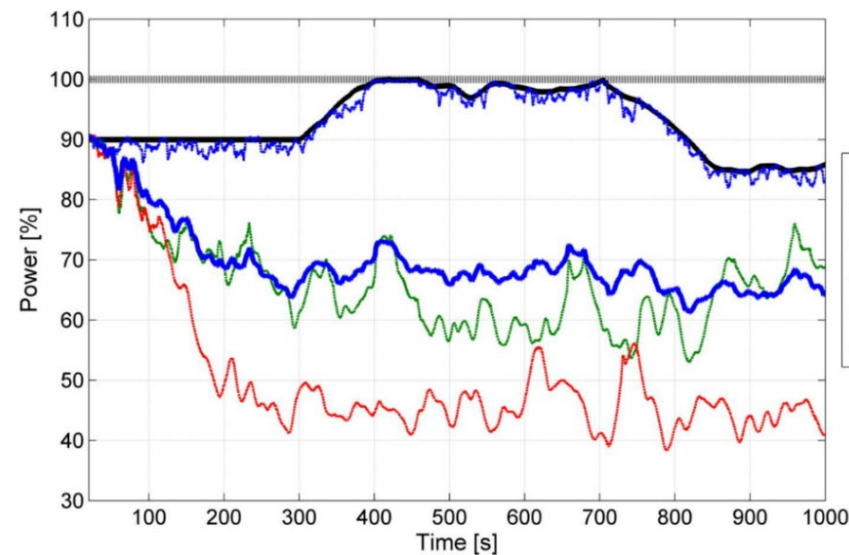
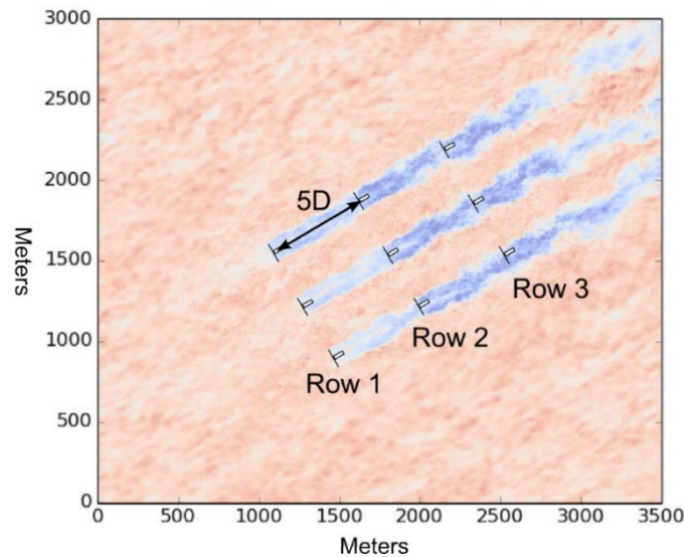
- Secondary frequency regulation is an important grid service that requires power tracking



- Reduce bulk power supply (i.e. do not maximize power output) $P_0 = (1 - \alpha)P_{max}$
 - Derate the turbine by some percentage $\alpha \times 100\%$
- Ideally up-ramp capability (upramp) $\gamma > \alpha$ (derate)

Frequency regulation: Challenges

- Direct economic trade-off between bulk power supply and regulation
 - Ideally up-ramp capability $\gamma > \alpha$ (derate) *Not possible with a single turbine*
- Individual turbine control (i.e., failure to take wake effects into account) even with $\gamma = \alpha$ fails even in small farms (except if $\gamma \ll \alpha$ e.g., van Wingerden et al. 2017)



Fleming et al 2016

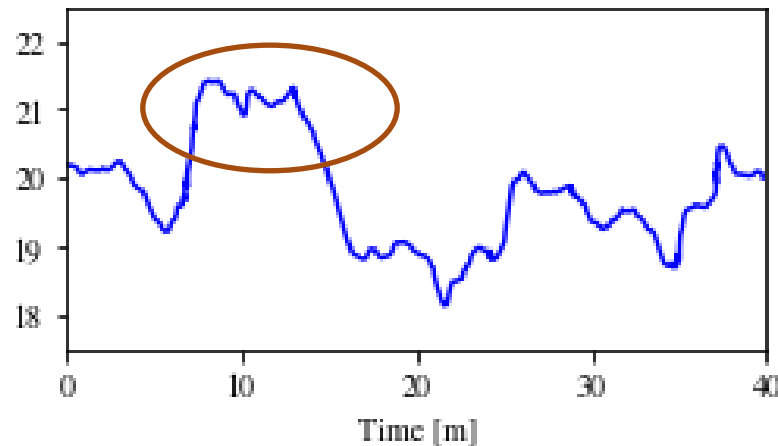
- Previous work using dynamic models that account for wake propagation have reduced required derates e.g., Shapiro et al. 2017, 2018, 2019; Vali et al 2018

Power tracking control

- Previous work using dynamic models that account for wake propagation have reduced required derates e.g., Shapiro et al. 2017, 2018, 2019; Vali et al 2018
- Pitch control can saturate in power tracking applications due to finite control authority



Genevieve Starke



Yawing turbines

- Yawing turbines has been shown to increase power output
e.g. Howland et al. 2019, 2022 , Fleming et al. 2017, Gebraad et al. 2016, Campagnolo et al. 2016

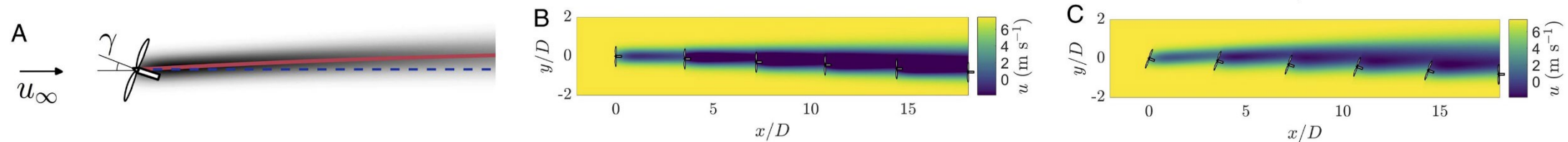
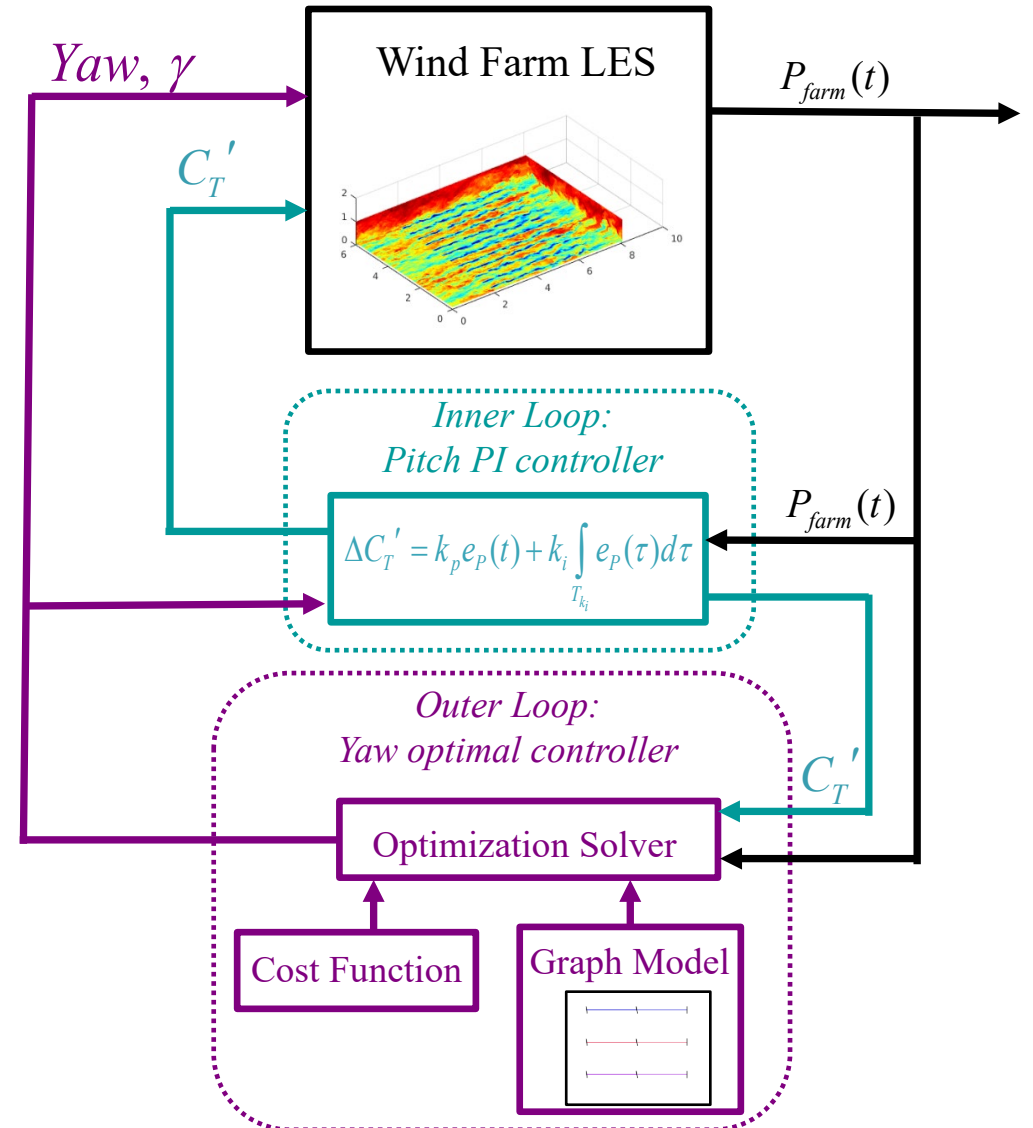


Figure adapted from Howland et al. 2019 demonstrating yaw optimization for power maximization

- Mostly in static setting and not taken in the timescales associated with dynamic yawing behavior (e.g. rate of yawing) the behavior of the farm as the effect of yaw actions propagate downstream
- Idea: use yaw to increase control authority in power tracking applications
 - Previously demonstrated in power maximization and tracking that did not aim to reduce derates e.g., Munters & Meyers 2018, Boersma et al 2019a, 2019b

Yaw augmented power tracking

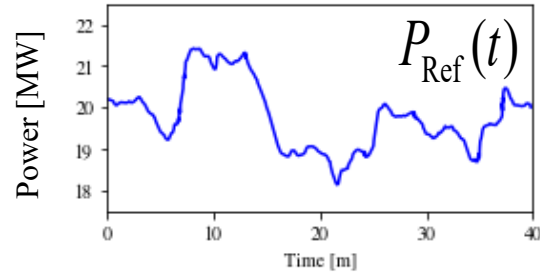
- Inner-outer loop control architecture
- Outer loop
 - model-constrained optimal control for the yaw
- Inner Loop
 - PI pitch controller



Inner loop: PI pitch control

- Control local thrust coefficient as a proxy for pitch

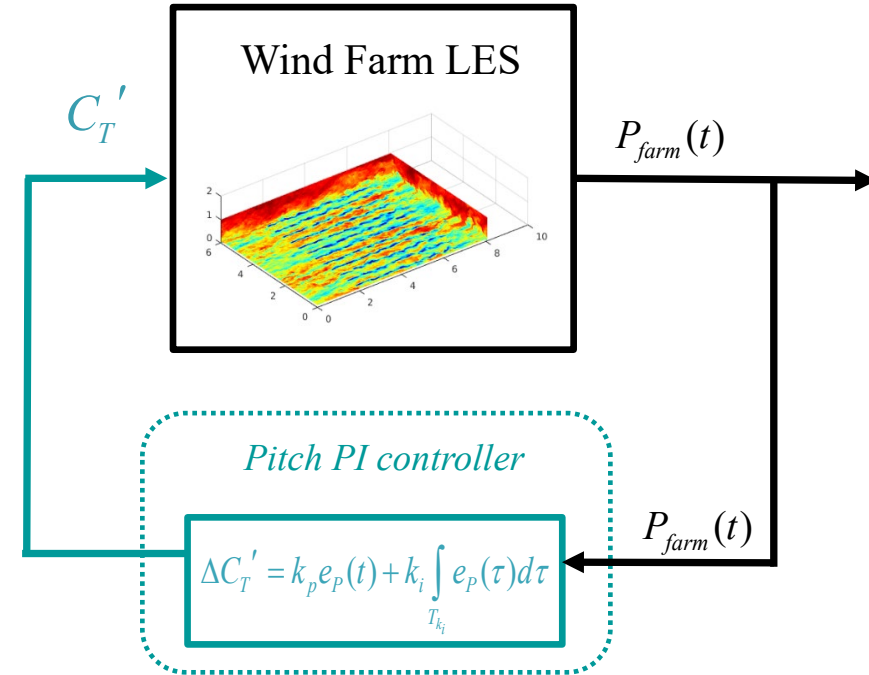
$$\Delta C_{T,i}' = k_p e_{P,i}(t) + k_i \int_{T_{k_i}} e_{P,i}(\tau) d\tau$$



$$e_{P,i} = P_{\text{Ref},i} - P_{\text{LES},i}$$

- Use measurements to distribute power reference across the turbines

$$P_{\text{Ref},i} = \frac{1/T_{C_T'} \int_{T_{C_T'}} P_{\text{LES},i}(\tau) d\tau}{1/T_{C_T'} \int_{T_{C_T'}} P_{\text{LES}}(\tau) d\tau} P_{\text{Ref}}$$



k_p, k_i : Proportional and integral gain

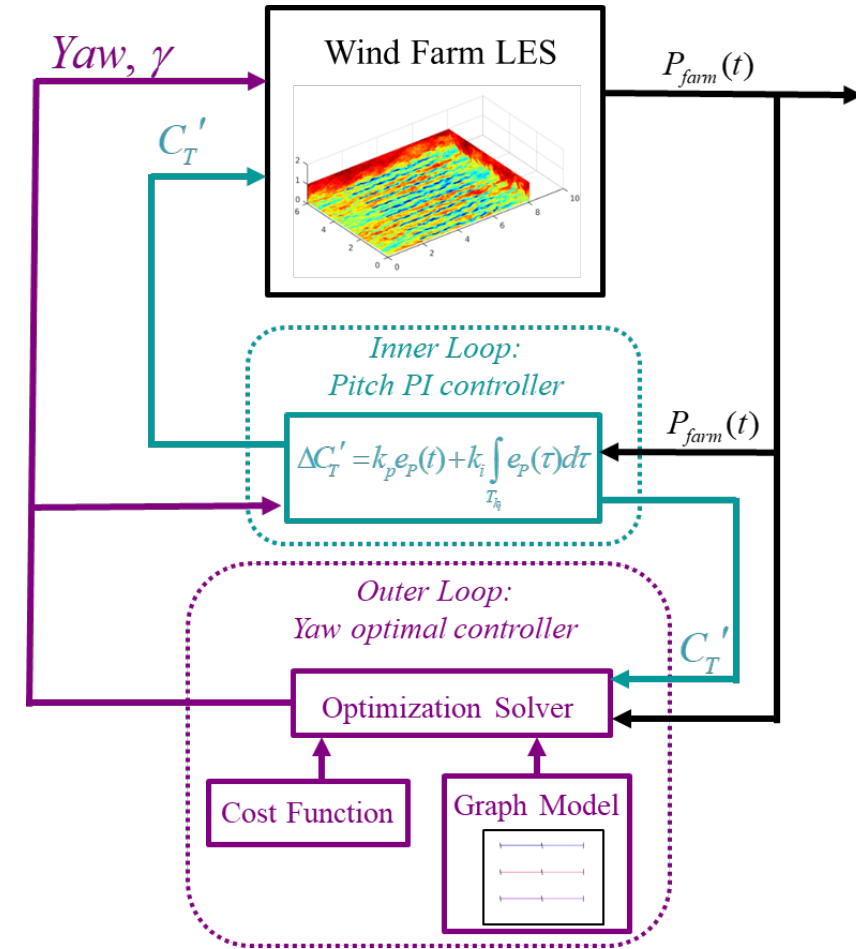
T_{k_i} : integral time

Incorporating power changes due to yaw actions

- Changes in power due to yaw are incorporated into the inner loop as a feedforward term
 - linear approximation for the change in the thrust around the cosine the angle change

$$\Delta C_{T,\gamma}' = \frac{\partial \Delta C_T'}{\partial \cos(\gamma)} [\cos(\gamma_2) - \cos(\gamma_1)]$$

$$\Delta C_T' = k_p e_P(t) + k_i \int_{T_{k_i}} e_P(\tau) d\tau + \Delta C_{T,\gamma}'$$



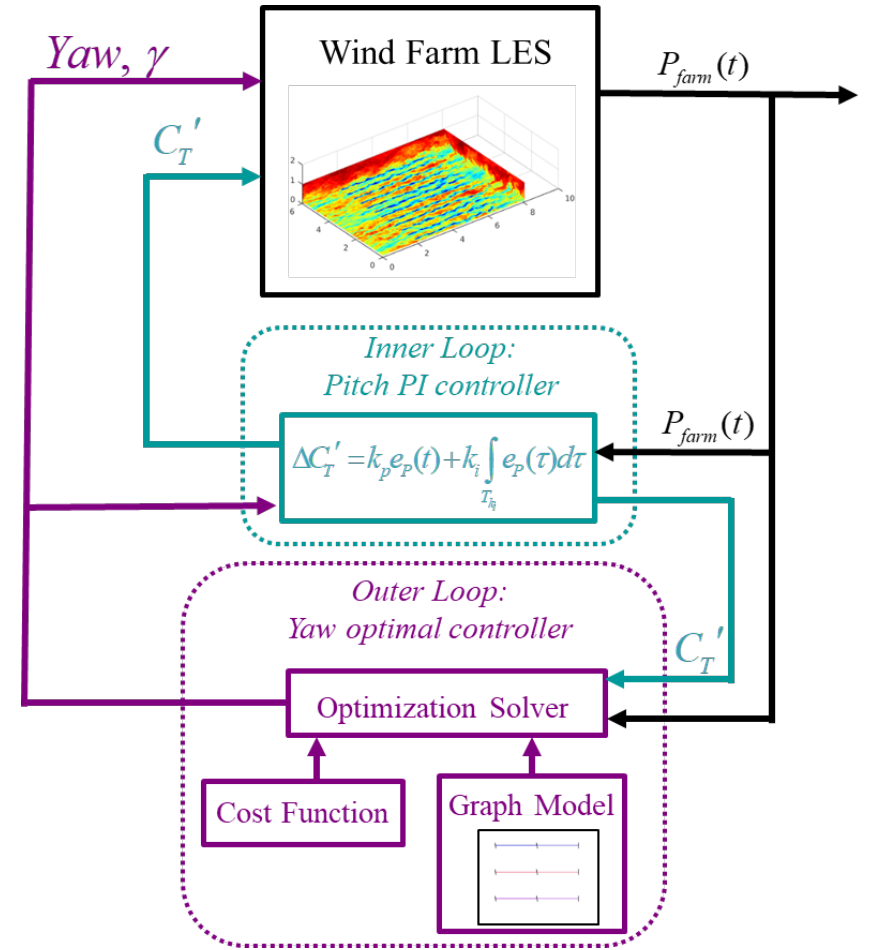
Outer loop yaw control (initial implementation)

- Optimize the cost function for a single yaw angle for each control period

$$J(\gamma) = \left(\int_0^{T_H} (P_{GM} - P_{ref})^2 dt \right)$$

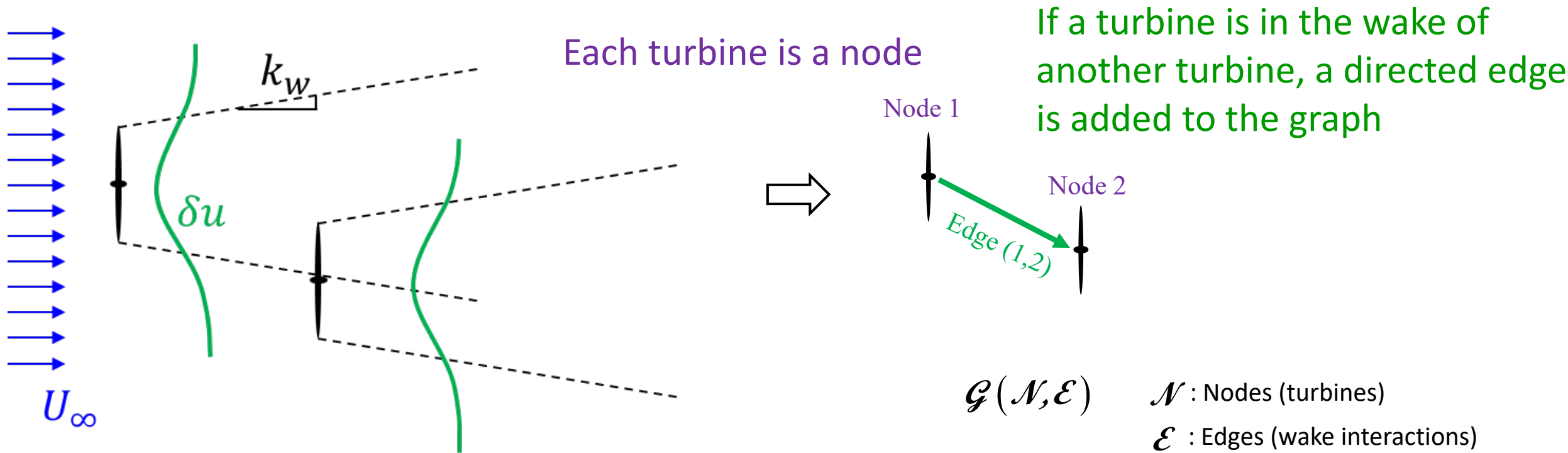
T_H : time horizon
 γ : turbine yaw
 T_γ : Yaw update interval

- Trade off:** Easier to implement but less efficient and requires more updates for accuracy



Computing time-dependent yaw angles

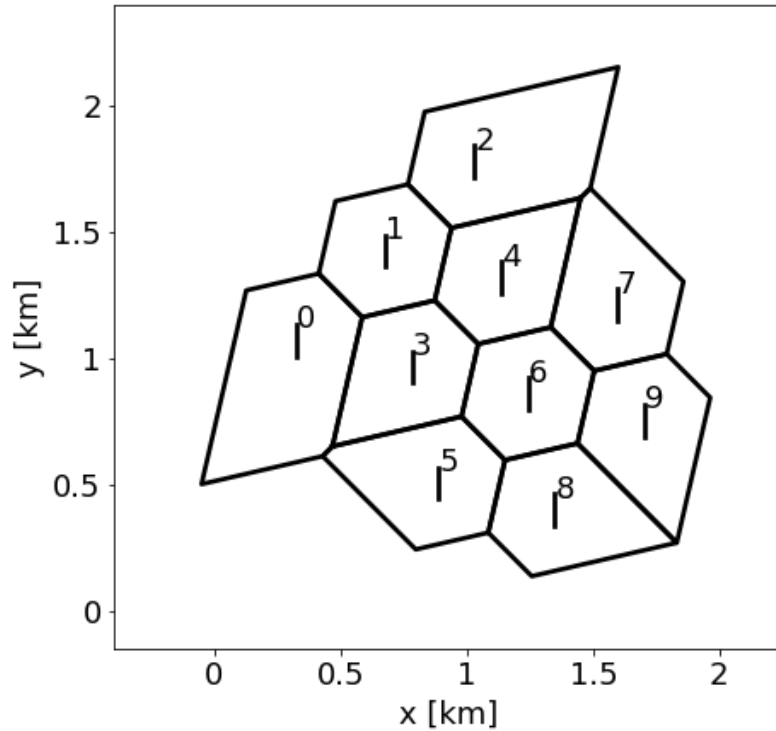
- Graph model of a wind farm (extends the approach in Annoni et al. 2019a, 2019b)



- Divide the farm into weakly-connected subgraphs based on a leader (node) turbine $\mathcal{G}(\mathcal{N}, \mathcal{E}) = \{g_1, g_2, \dots, g_m\}$

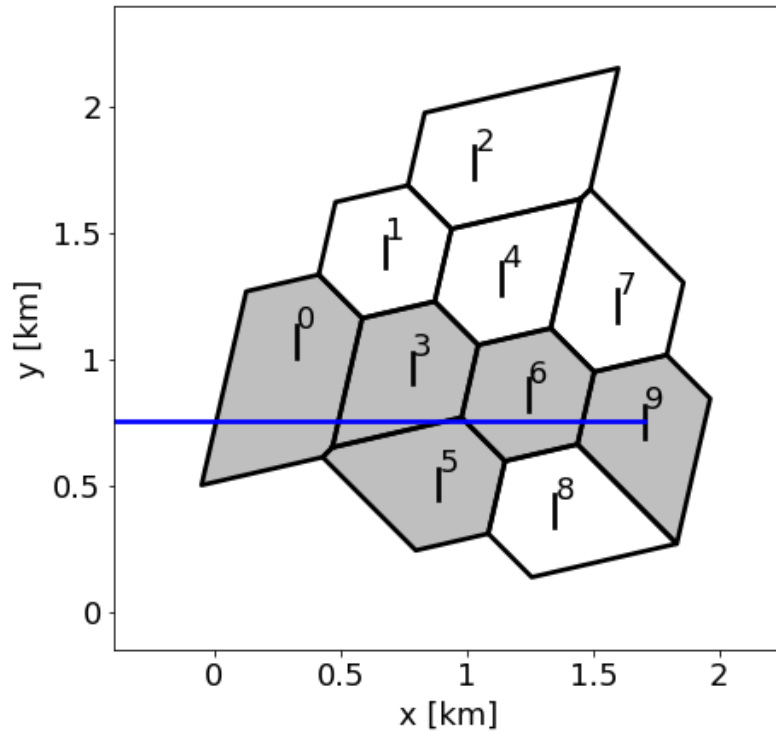
Generating a graph of an arbitrary wind farm geometry

- Define local turbine areas using Voronoi tessellation



Generating a graph of an arbitrary wind farm geometry

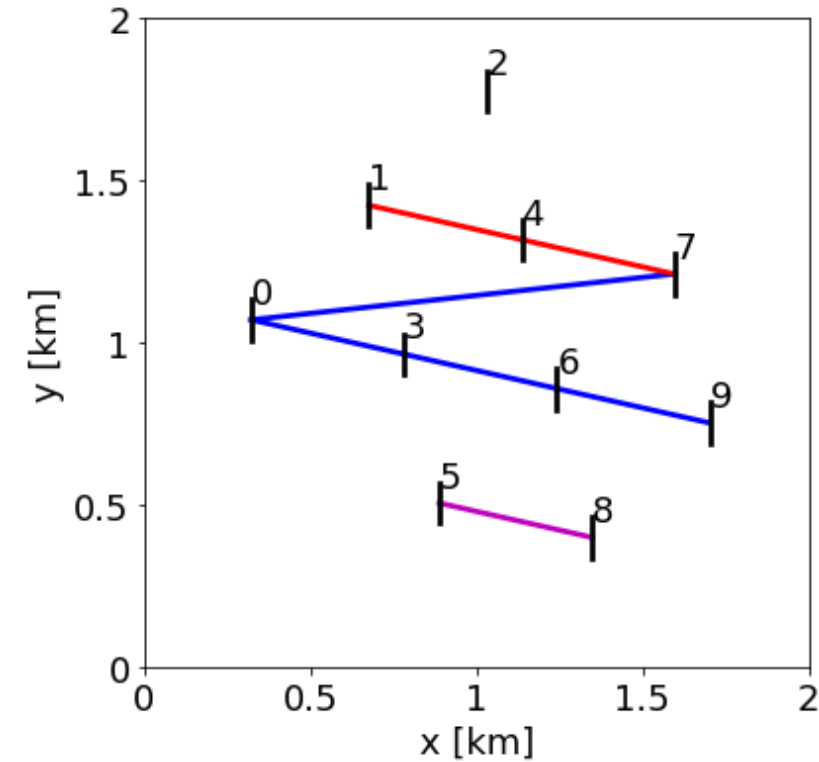
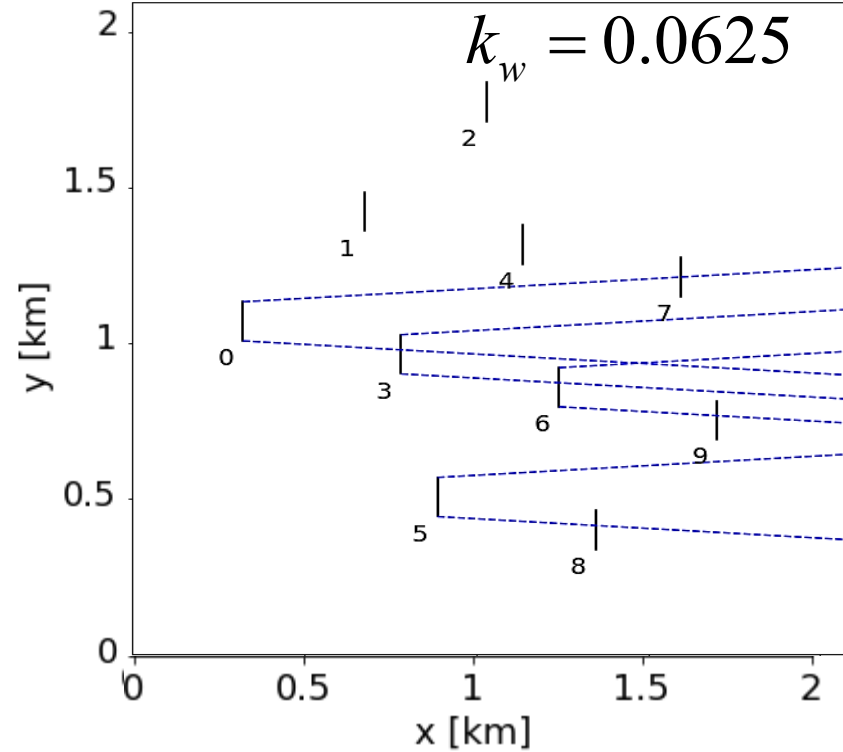
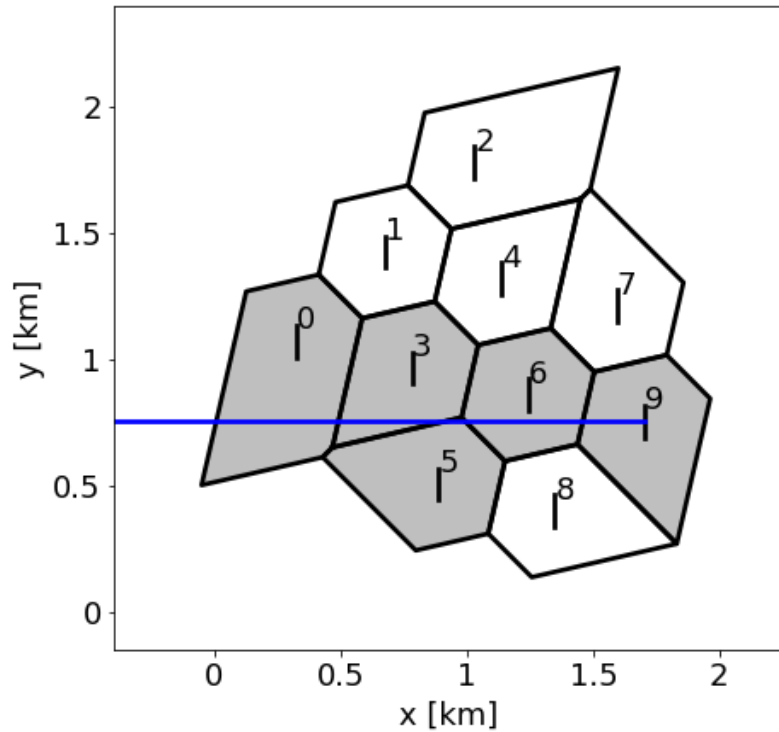
- Define local turbine areas using Voronoi tessellation



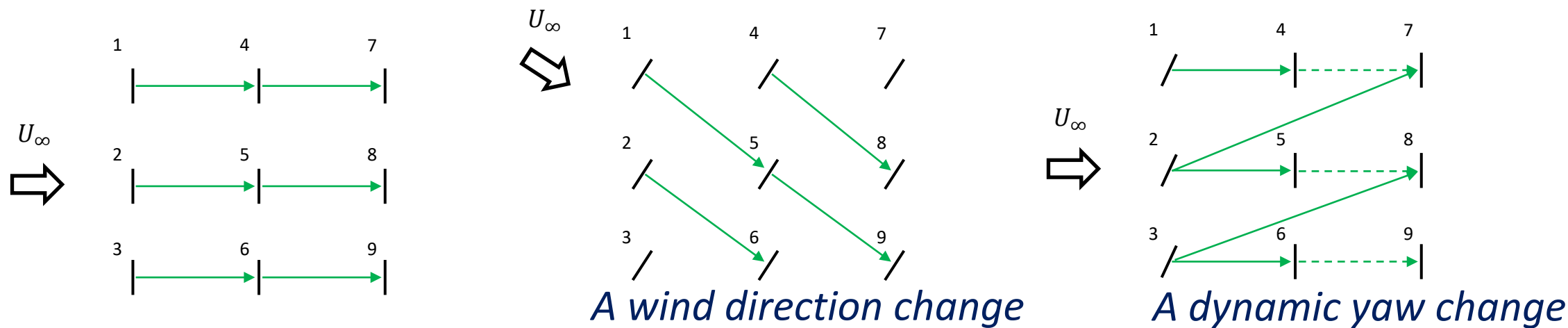
- Given an initial wind direction
 - Lead turbines and interconnections are defined based on the cells crossed as one traverses to the front of the farm
 - The wakes are defined using a linear wake growth (e.g. Jensen 1983 model)

Generating a graph of an arbitrary wind farm geometry

- The turbine wakes are described using linear wake growth



Change in wind farm condition = new graph topology

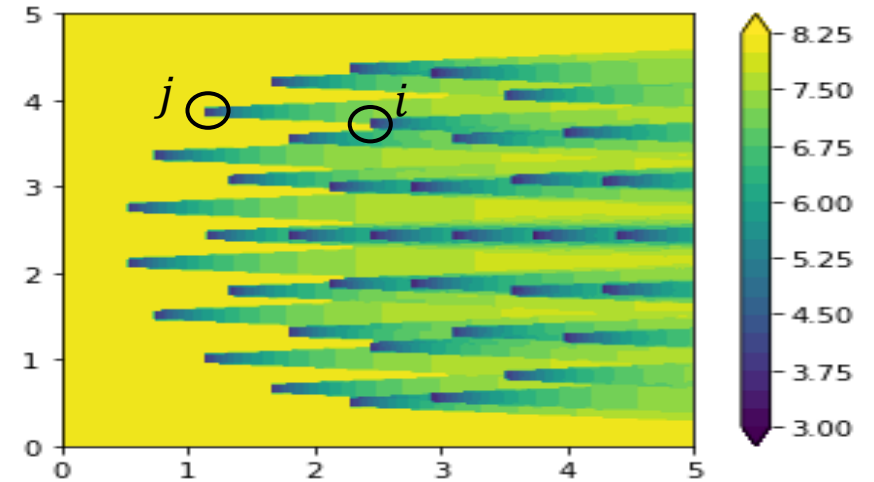
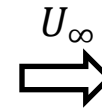


State dynamics

State Update Map $\Phi_{k+1} = \Phi_k + E_k$

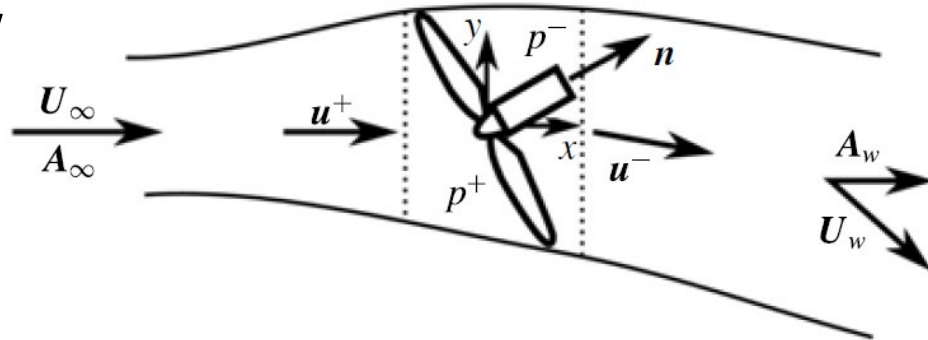
- States: deficits between turbine pairs ϕ_i^j

$$\Phi_k = \begin{bmatrix} \phi_1^1 & \phi_1^2 & \phi_1^3 & \dots & \phi_1^N & \phi_2^1 & \dots & \phi_N^{N-1} & \phi_N^N \end{bmatrix}^T$$

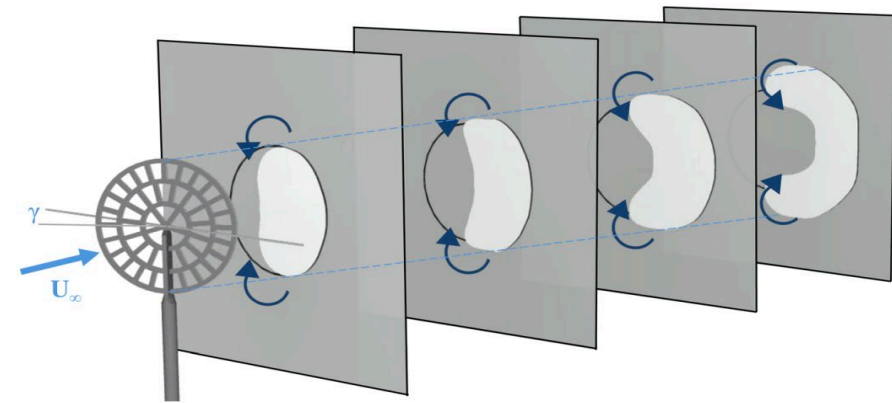


- Deficit model needs to account for deflection and curling of the wake

Wind turbine yaw



(c) Howland et al (2016)

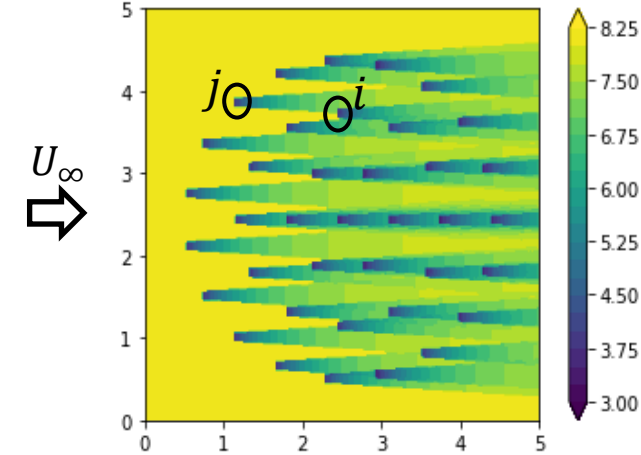


Dynamic graph for yawing turbine

Linear Map $\Phi_{k+1} = \Phi_k + E_k$

Normalized deficits at turbine i due to turbine j based on analytical curled model Bastankhah et al, 2021

$$\phi_i^j = \frac{1}{Area_{j^{th} \text{ disk}}} \int_{Area_{j^{th} \text{ disk}}} C(\Delta x_{i,j}) \exp\left[-\frac{(y-y_c)^2 + (z-z_h)^2}{2\sigma(\Delta x_{i,j}, \theta)^2}\right] dy dz$$



Dynamic graph for yawing turbine

Linear Map $\Phi_{k+1} = \Phi_k + E_k$

Normalized deficits at turbine i due to turbine j based on analytical curled model Bastankhah et al, 2021

$$\phi_i^j = \frac{1}{Area_{j^{th} \text{ disk}}} \int_{Area_{j^{th} \text{ disk}}} C(\Delta x_{i,j}) \exp\left[-\frac{(y-y_c)^2 + (z-z_h)^2}{2\sigma(\Delta x_{i,j}, \theta)^2}\right] dy dz$$

$\sigma(x, \theta) = k x + 0.4\xi(x, \theta)$ wake shape over distance, polar angle

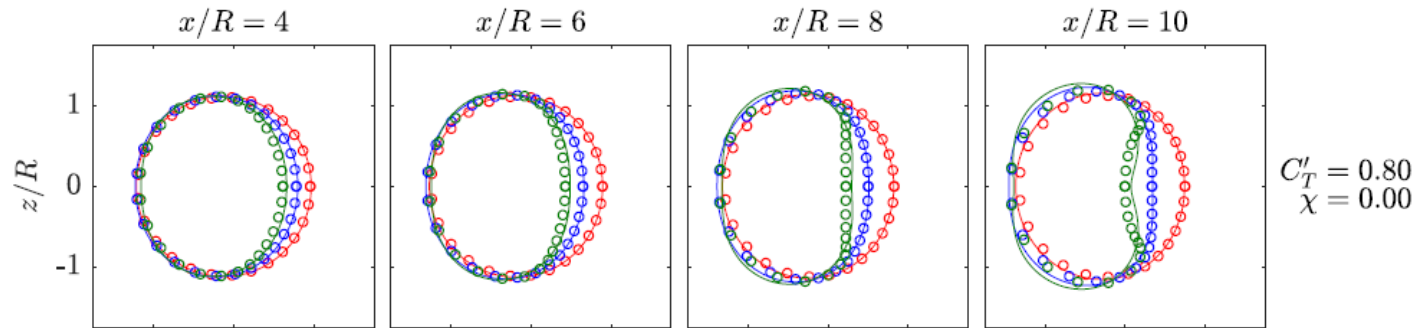
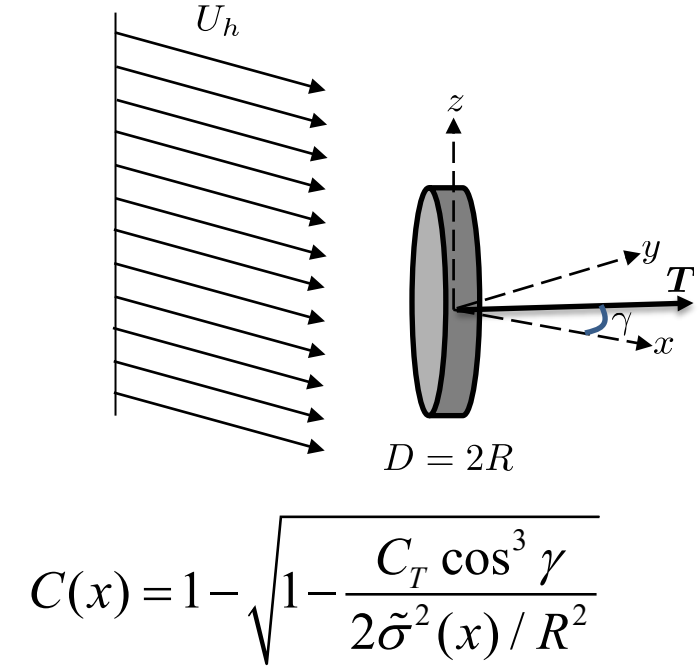


Figure from Bastankhah et al, 2021

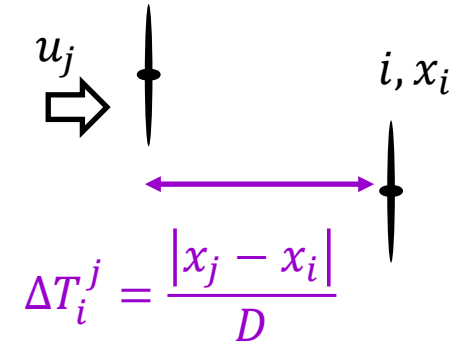
Solid lines: model results; symbols: LES results for different yaw angles

State update map $\Phi_{k+1} = \Phi_k + E_k$

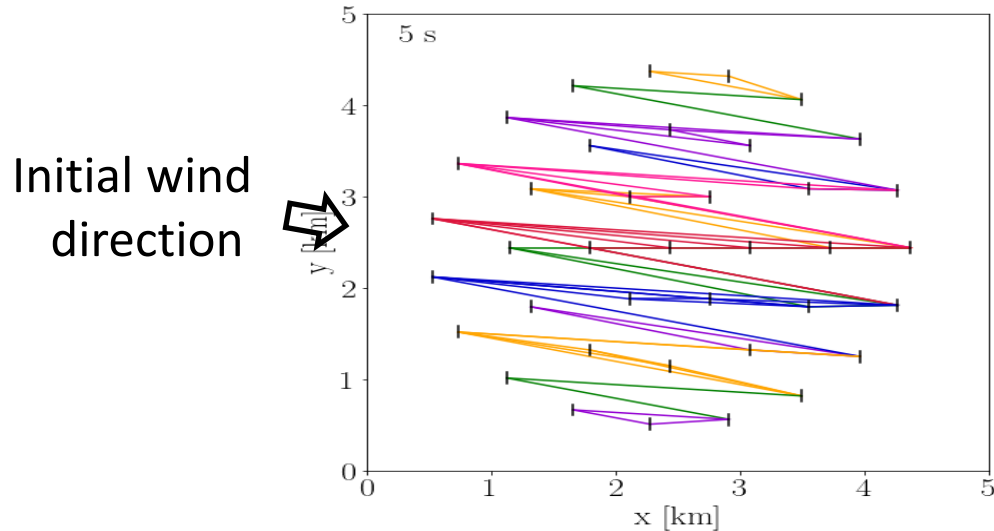
Event Driven Input $E_k (\Phi_{e,k}, \tau_{e,k}, \Delta \mathcal{E}_{e,k})$

$\tau_{k,(i)}^j = \frac{D \Delta T_i^j}{u_j}$: Edge weights based on delays associated with information propagation over each edge

$\Delta \mathcal{E}_{e,k}$: a list of the edge changes

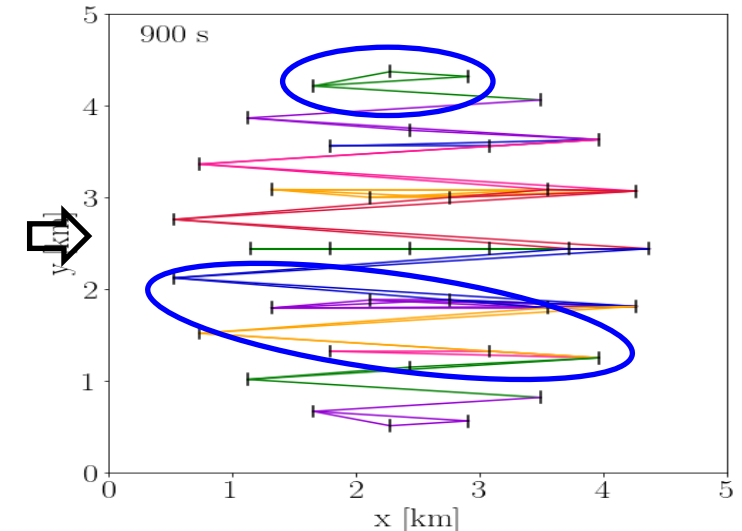


- System graph changes each timestep k (e.g. wind direction change over N timesteps)



Wind direction change over N update steps

$$\Phi_{k+1} = \Phi_k + E_k$$



System of equations

Update map

$$\Phi_{k+1} = A\Phi_k + E_k$$

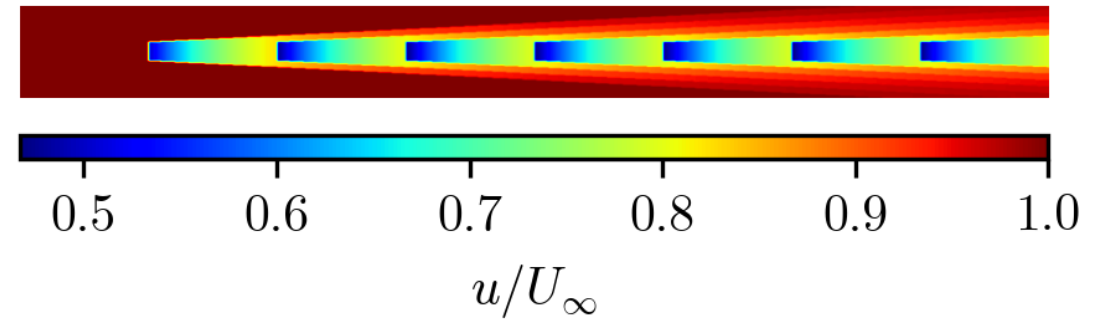
System output

$$\alpha_{k+1} = \Lambda(\tau_k)\Phi_k(\tau_k)$$

Velocity at each turbine (disk velocity)

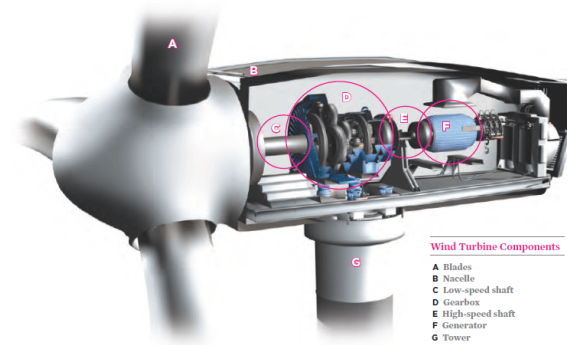
$$U_{d,k+1} = U_\infty (1 - \alpha_{k+1}) \left(1 - \frac{C_T'}{4 + C_T'} \right)$$

Linear wake superposition



Turbine power output

$$P_k = \frac{1}{2} \rho \left(\frac{1}{4} \pi D^2 \right) U_{d,k+1}^3 C_P'$$

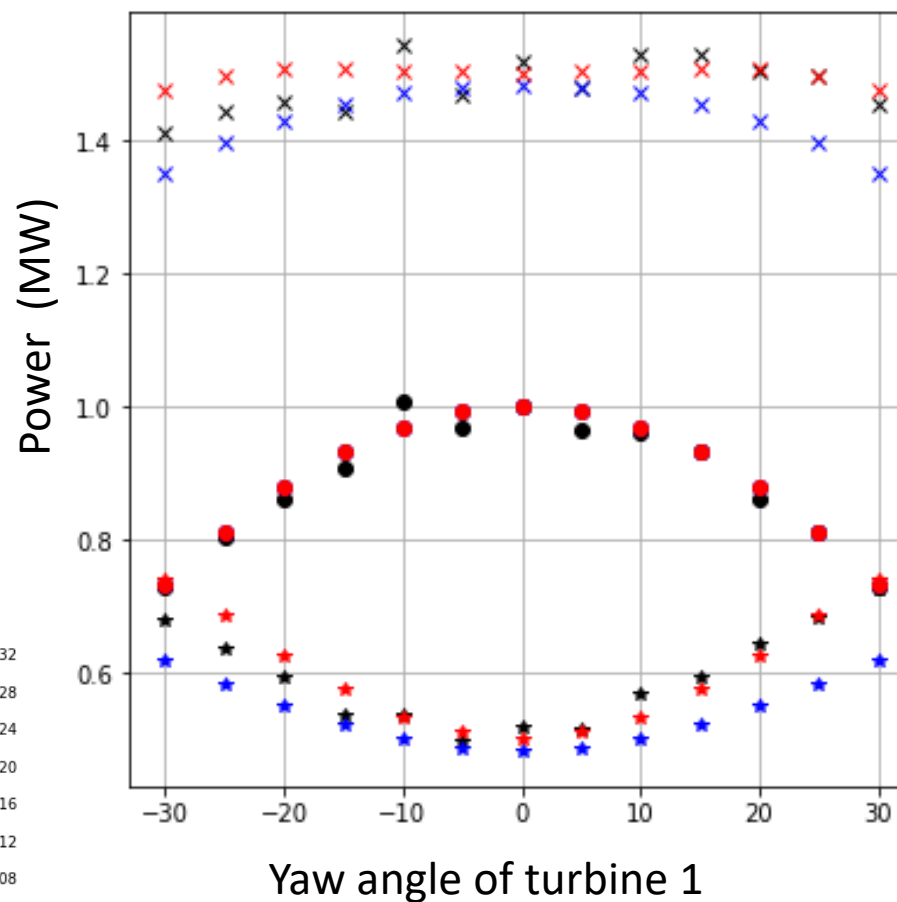
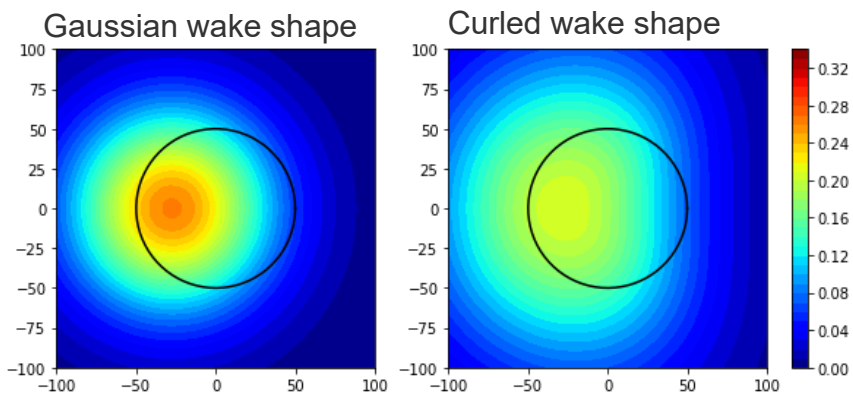
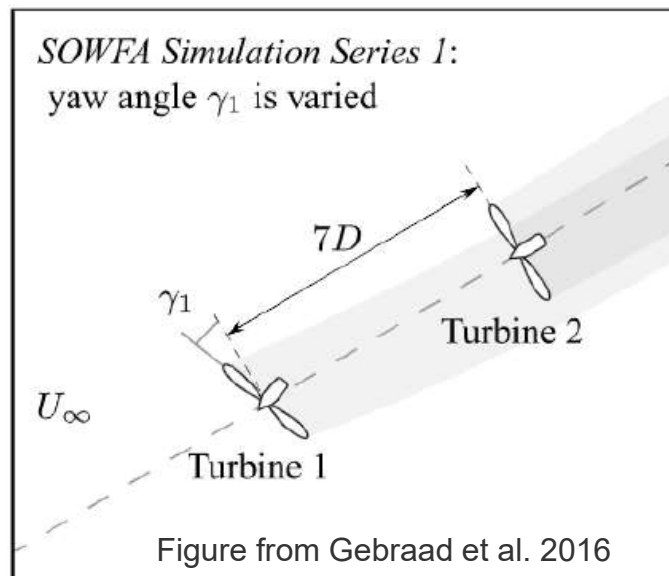


Wind Turbine Components
A Blades
B Nacelle
C Low-speed shaft
D Gearbox
E High-speed shaft
F Generator
G Tower

Illustration © TurboSquid.com/Artist Rendering

Yaw model validation: static case

- Static study using JHU LESGO code (Open source code at: <https://github.com/lesgo-jhu>)

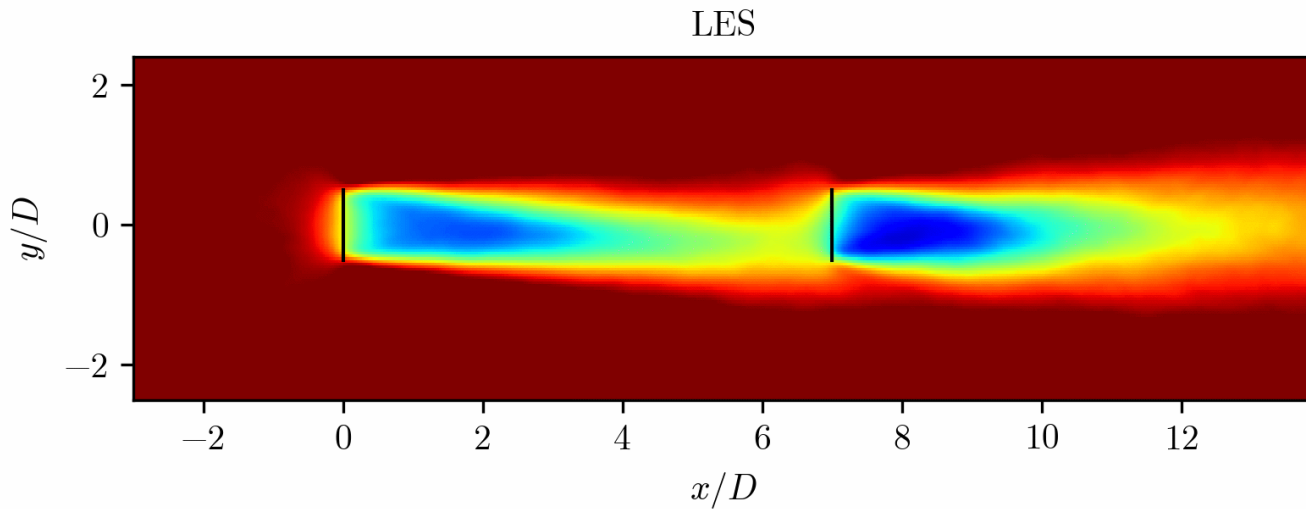


- LES, Turbine 1
- ★ LES, Turbine 2
- × LES, total
- GM gaussian $k = 1.1k^*$, T 1
- ★ GM gaussian $k = 1.1k^*$, T 2
- × GM gaussian $k = 1.1k^*$
- GM curled $k = 0.3k^*$, T 1
- ★ GM curled $k = 0.3k^*$, T 2
- × GM curled $k = 0.3k^*$

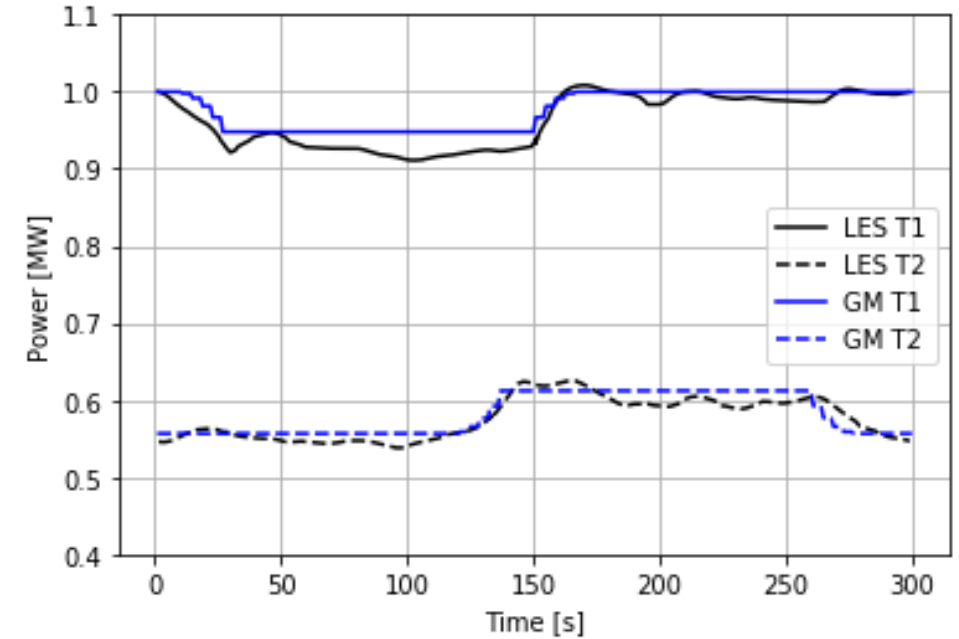
[Starke et al. 2023]

Dynamic yaw model validation

- Dynamically yaw the first turbine 15 degrees at 150 s



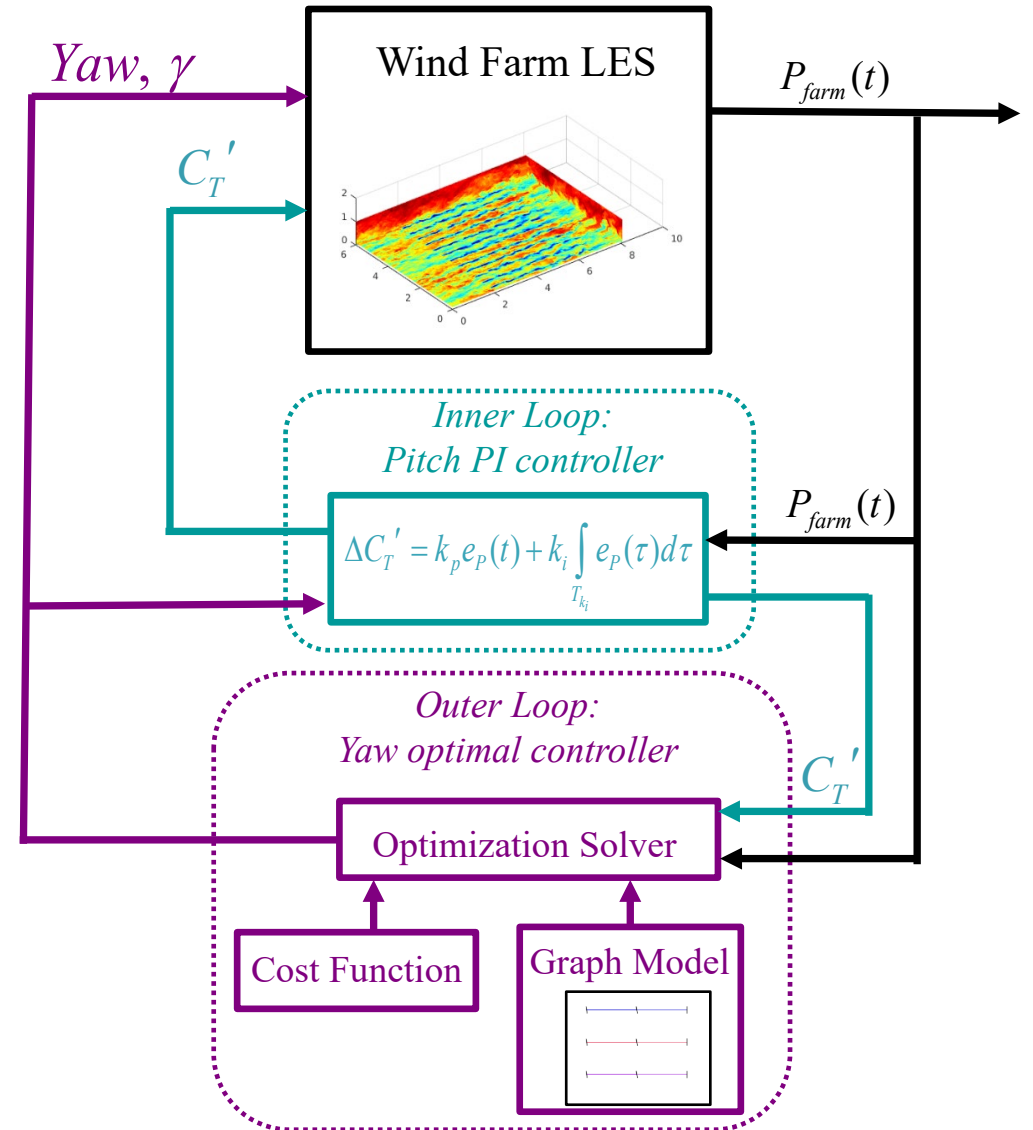
JHU LESGO code phase-averaged over 120 realizations



[Starke et al. Preprint]

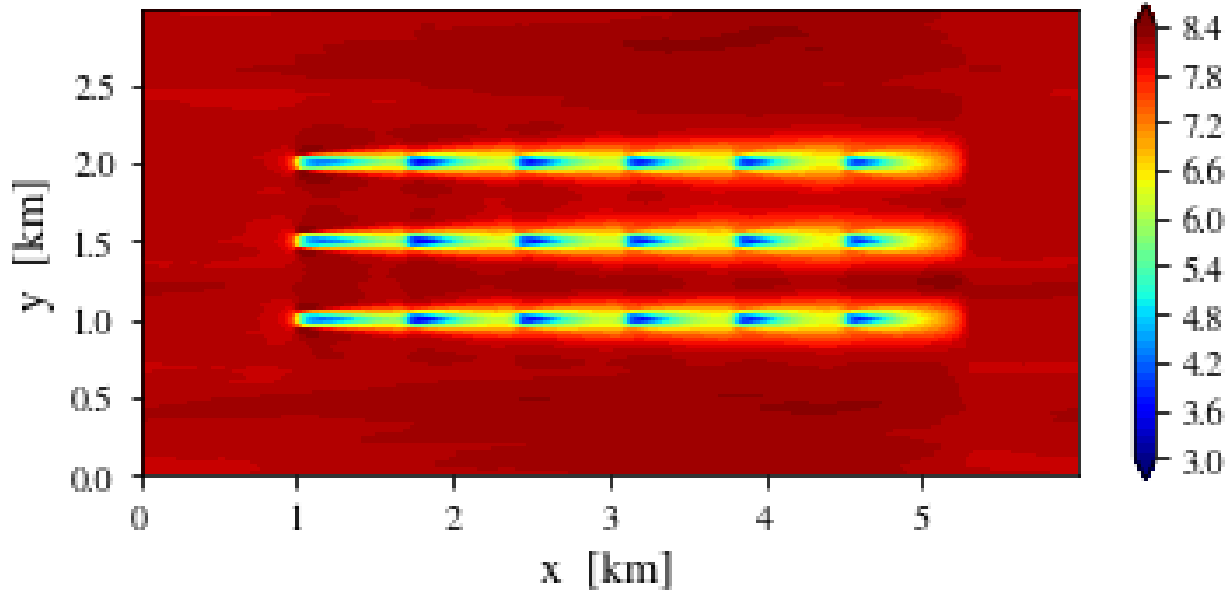
Yaw augmented power tracking

- Inner-outer loop control architecture
- Outer loop
 - model-constrained optimal control for the yaw
- Inner Loop
 - PI pitch controller

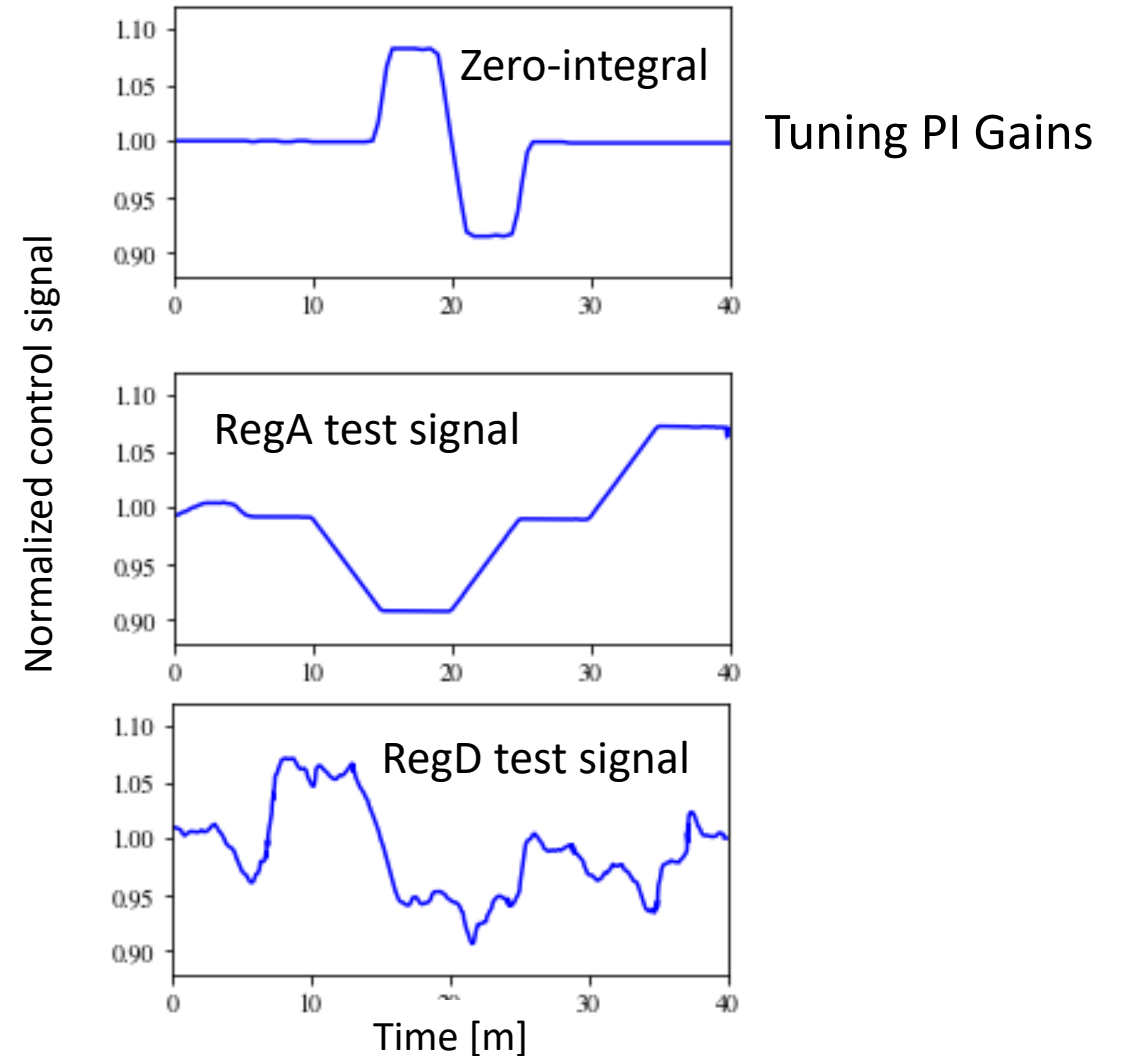


Preliminary control test case

18-turbine LES wind farm



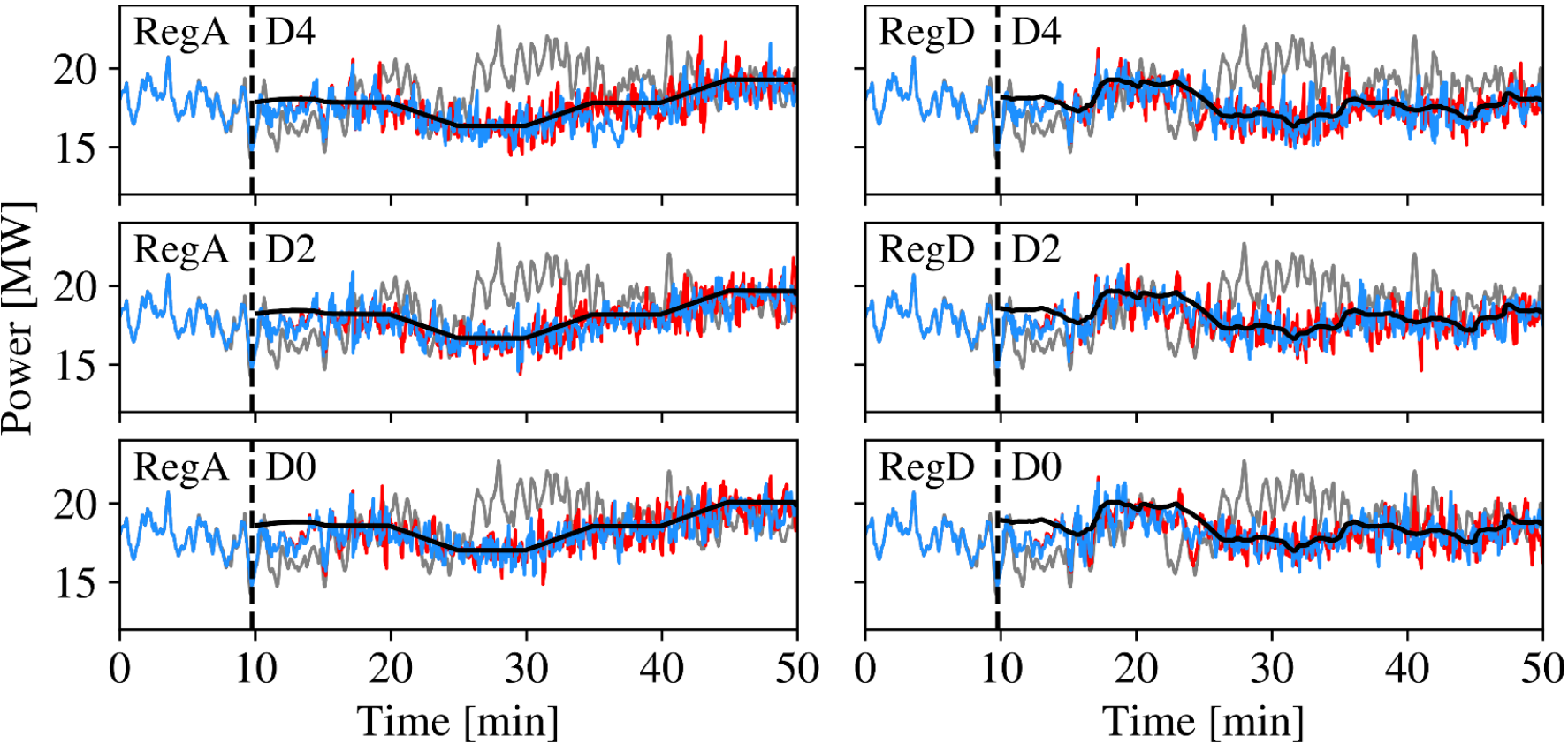
3 test signals (8% regulation)



Performance metric

$$RMSE = \sqrt{\frac{1}{N_{ST}} \sum_{i=1}^{N_{ST}} (P_{LES,i} - P_{Ref,i})^2}$$

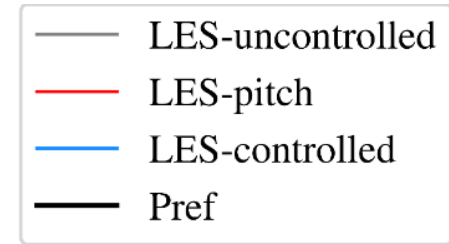
Frequency regulation results (preliminary)



$$P_{\text{Ref}}(t) = (1 - \alpha_d)P_0 + r(t)P_0$$

3 derate values (0, 2, 4)

$$P_0 = 18.75 \text{ MW}$$



$$T_H = 5 \text{ min}$$

$$T_\gamma = 2 \text{ min}$$

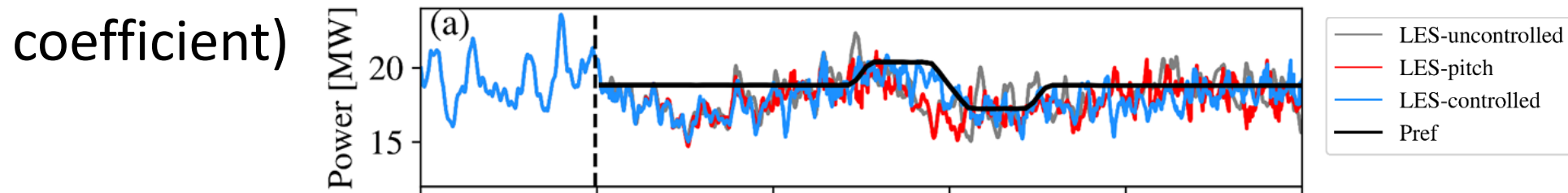
$$T_{C_r'} = 10 \text{ sec}$$

Signal Type	4% derate		2% derate		0% derate	
	Yaw + Pitch	Pitch	Yaw + Pitch	Pitch	Yaw + Pitch	Pitch
RegA	0.90	0.82	0.84	0.85	0.90	0.93
RegD	0.82	0.84	0.85	0.92	0.97	1.01

[Starke et al. ACC 2023]

Yaw augmented pitch control (preliminary conclusions)

- Overall use of yaw for power tracking is complicated by the timescales (yaw is slow)
- Yaw seems to have added benefit when derates are lower
 - Noted benefit if the system is using greedy control (maximum thrust coefficient)



- Implementation of receding horizon approach in yaw loop may improve these results
 - New approaches needed
 - Computational trade-off needs to be examined

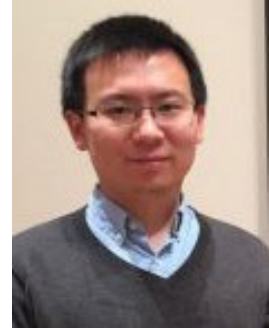
Acknowledgements



Collaborators: Charles Meneveau,
Jennifer King and Johan Meyers



Students and Postdocs (current and former)
Carl Shapiro (AAAS Fellow), Genevieve Starke (NREL),
Ghanesh Narasimhan, Manuel Ayala and Chengda Ji



Additional Wind Energy Collaborators
Majid Bastankhah Sina Shamsoddin,
Raúl Bayoán Cal

*Special thanks to Charles Meneveau
for publically sharing the JHU LES code*



JOHNS HOPKINS

RALPH O'CONNOR SUSTAINABLE
ENERGY INSTITUTE