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Turbulence, wakes and wind farm control

Dennice F. Gayme
Department of Mechanical Engineering
Johns Hopkins University

Support from the National Science Foundation is gratefully acknowledged

Horns Rev 1: Photograph: Christian Steiness

Energy at Hopkins

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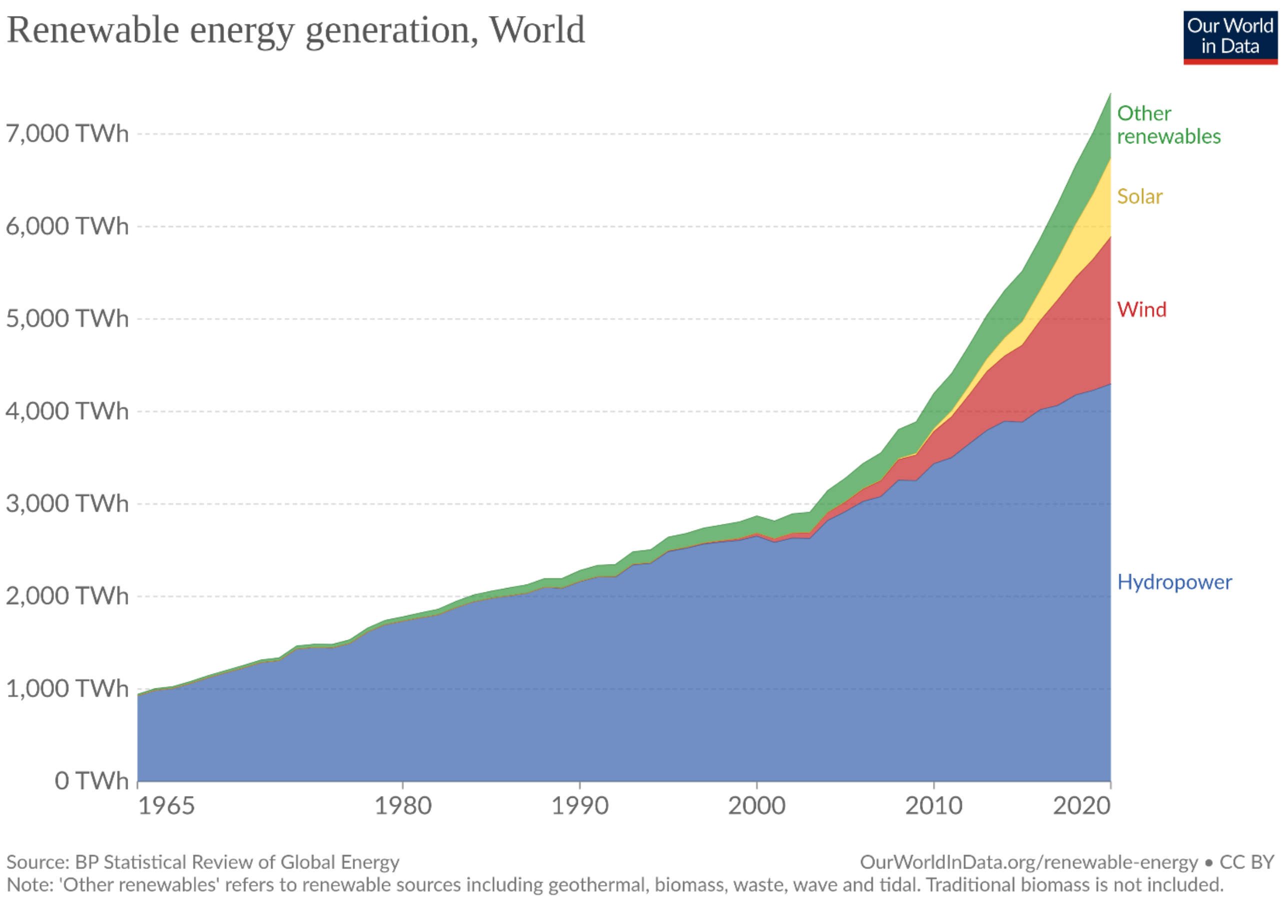
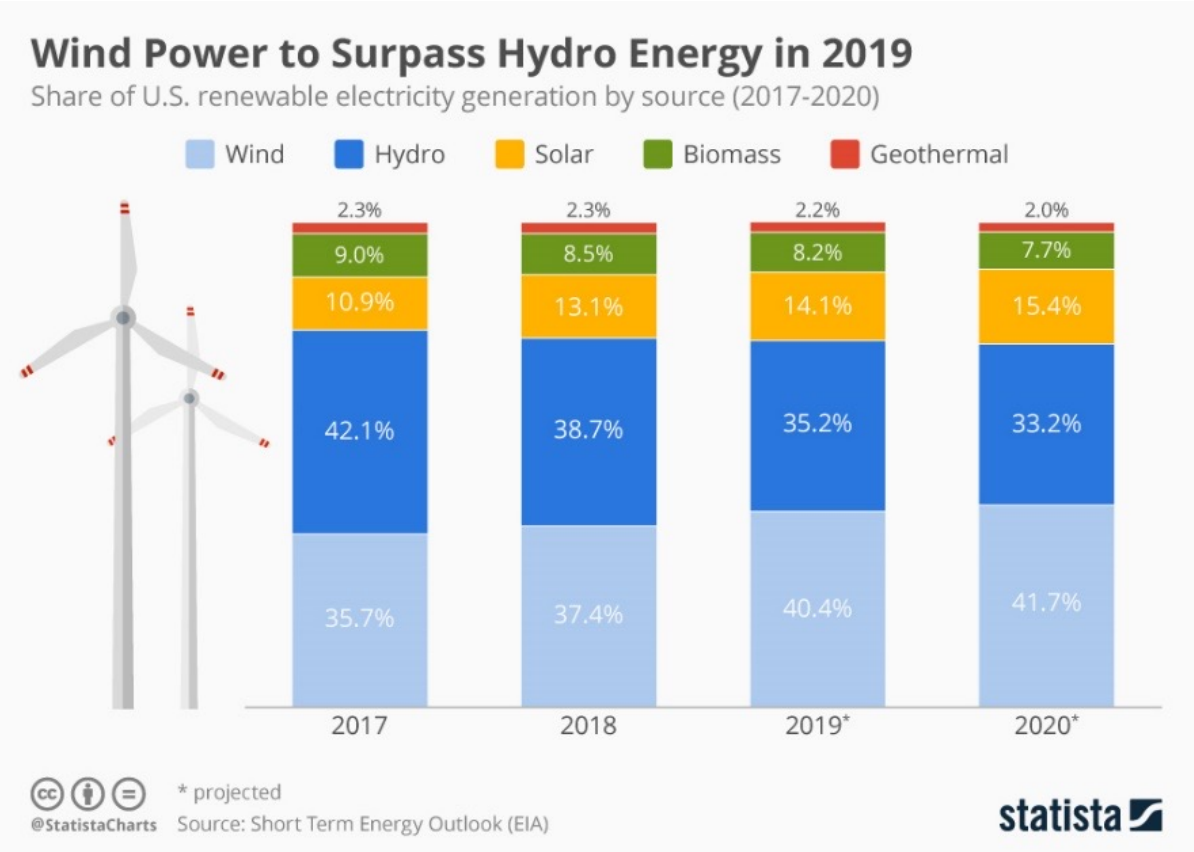
Significant sustained renewable energy growth



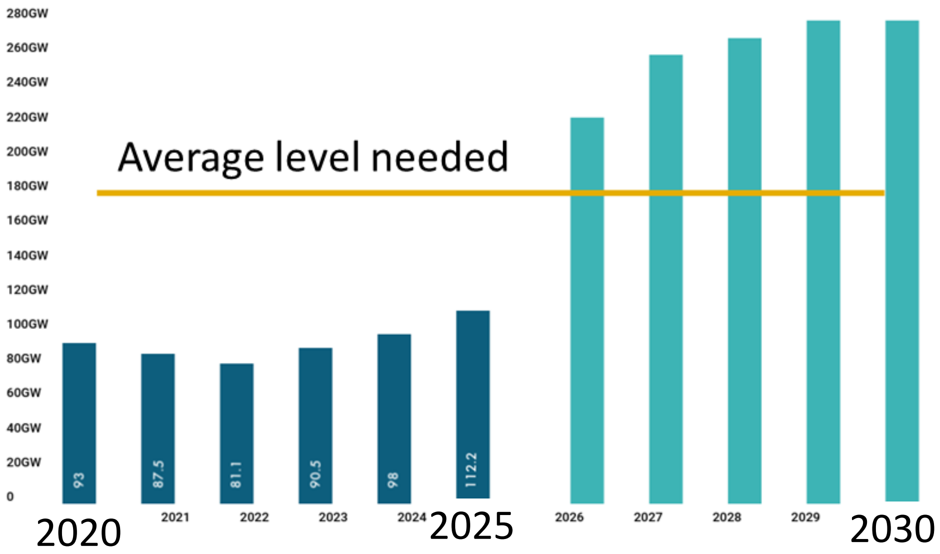


- Largest capacity additions in the US from 2015 - 2021 were wind and solar energy

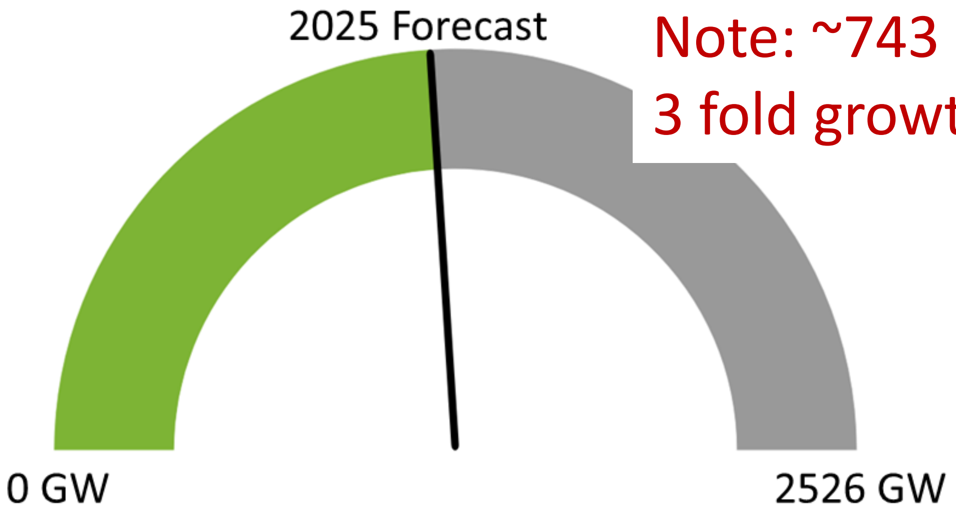
Unprecedented growth required

- All scenarios for limiting global warming require acceleration of wind installation efforts

Annual wind installations must ramp up in this decade to keep global warming well below 2°C*



Wind power market outlook vs required installation levels over this decade to keep global warming well below 2°C

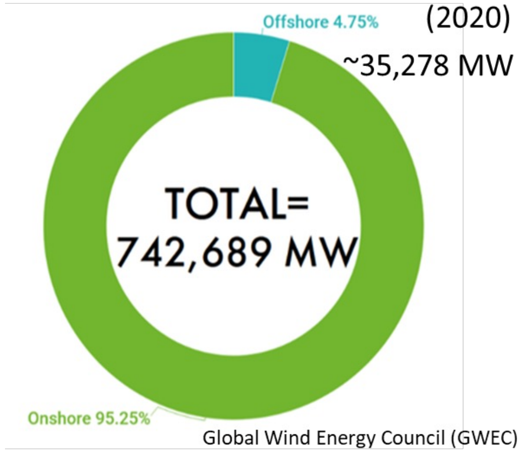


Note: ~743 GW in 2020
3 fold growth in ten years

GWEC
GLOBAL WIND ENERGY COUNCIL

- Creates e.g., manufacturing and infrastructure challenges

Challenges to rapid wind energy expansion

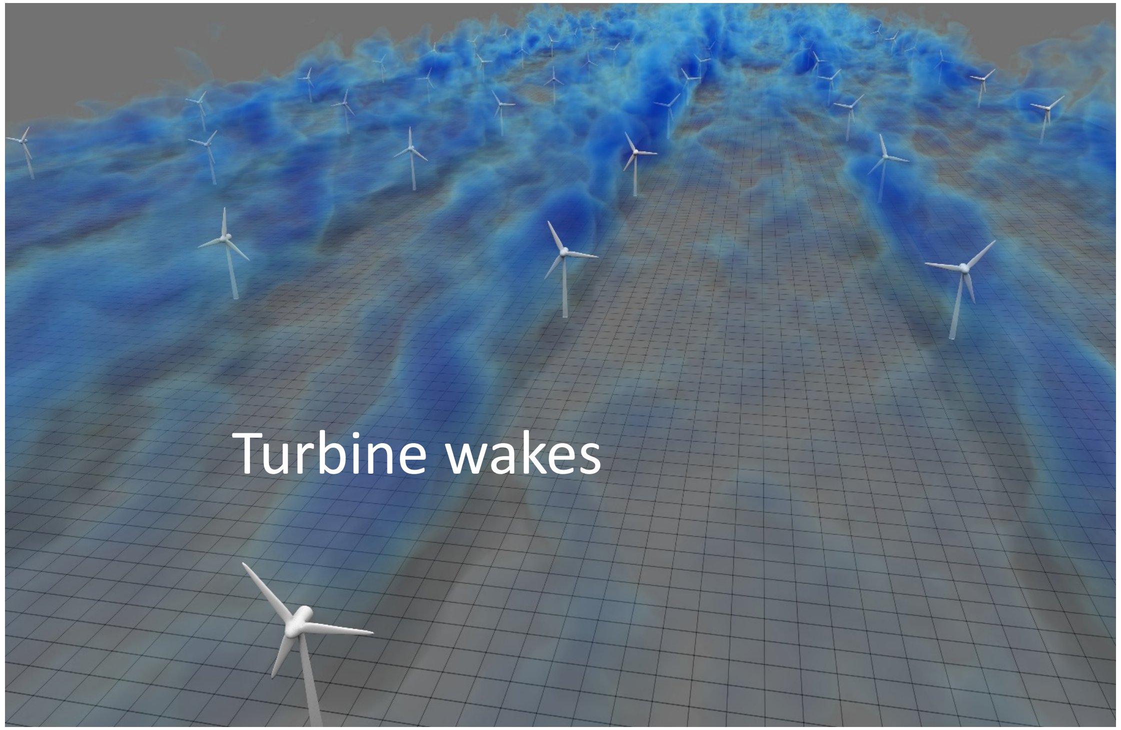


- Siting challenges (e.g. land/ocean use, regulatory …)
- Integration challenges
  - Dispatchability/uncertainty often cited
  - IMPORTANT issue but …
    - Forecasting is rapidly improving
    - Offshore farms have stronger, steadier winds, arranged into larger farms with more power output potential
      - Strong and growing offshore pipeline globally
        - » 35, 324 MW currently in development in US,
        - » Global pipeline for floating more than tripled in 2020 to 26,529 MW

Efficient design and operation of wind farms is critical

Efficient design and operation of wind farms is critical

- Wind turbines are arranged into farms (wind power plants) leading to wake interactions that affect available power

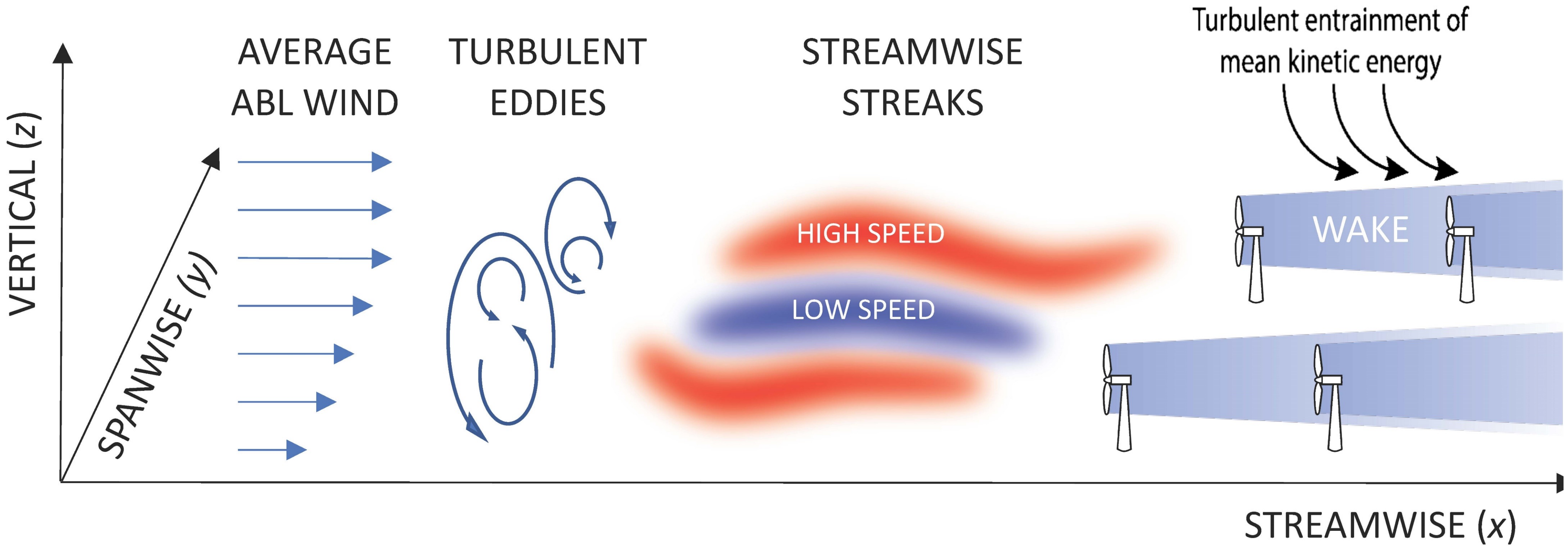


Turbine wakes (in blue): velocity deficits after 'kinetic energy' is taken out of the fluid and transferred to mechanical energy

Meneveau group simulation
Visualization courtesy of D. Bock (Extended Services XSEDE)

Wind turbine array interactions with the ABL

- Turbines also interact with the atmospheric boundary layer (ABL)

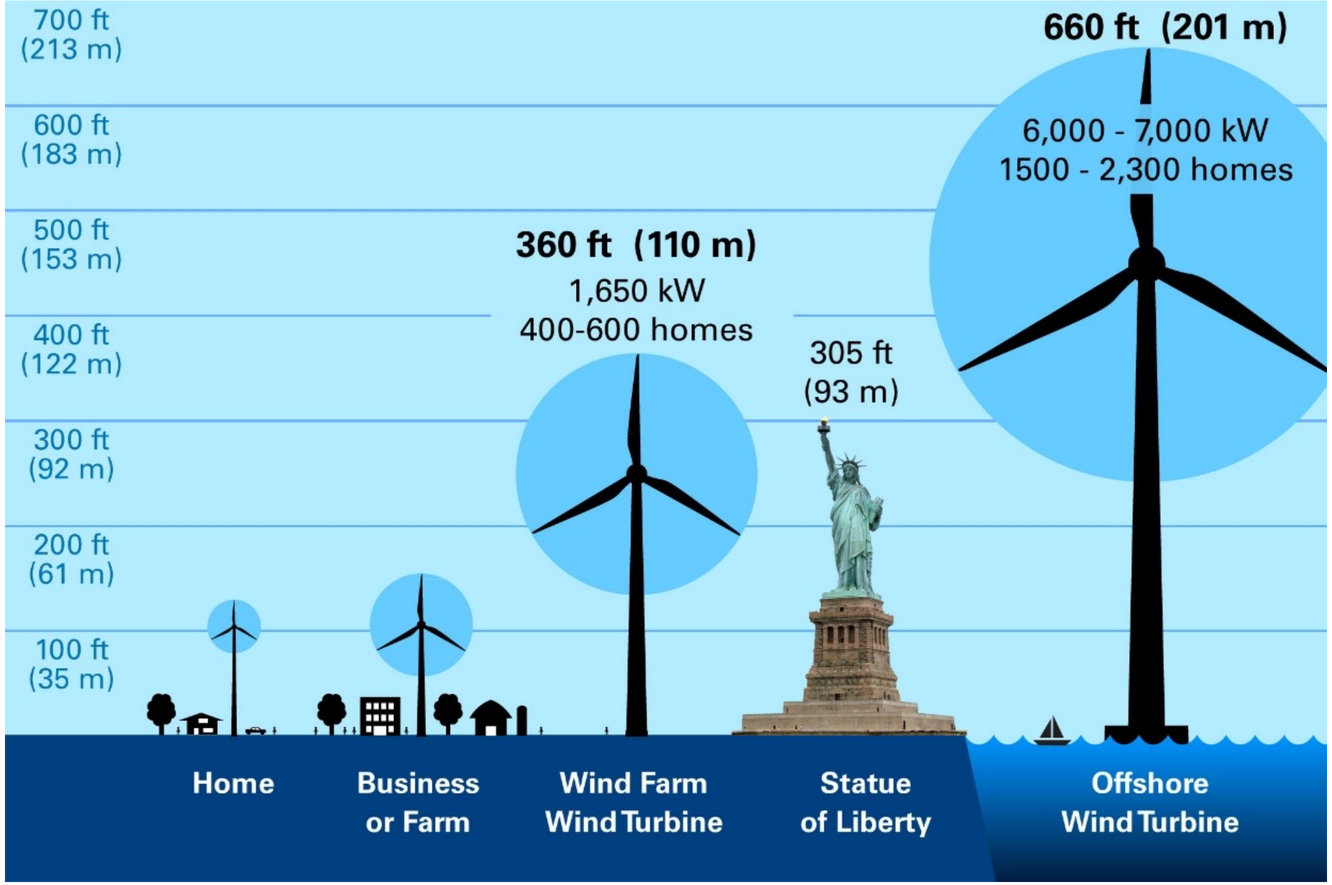


- Regeneration mechanism requires large land area (low power density)

Wind farm power output largely depends on these interactions!

Figure adapted From: C. Shapiro et al 2022

Size and scale of the physical problem



- Turbine diameter 200 m
- Operational speed 10 m/s
- Spacing 7D apart

Inter travel turbine time

$$\frac{1400\ \mathrm{m}}{10\mathrm{m/s}} = 140\ \text{seconds}$$

- 10 row farm 1400 s (24 min)

- Time for flow to pass through a large wind farm is significant

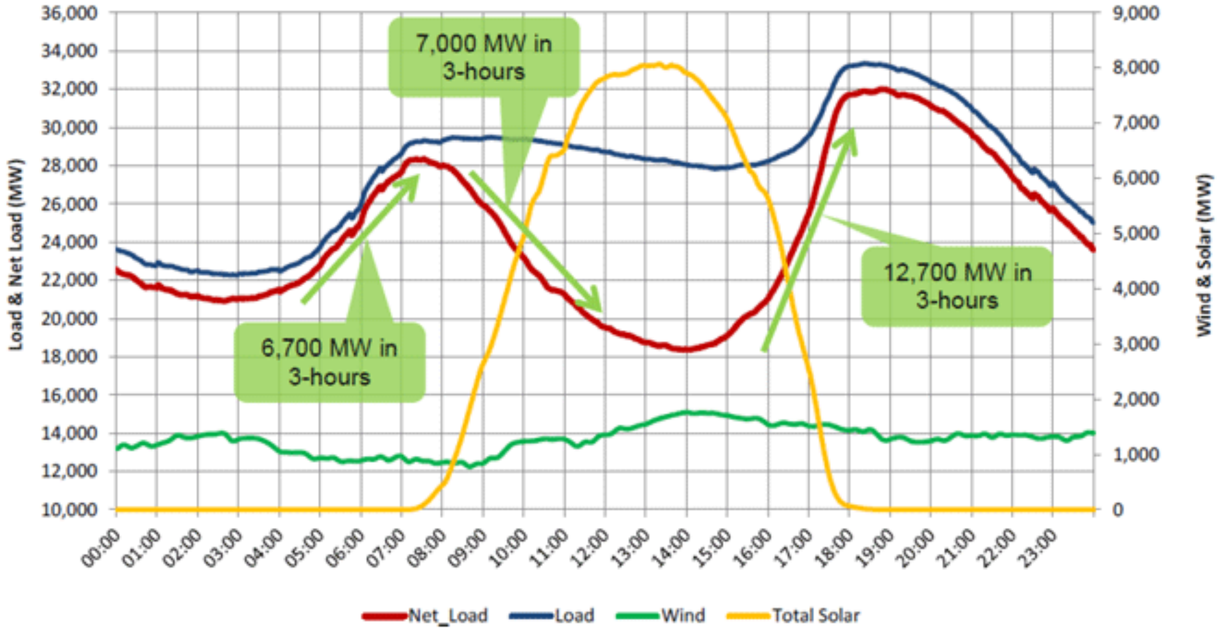
Market challenges to large-scale wind integration

Model of wind as "negative demand/must take/free" poses fundamental system problem

- Underlying assumption: niche supplier
- Incentive: maximize power output without regard for the grid

When wind penetration gets too high this model is not feasible!

- Lots of over supply for balancing
- Additional resources needed for other grid services

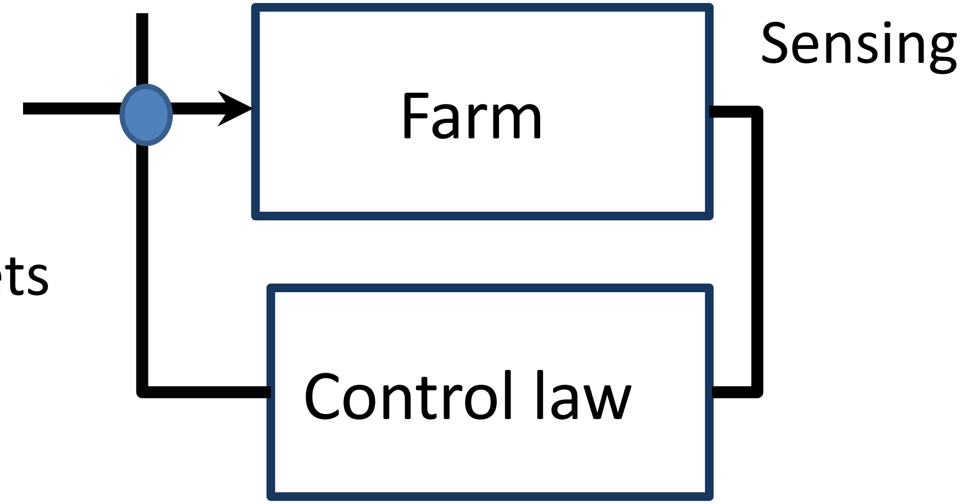


Overcoming challenges to large scale wind integration

Efficiently designed wind farms that can move beyond their current role as a "niche" energy providers requires:

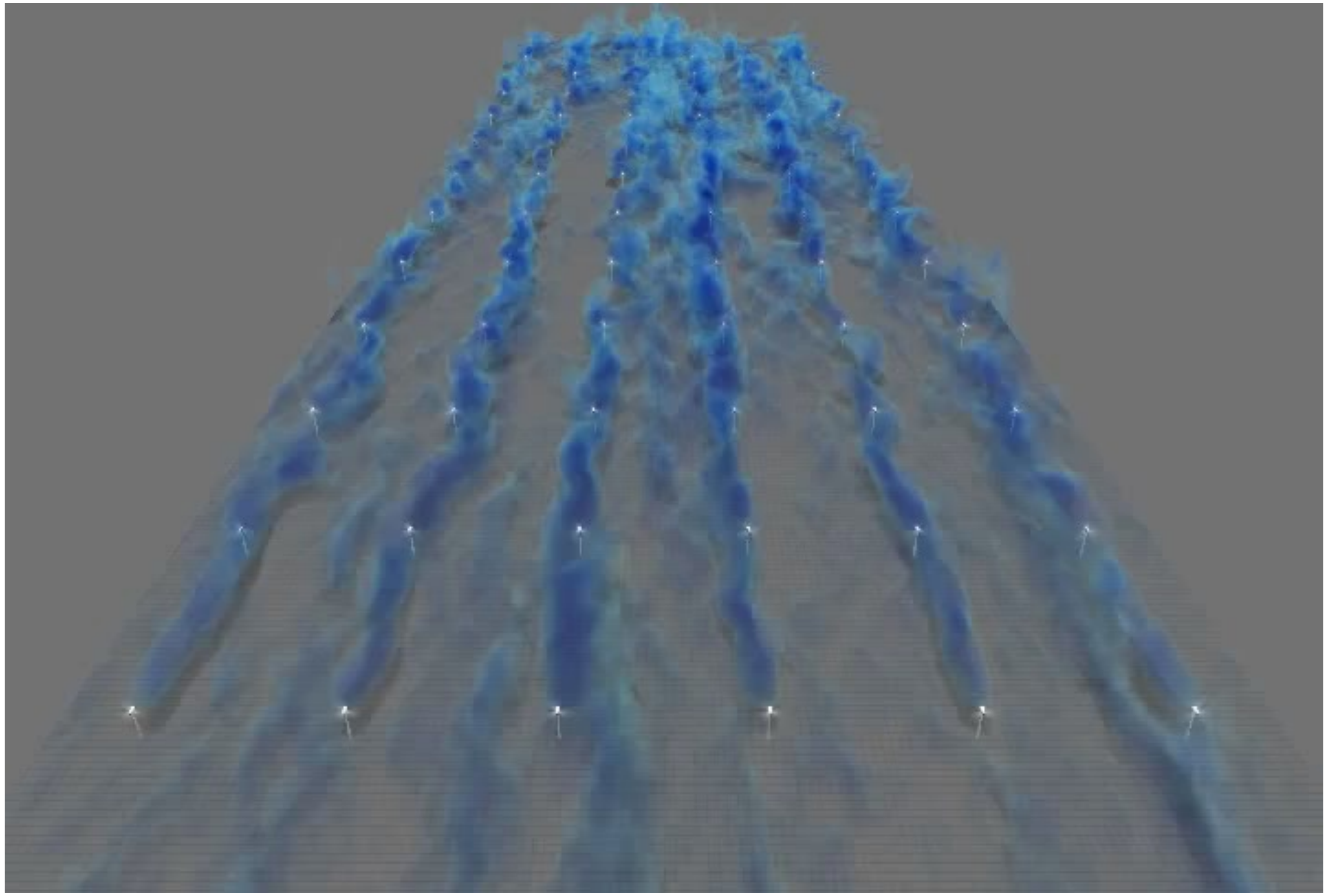
1. Accurate predictions for wind farm power output levels over a wide range of farm layouts and operating conditions (A modeling problem)
   - Area localized model (design)
   - Dynamic graph model (estimation and control)

2. Operational paradigms that enable successful participation in current and anticipated energy markets (A control problem)



Modeling a wind farm

High fidelity simulations (LES) capture all aspects of the physics



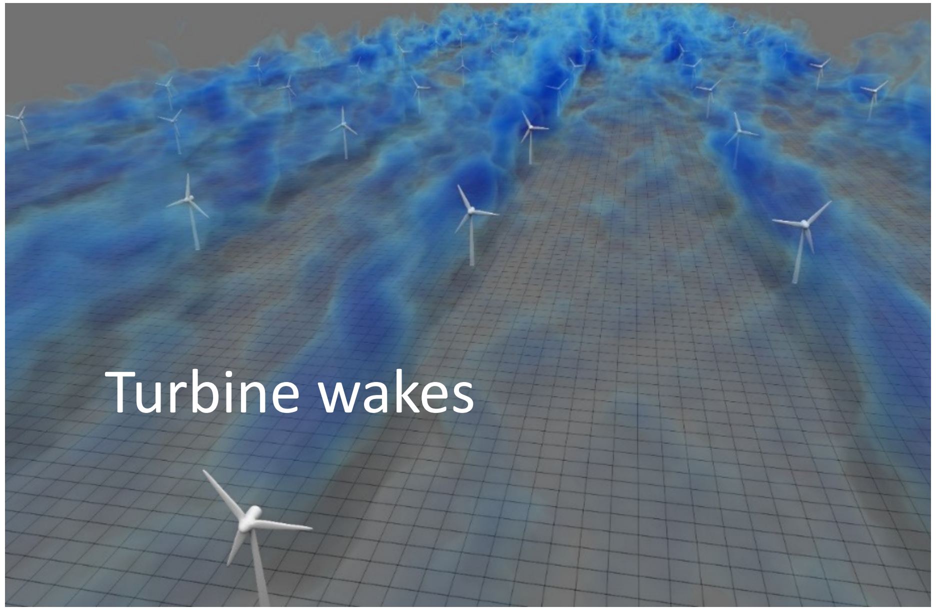
Meneveau group simulation: Visualization courtesy of D. Bock (Extended Services XSEDE)

Modeling a wind farm

High fidelity simulations (LES) capture all aspects of the physics

$$\text{Grid}: \quad 128 \times 128 \times 128 \approx 2.1 \text{ million grid points}$$

$$\text{Time}: \quad 1 \text{ hour at } 0.1 \text{ second steps } = 36000 \text{ time steps}$$

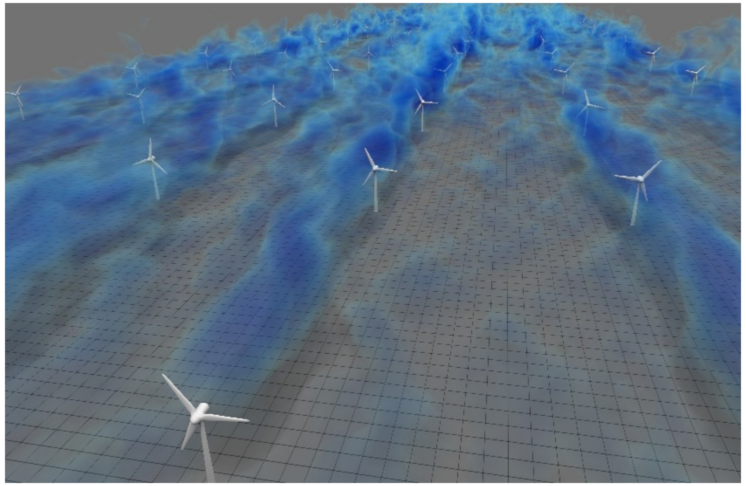


Meneveau group simulation Visualization courtesy of D. Bock (Extended Services XSEDE)

- Computationally intractable for farm layout design and/or operational questions that require parametric studies
- Cannot be used for real-time control

- Important tool in understanding the flow physics
  – To inform models (illustrate the importance of wake growth and interactions)
  – As a platform for model and control validation

Wind farm models for design and operation



- Simplified models need to capture the key spatial and temporal interactions of the phenomena of interest

All models are wrong, but some models are useful!

Attributed to George Box

- Utility of a model is determined by the information one is seeking with its use
- Key: know what you want/expect from the model and understand its limitations

Wind farm design oriented modeling needs

- Need to run quickly enough to evaluate many design options (turbine size, spacing, layout)
- Quantities of interest: velocity $U(x,y,z)$, turbulent kinetic energy $TKE(x,y,z)$,
- Computed quantities
  – Velocity at teach turbine $U_{\text{turb}} = \langle U \rangle_T (x_T, y_T, z_h)$
  – Associated forces/moments
  – Power output

$$P_{\text{turb}} = \frac{1}{2} C_P \rho \frac{\pi}{4} D^2 \; U_{\text{turb}}^3$$

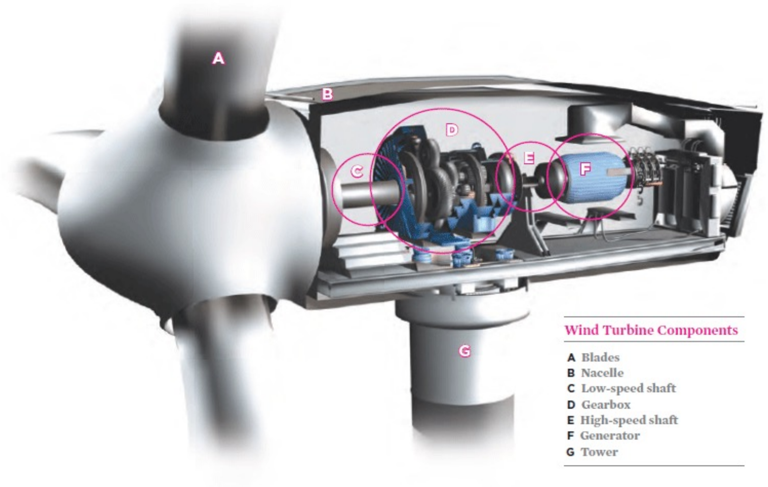
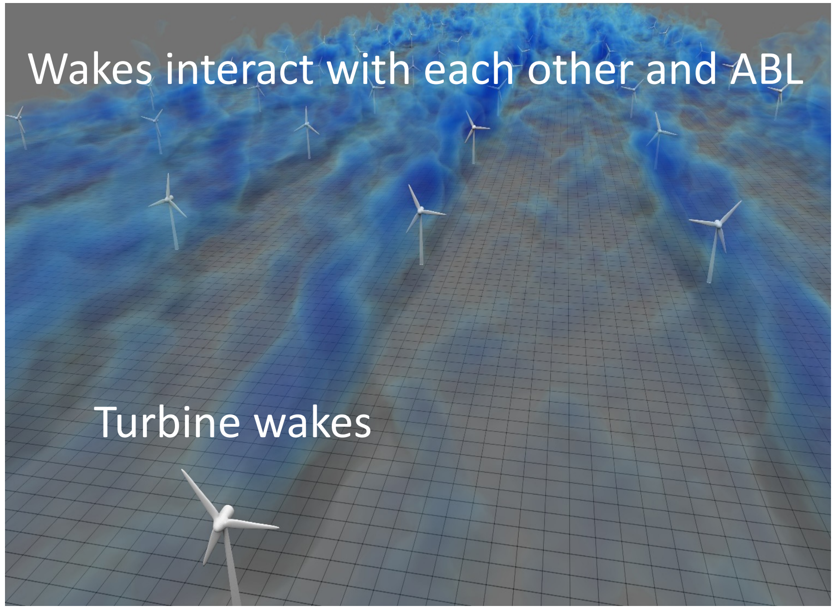


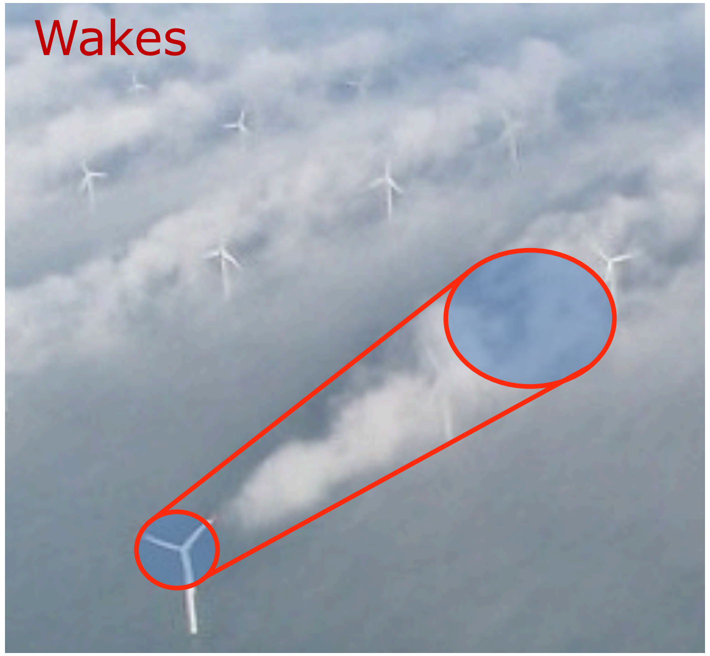
Illustration: © TurboSquid.com/Artist Rendering



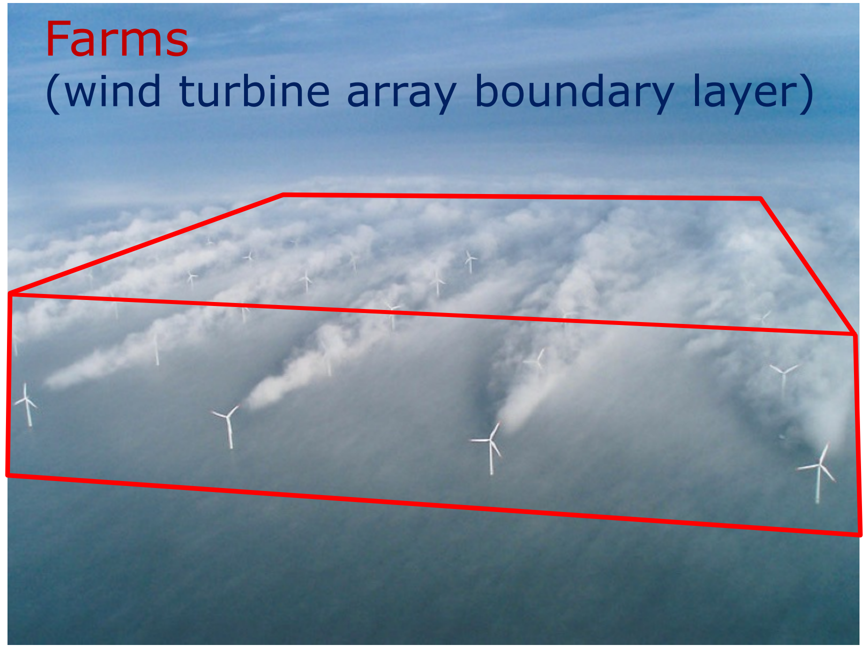
Meneveau group simulation
Visualization courtesy of D. Bock (Extended Services XSEDE)

Design oriented wind farm models

- Engineering and analytical wake models, e.g. Lissaman 1979, Katić et al. 1986, Bastankhah & Porte Agel 2014, Tian et al 2015, Luzzatto-Fegiz & Caulfield 2018, Ge et al 2019
- Atmospheric boundary layer (ABL) based (top-down) models, e.g. Frandesen 1992, Frandsen et al., 2006; Calaf et al., 2010, Menveau 2012, M. Abkar & F. Porté-Agel 2015, Stevens 2015



Horns Rev 1: Photograph: Christian Steiness



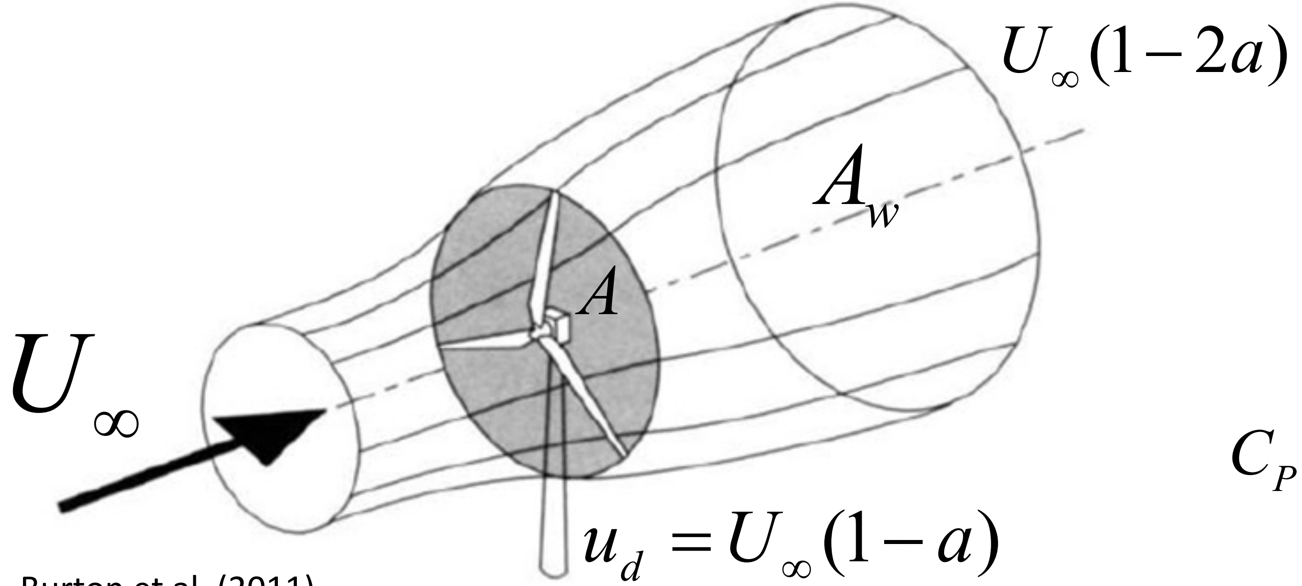
Horns Rev 1: Photograph: Christian Steiness

Engineering (wake) models

- Many based on Jensen or Park model, e.g. Lissaman 1979, Katić et al. 1986

Actuator disk theory

- 1D linear or angular momentum theory



Burton et al. (2011)

Axial induction factor *a* is the fractional decrease in between the freestream and rotor plane wind speed

$$a = \frac{U_\infty - u_d}{U_\infty}$$

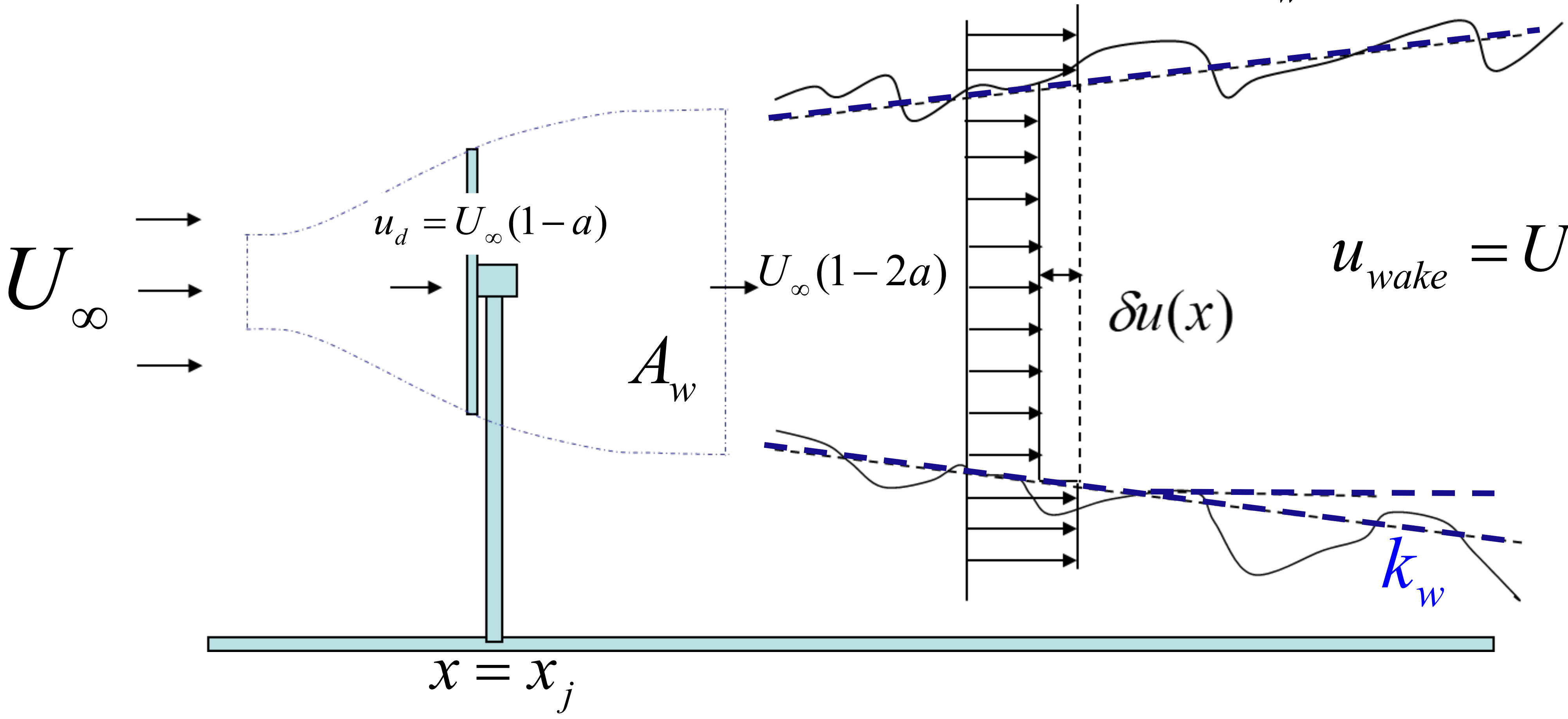
$$C_P = \frac{\text{Rotor power}}{\text{Power in the wind}} = \frac{P}{\frac{1}{2}\rho U^3 A} = 4a(1-a^2)$$

$$P_{\text{turb}} = \frac{1}{2} C_P \rho \frac{\pi}{4} D^2 \; U_{\text{turb}}^3$$

Modeling wake behavior: Jensen model

- Far wake: turbulent mixing governs wake growth
  - linear wake expansion at rate k_w

$$D_w(x) = D + 2k_w(x - x_j)$$

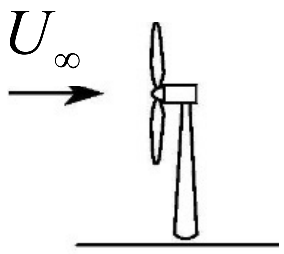


$$u_{wake} = U_\infty - \delta u(x)$$

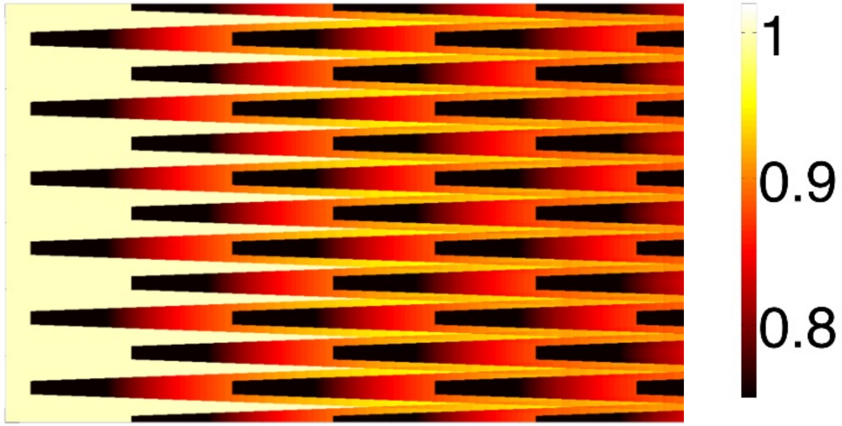
Wake deficit function

Jensen model wake interactions

- Calculate velocity deficit of each turbine δu_j using U_∞
- Superpose kinetic energy deficits (idea Lissaman 1979)



k.e. deficit in farm = sum of k.e. deficit of isolated wakes



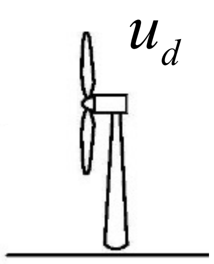
$$u(x) = U_\infty - \sqrt{\sum_{j\in J} \delta u_j(x)^2}$$

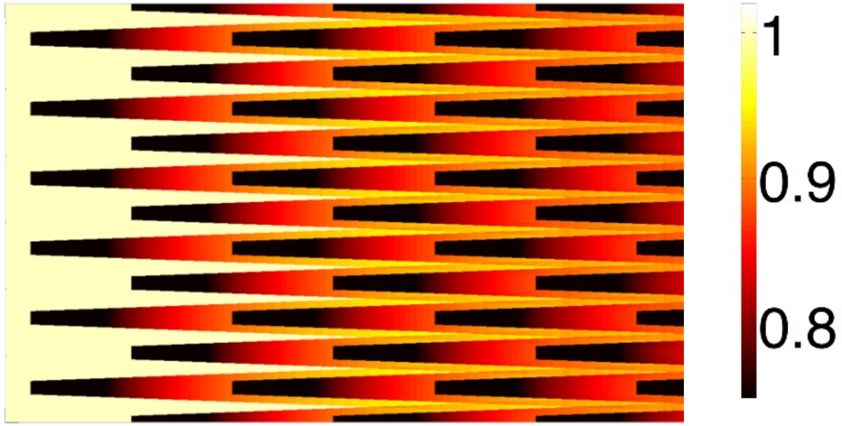
Idea: kinetic energy is additive (made up of independent turbulent fluctuations)

e.g. Stevens and Meneveau 2017

Jensen model wake interactions

- Linear super position approaches calculate velocity deficit of each turbine δu_j using u_d e.g., Zong and Porté Agel 2020



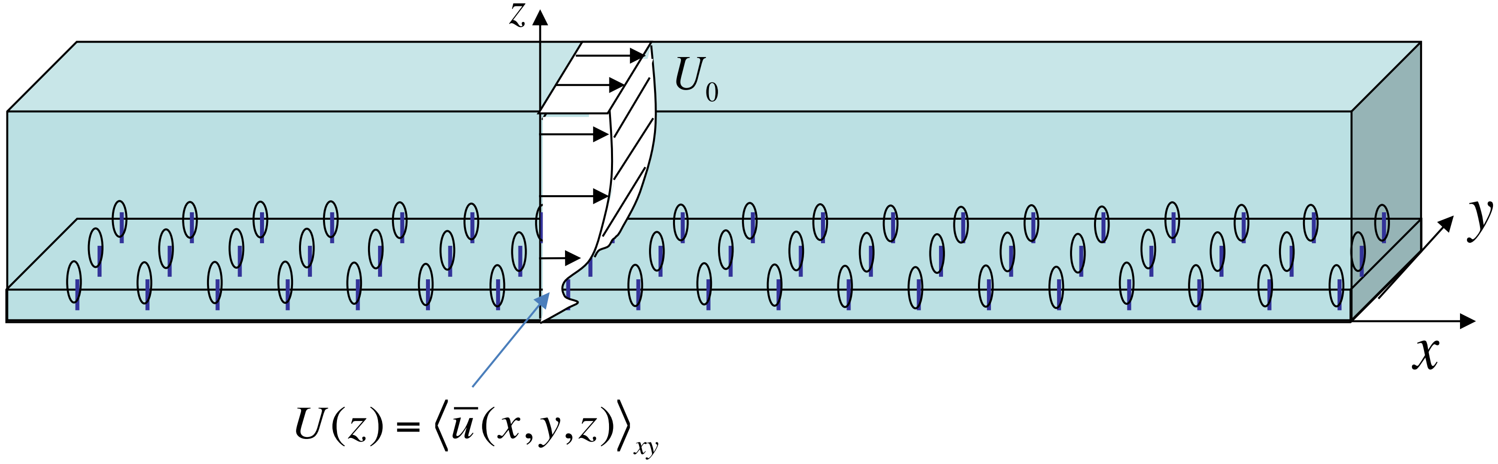


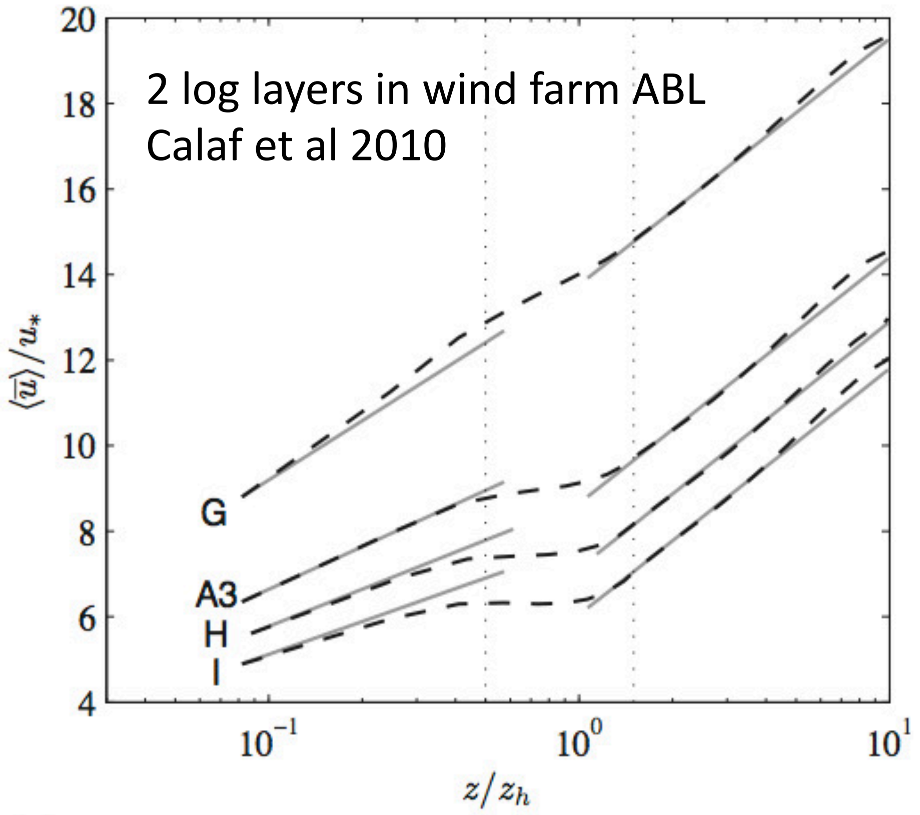
$$u(x) = U_\infty - \sum_{j \in J} \left(u_d^j(x) - u_{wake}^j(x) \right)$$

Connection to the atmospheric boundary layer is loose (k)

Boundary layer models

- Top down models capture the effect of the farm on the atmospheric boundary layer Newman 1976, Frandsen et al. 2006, Calaf et al. (2010) , Meneveau 2012



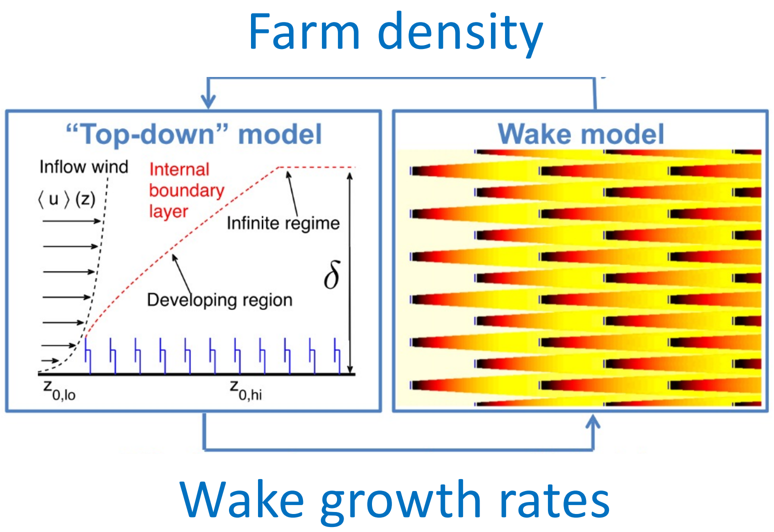


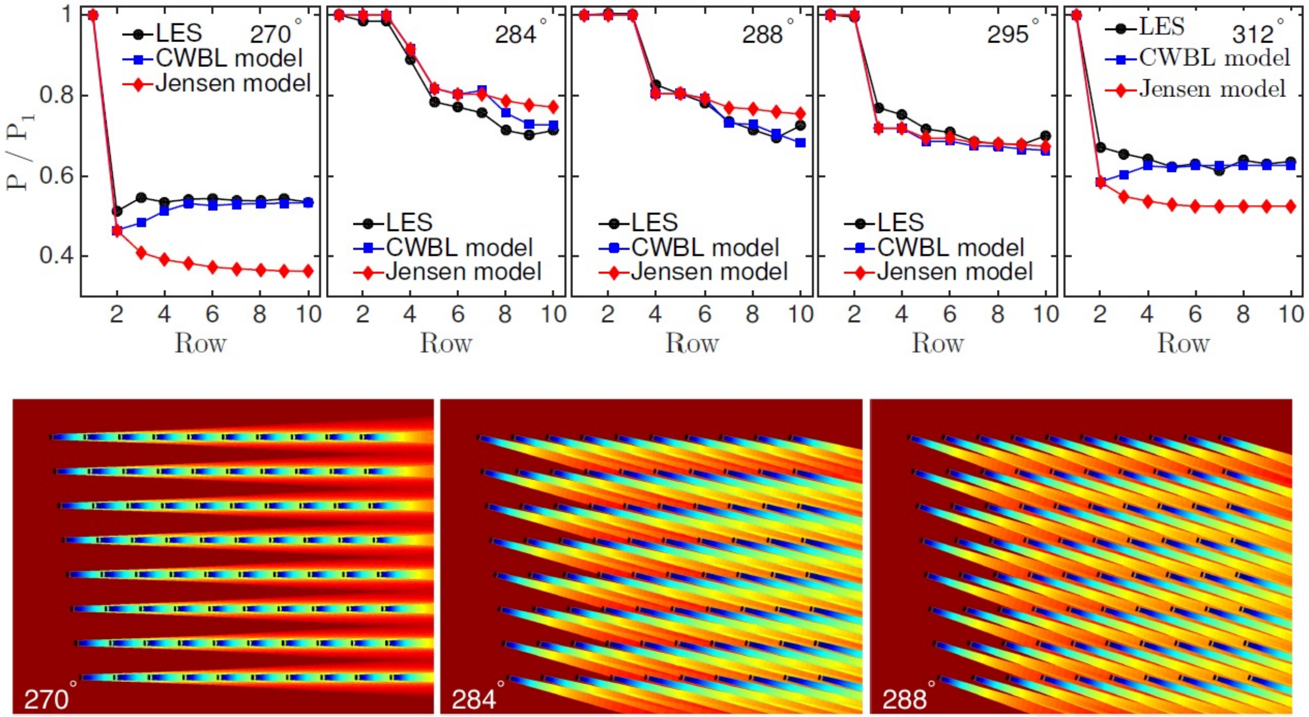
- Wind farm extraction of energy leads to 2 log layers with differ intercepts

$$\frac{U_h(s,C_T,...)}{U_{h0}} = \frac{\ln(\delta / z_{0,\mathrm{lo}})}{\ln(\delta / z_{0,\mathrm{hi}})} \ln\left[\left(\frac{z_\mathrm{h}}{z_{0,\mathrm{hi}}}\right)\left(1+\frac{D}{2z_\mathrm{h}}\right)^{\beta}\right]\left[\ln\left(\frac{z_h}{z_{0,\mathrm{lo}}}\right)\right]^{-1}$$

Coupled models

- Multi-region models e.g. Frandsen et al., 2006
- Coupled wake boundary layer (CWBL) models, Stevens et al., 2015, Shapiro et al. 2019

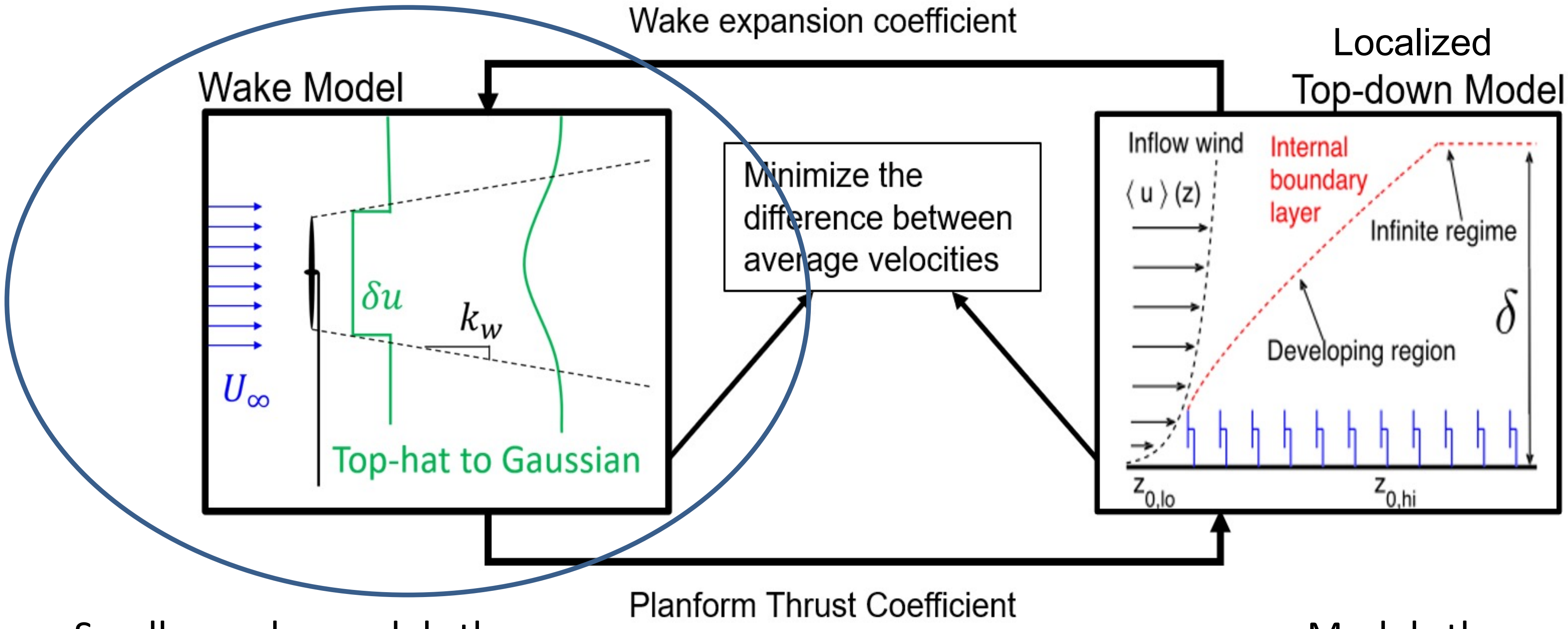




- Improves power output predictions over its constituent parts

Area Localized Coupled (ALC) model

- Coupled model for arbitrary wind turbine arrays



Smaller-scale, models the individual turbine wakes and wake interactions

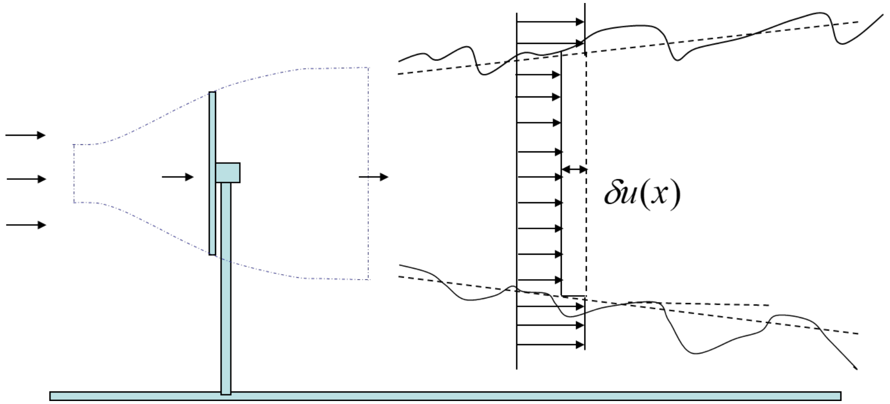
Models the average effect of placing wind farm in the atmospheric boundary layer

[Starke et al. 2021]

ALC wake model

Wake growth function

$$d_w(x) = f(k_{w,n}, D)$$

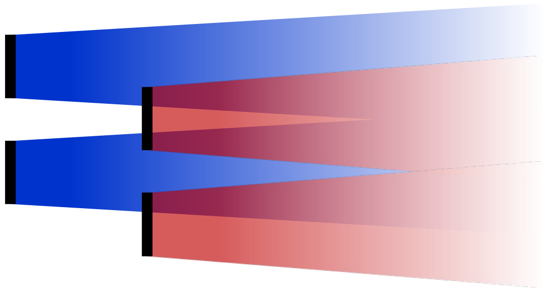


- At each turbine $$k_{w,n} = \alpha \frac{u_{*,n}}{u_{\infty,n}}$$

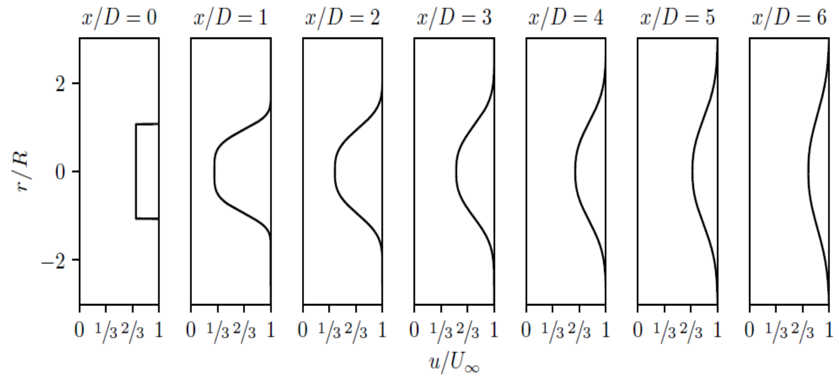
$u_{*,n}$: Friction velocity for n^{th} turbine
$u_{\infty,n}$: Freestream velocity for n^{th} turbine

- For subsequent turbines

$$u(\boldsymbol{x},t) = U_\infty(\boldsymbol{x},t) - \sum_n \delta u_n(x,t) W_n(\boldsymbol{x})$$

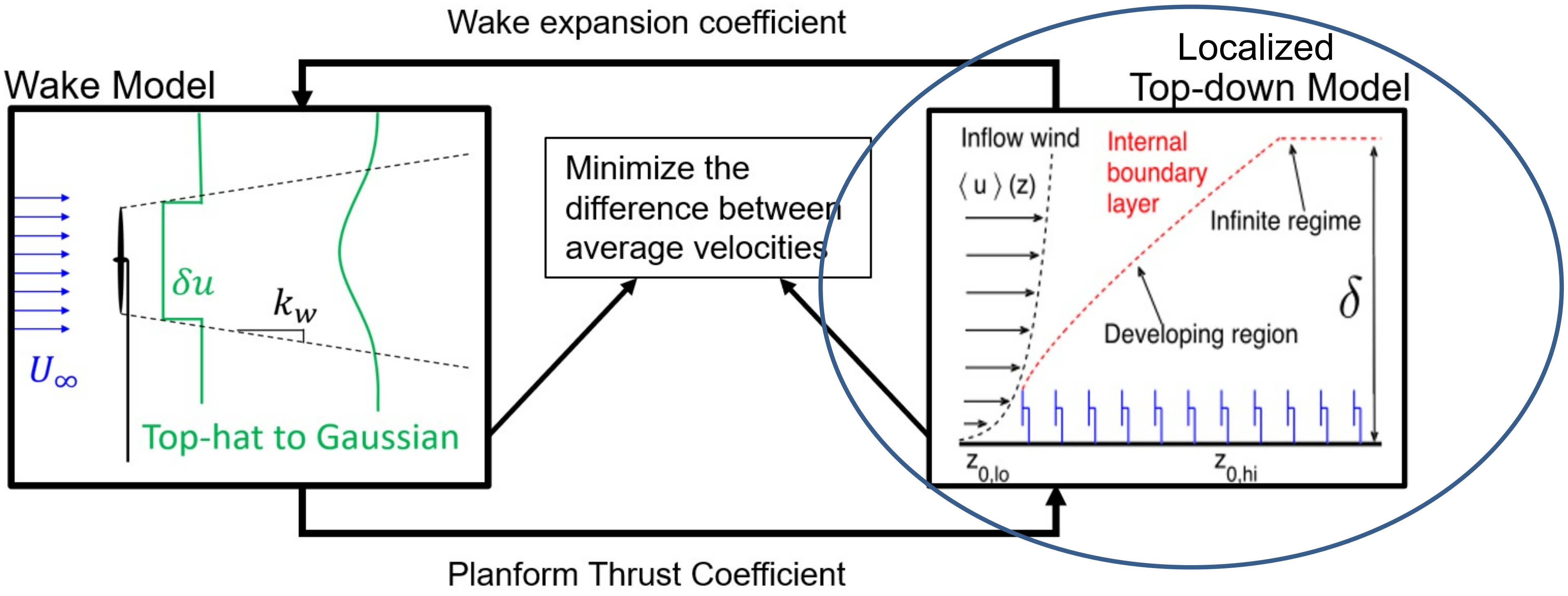


Wake shape function



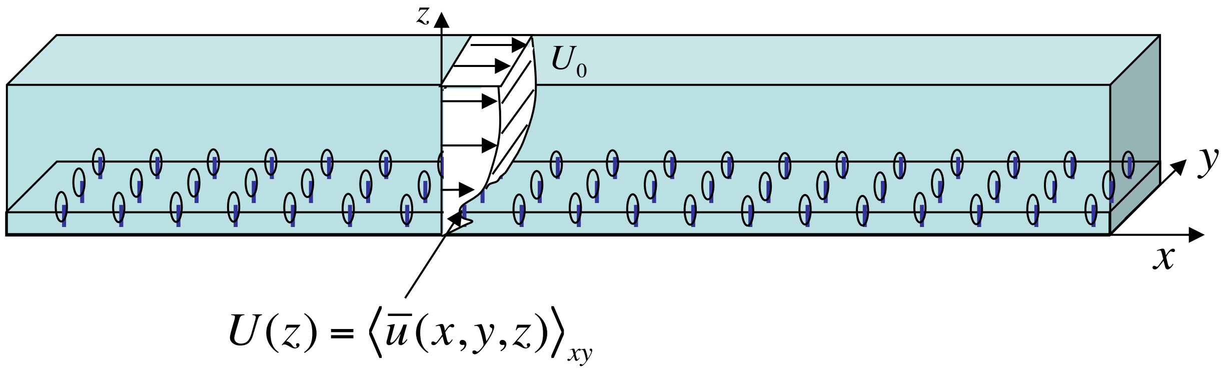
ALC wake model parameter

- Fully specified wake model except for the parameter α



[Starke et al. 2021]

ALC top-down model



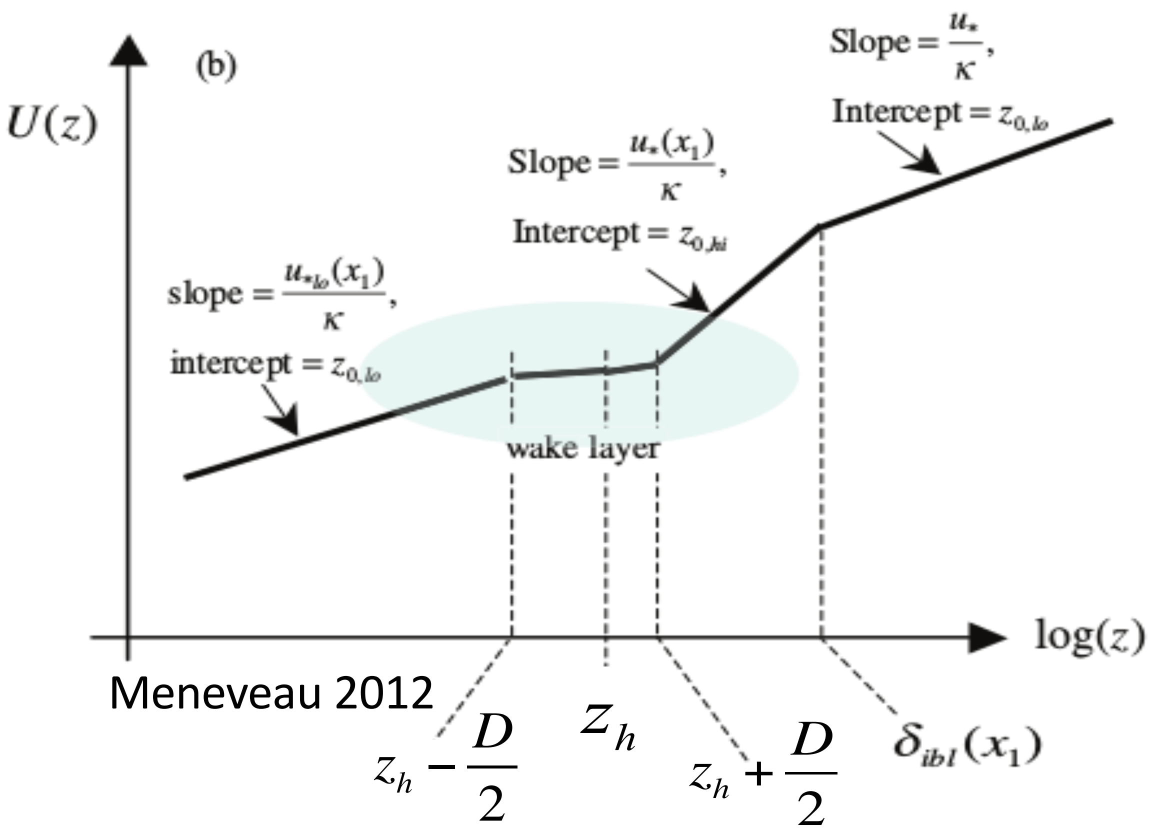
- Constant stress layers with friction velocities

$$u_{*,lo}, u_{*,hi} := u_*(x_1), u_*$$

- Reduced slope in the wake layer;

$$\frac{\partial \langle \overline{u} \rangle}{\partial z} = \frac{1}{\kappa u_* z_h + \nu_w} u_*^2$$

  – turbine effects incorporated through an added eddy viscosity ν_w



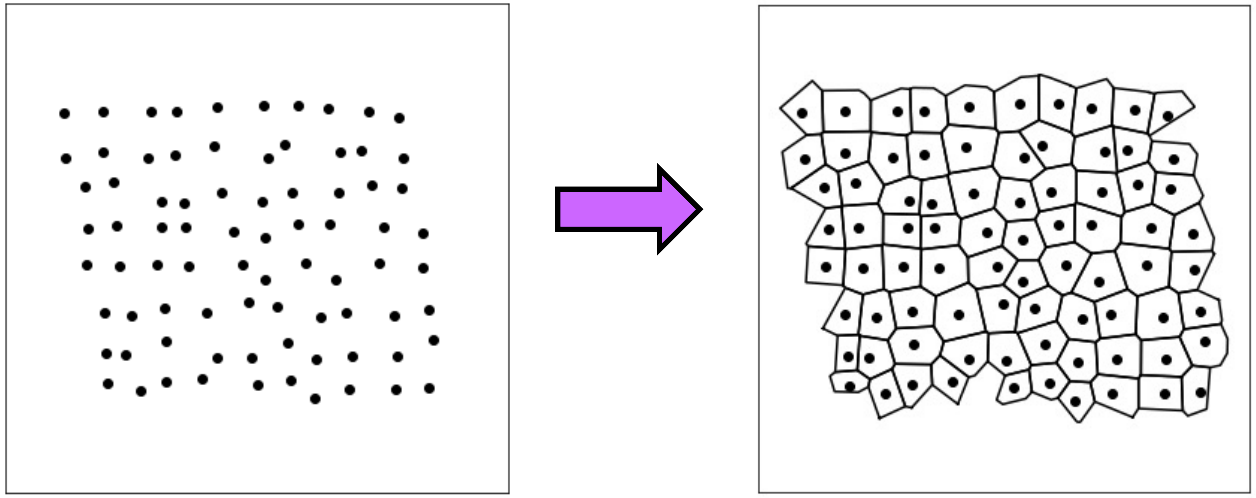
Meneveau 2012

Planar average momentum balance $u_{*,hi}^2 = u_{*,lo}^2 + \frac{1}{2} c_{ft} \overline{u}_h^2$

c_{ft} : planform thrust coefficient

ALC model: defining local turbine areas

- Define area associated with each turbine using Voronoi tessellation



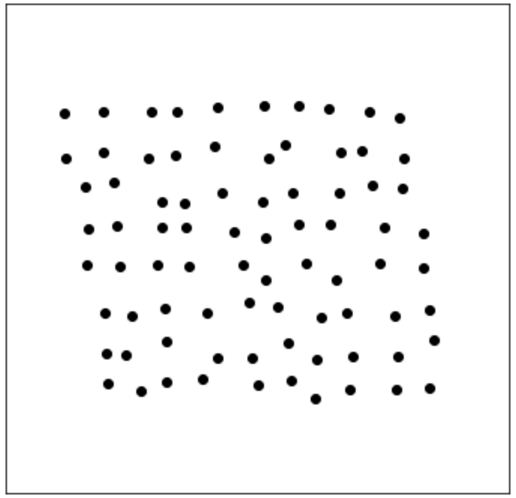
Friction velocity for cell n

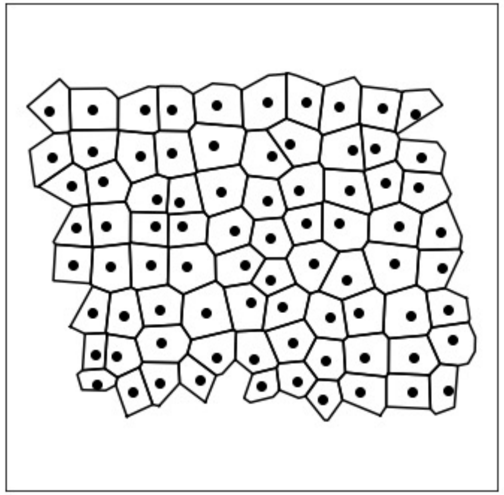
$$u_{*,n} = U_{\infty,n} \frac{\kappa}{\ln\left(z_h / z_{0,lo}\right)}$$

Account for variations in inlet velocity

ALC model: defining local turbine areas

- Define area associated with each turbine using Voronoi tessellation



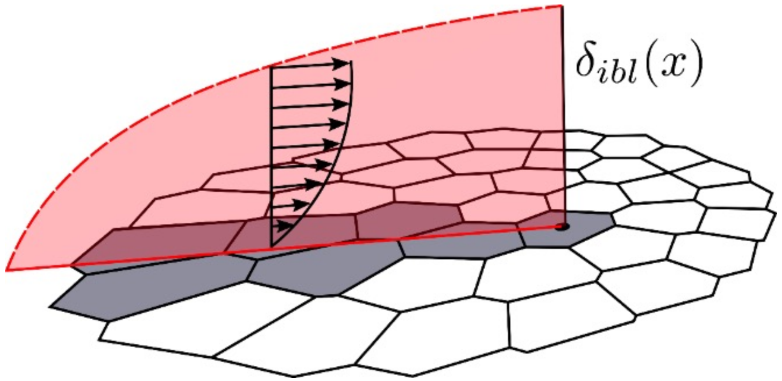


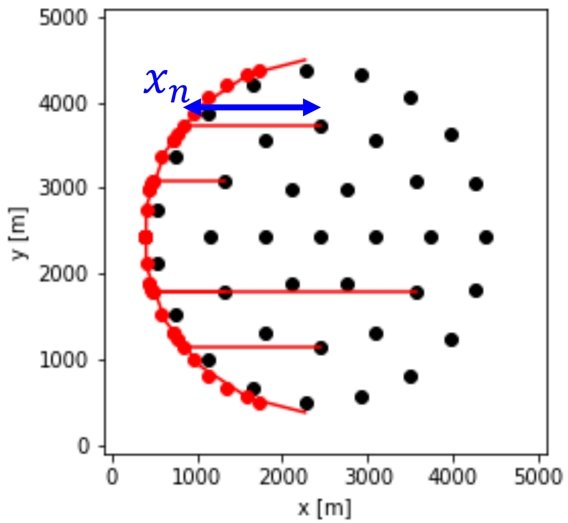
Friction velocity for cell n

$$u_{*,n} = U_{\infty,n} \frac{\kappa}{\ln\left(z_h / z_{0,lo}\right)}$$

Developing boundary layer height in each cell

$$\delta_{ibl,n}(x) = \min\left[z_h + z_{0,hi}\left(\frac{x_n}{z_{0,hi}}\right)^{4/5}, \delta \right]$$





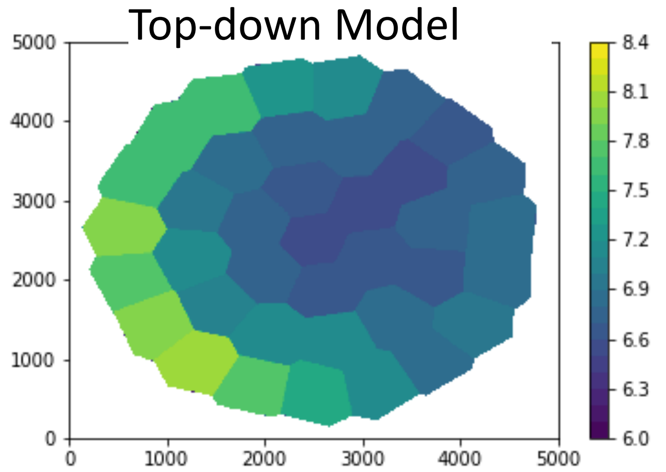
ALC model: iterative coupling

- Top-down model planar-averaged hub-height velocity in each cell

$$\bar{u}_{h,n} = \frac{u_{*,hi,n}}{\kappa} \ln\left(\frac{z_h}{z_{0,hi,n}} \left[1 + \frac{R}{z_h} \right]^{\frac{\nu_{w*}}{(1+\nu_{w*})}} \right)$$

$$\nu_{w*} \approx 28\sqrt{\frac{1}{2} c_{ft}}$$ Added eddy viscosity due to turbines

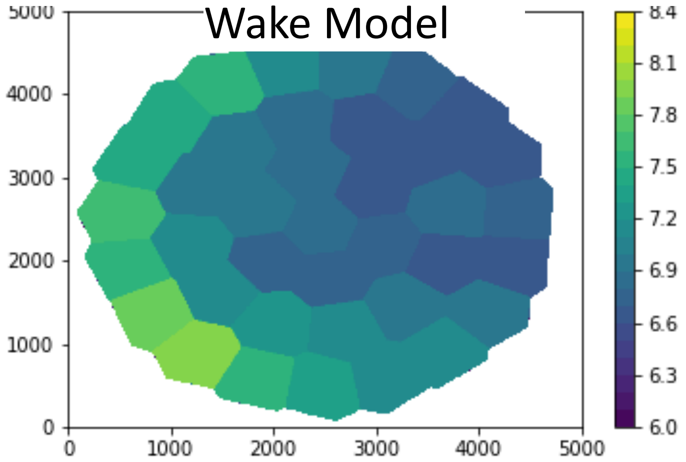
- Average of the wake model velocity field in each cell $\bar{u}_n^{wm}$



$$u_{*,hi}^2 = u_{*,lo}^2 + \frac{1}{2} c_{ft} \bar{u}_h^2$$

Planform thrust coefficient in each cell (determines velocity)

$$\min_{\alpha} \sum_{n \in D} \left(\bar{u}_{h,n}^{wm} - \bar{u}_{h,n}^{td} \right)^2$$

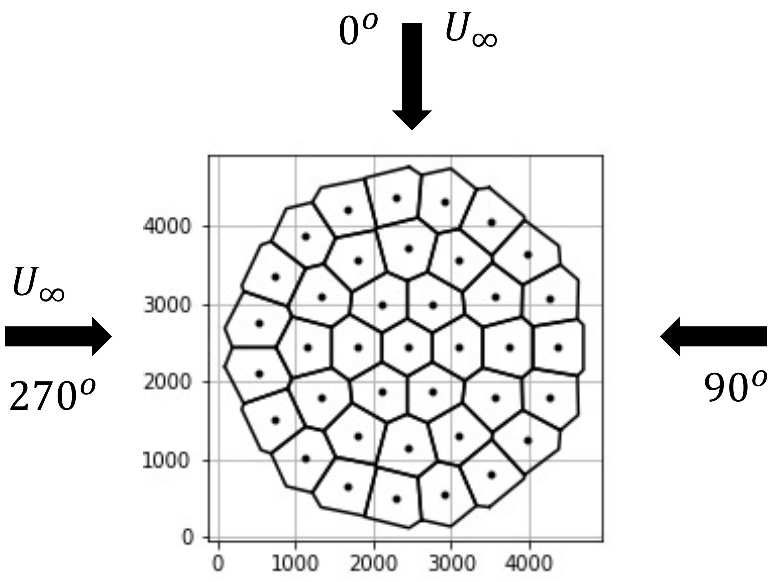


$$k_{w,n} = \frac{\alpha}{2} \left(\frac{u_{*,lo} + u_{*,hi}}{\bar{u}_h} \right)_n$$

$Power_{farm}$

$$P_n = \frac{1}{2} \rho \pi R^2 C_T' u_{d,n}^3$$

Validation: circular wind farm



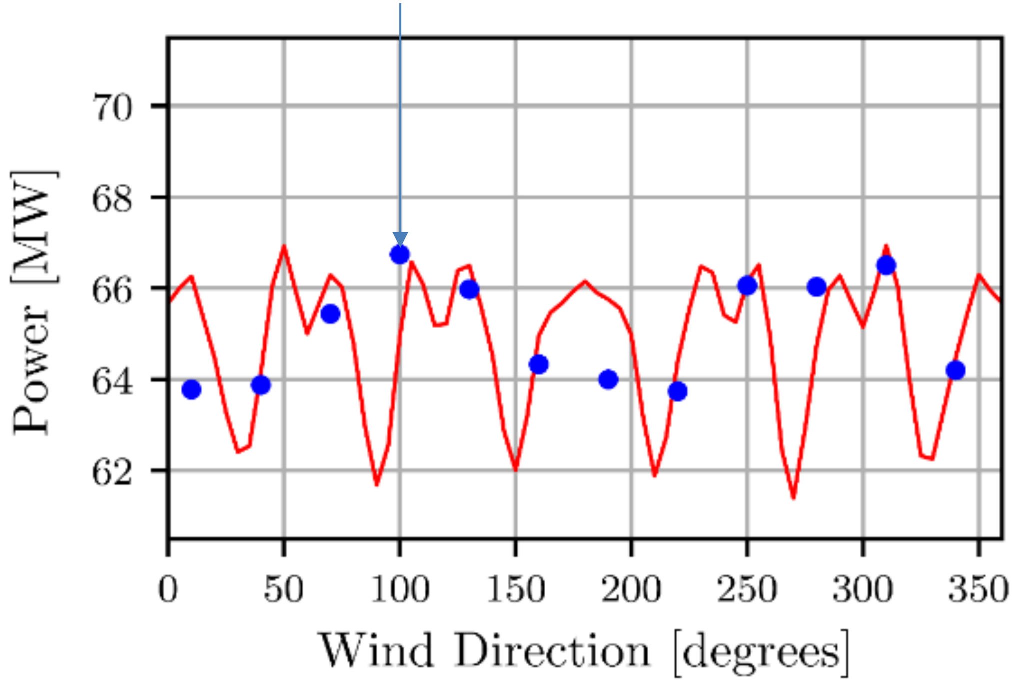
NREL 5 MW Reference Turbine:

- Diameter: $D = 126\ m$
- Hub Height: $z_h = 90\ m$

Flow Conditions:

- Lower roughness: $z_0 = 0.15$
- Inversion layer height: $\delta_{max} = 750\ m$

- Data Comparisons
  - SOWFA LES (Churchfield & Lee 2013) data from NREL (data every 30 degrees)

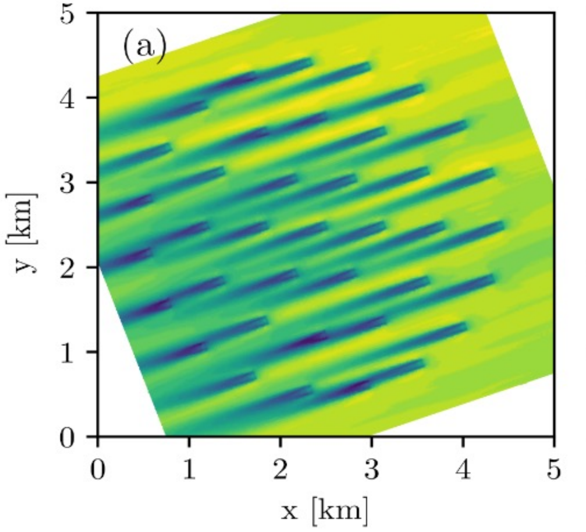


  - Area Localized Model run every 5 degrees

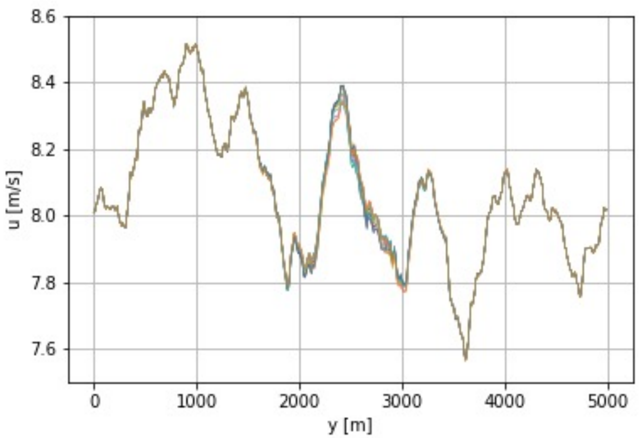
[Starke et al. 2021]

Detailed comparisons at 70 degrees

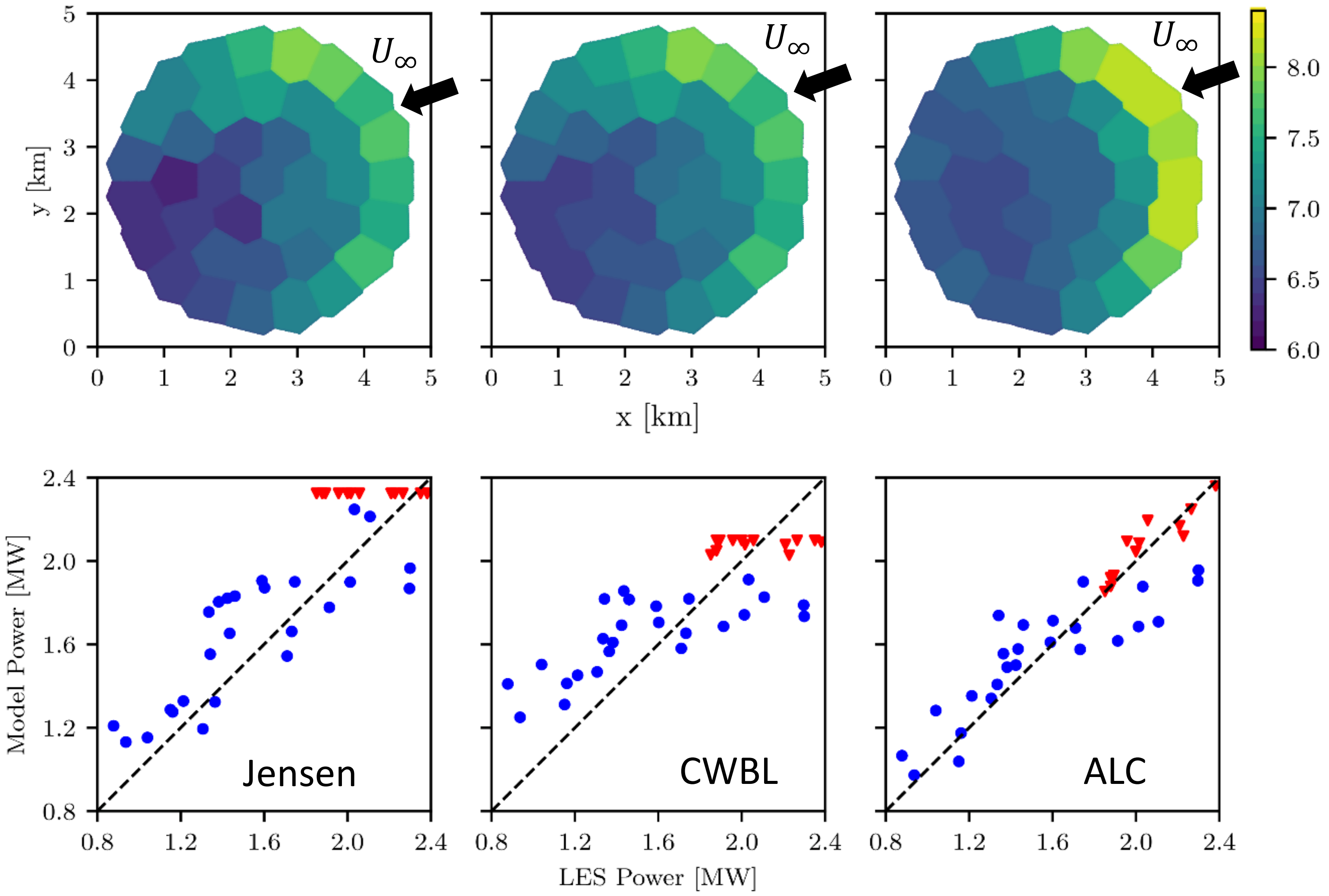
Averaged LES field



Inlet velocity profile

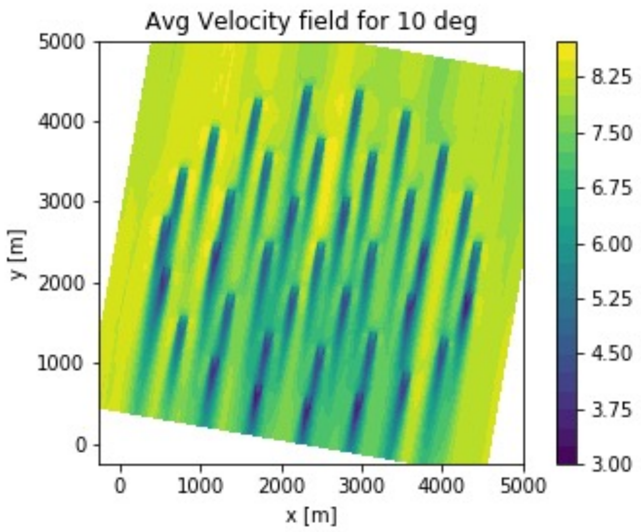


LES Planar Average Velocity | Wake Model | Top-down Model

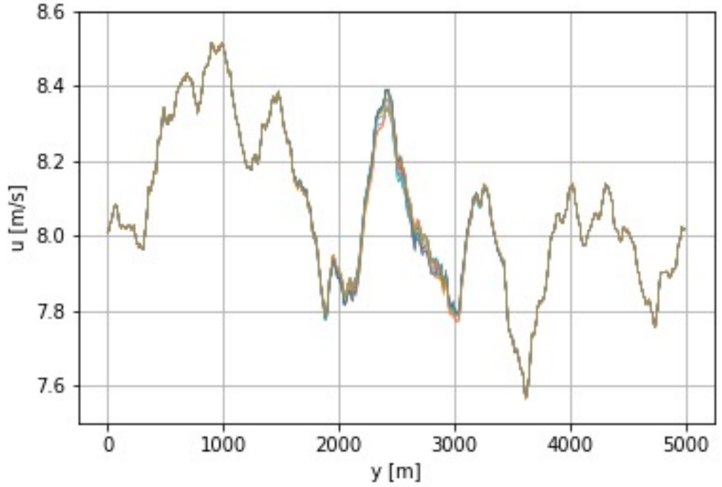


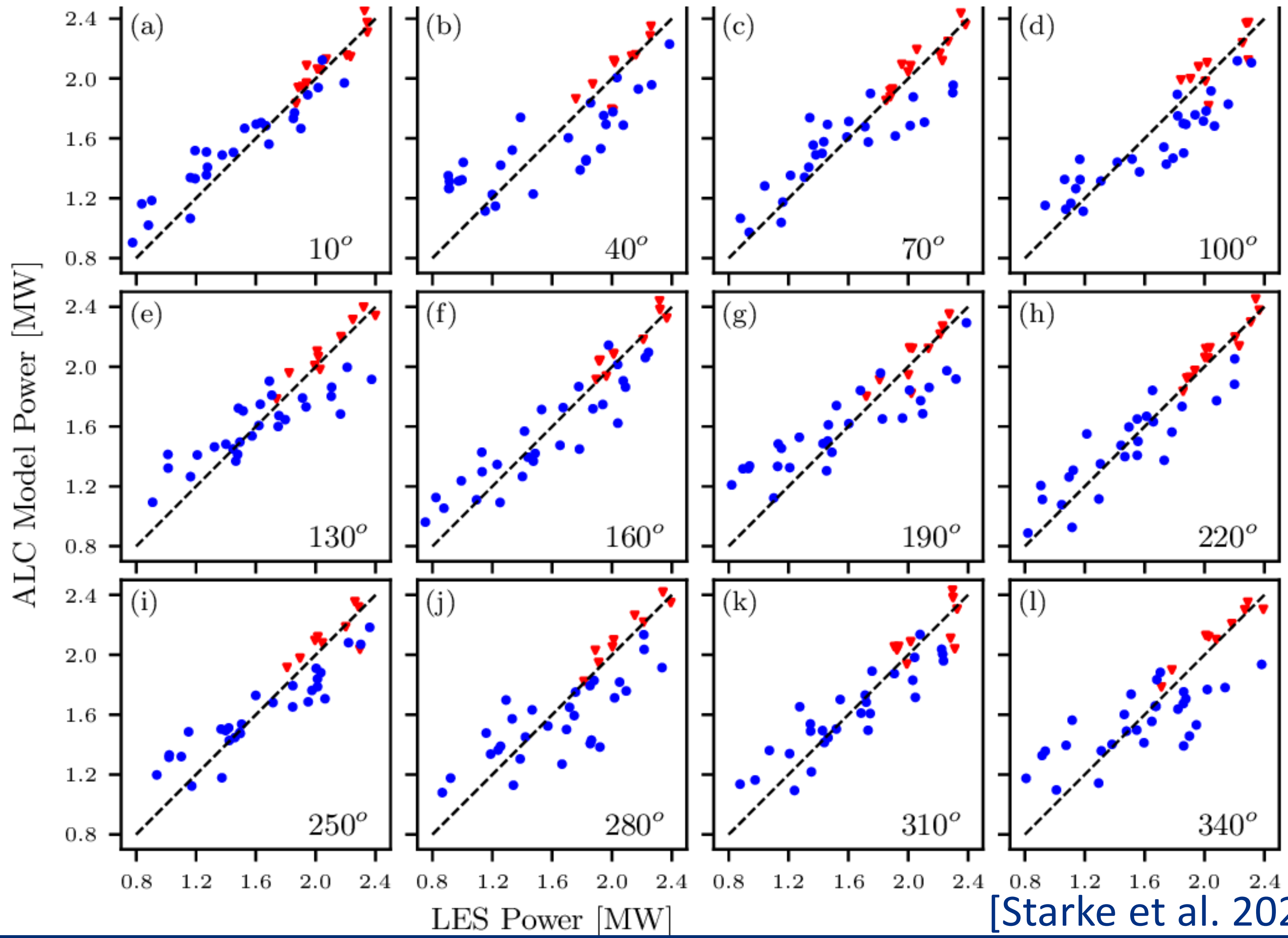
[Starke et al. 2021]

Detailed power comparisons over angle range



Inlet velocity profile

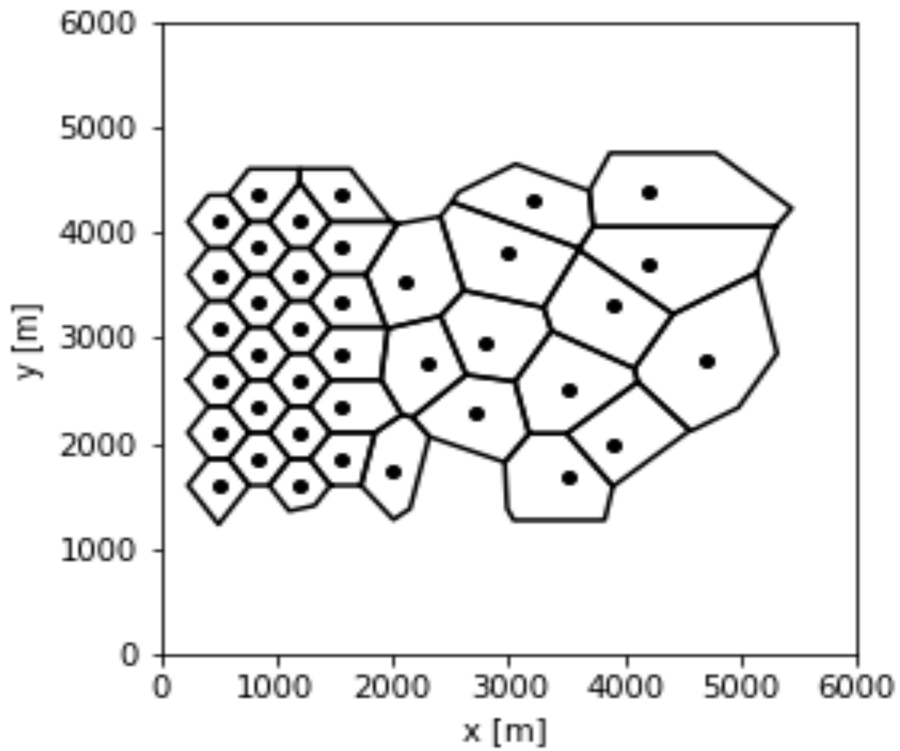


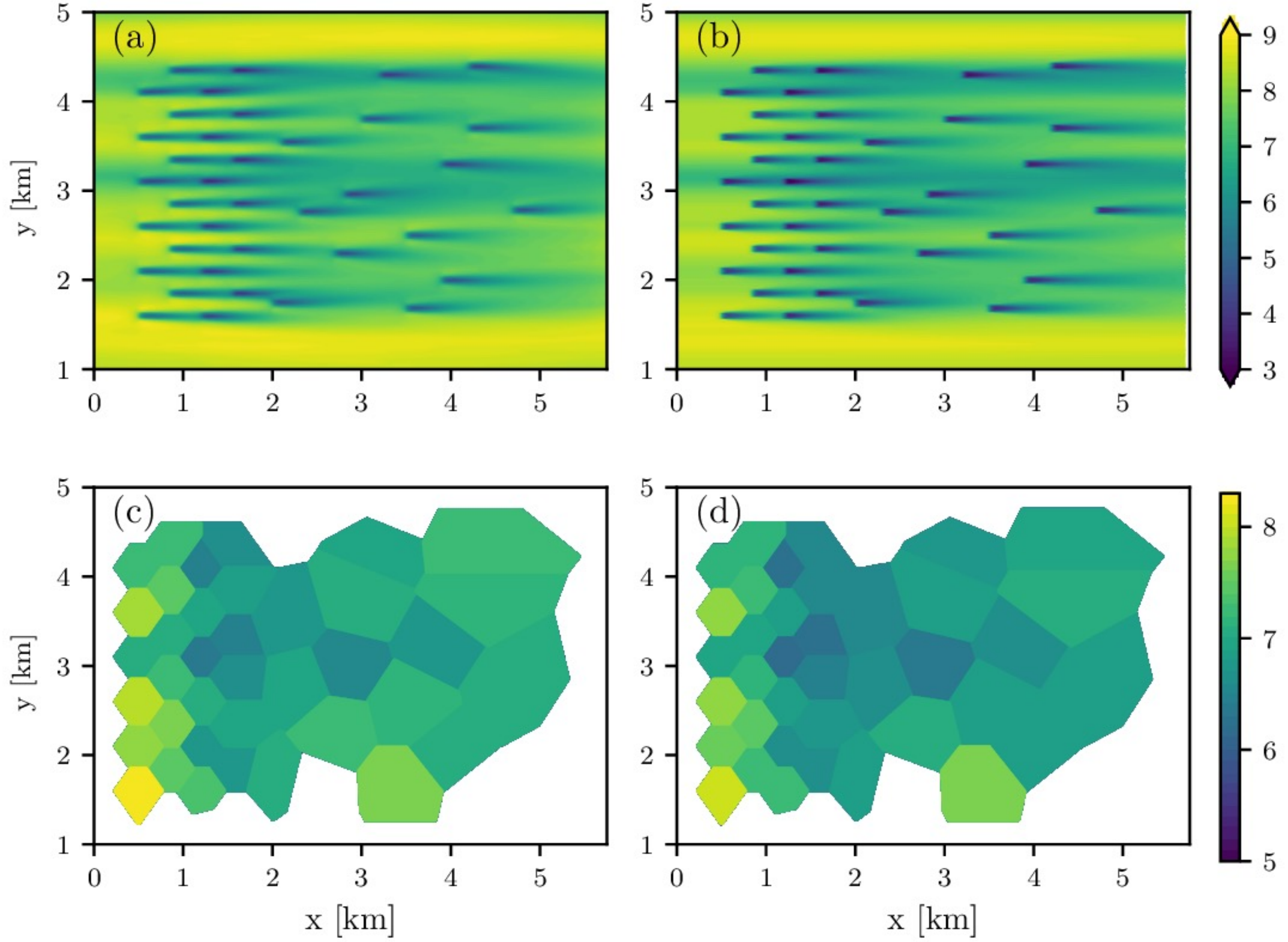


[Starke et al. 2021]

Random wind farm case

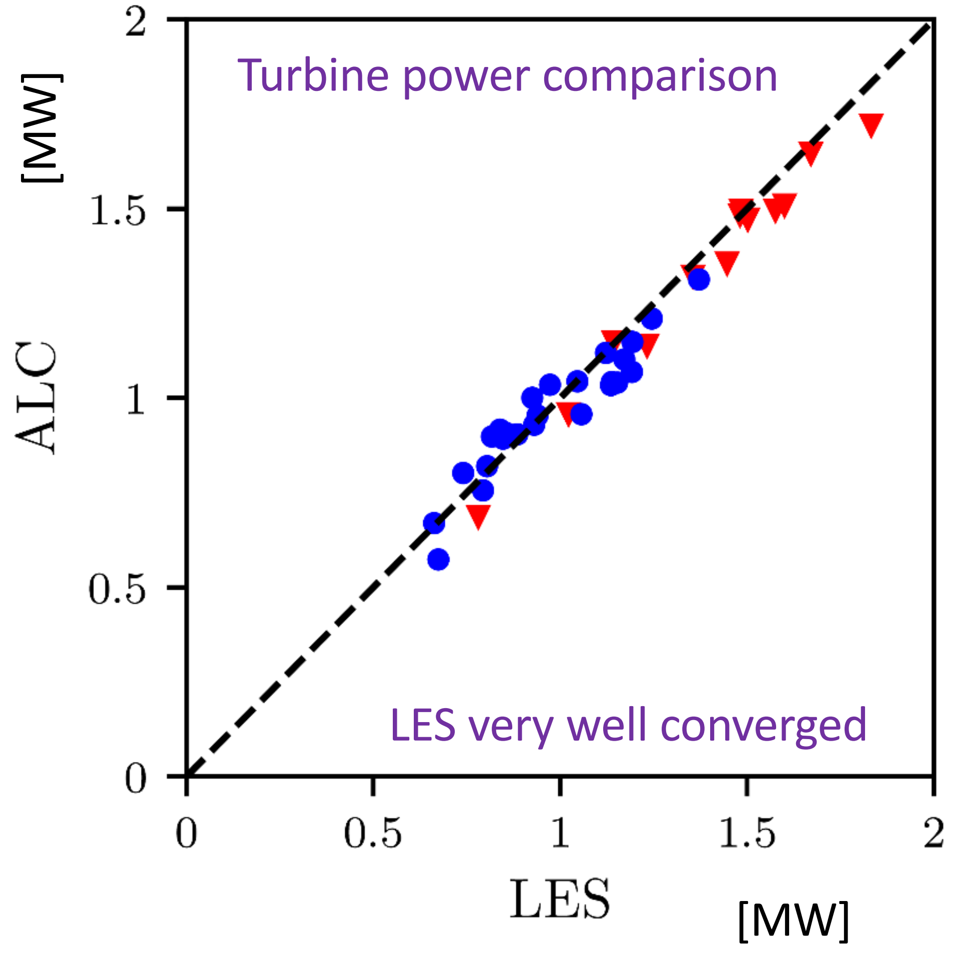
- Compared to JHU LES code averaged over 10 flow through times

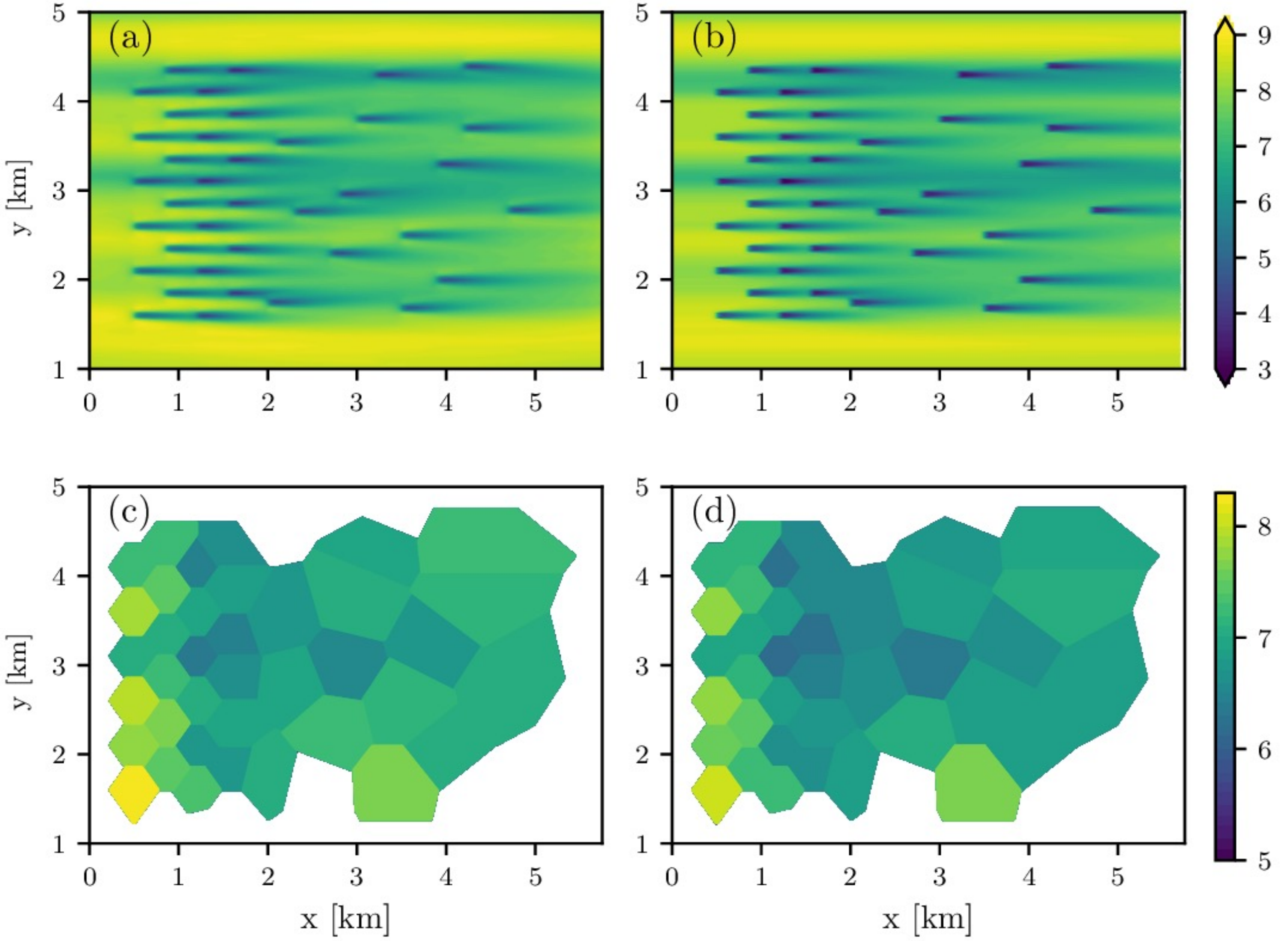




Random wind farm case

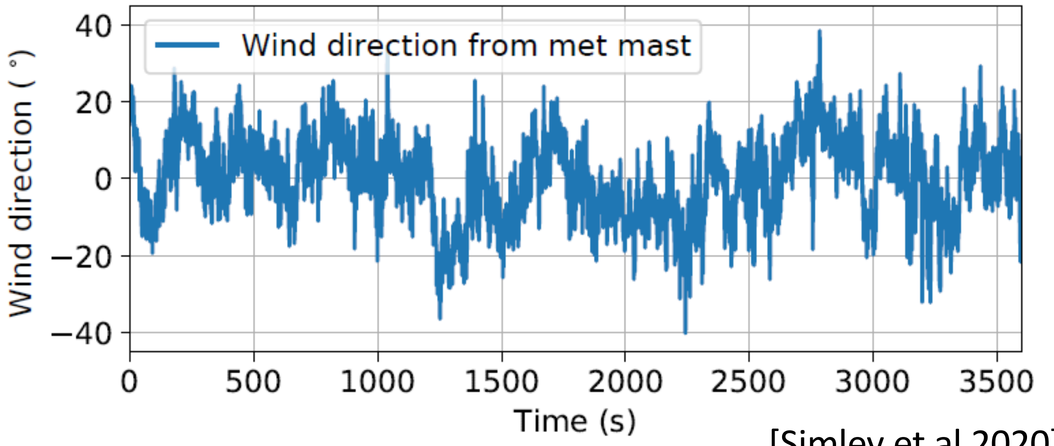
- Compared to JHU LES code averaged over 10 flow through times





Dynamic changes in wind farm state

- Wind direction can change abruptly or vary with time
  - Failing to account for leads reduces power prediction accuracy, e.g. Porte-Agel et al. 2013, Antonini et al. 2019



[Simley et al 2020]

- Control actions such as wake steering are designed to change power output

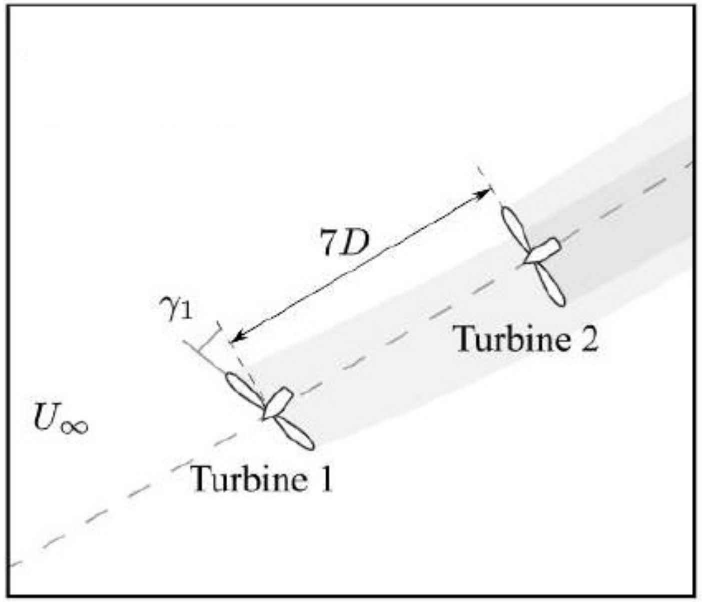
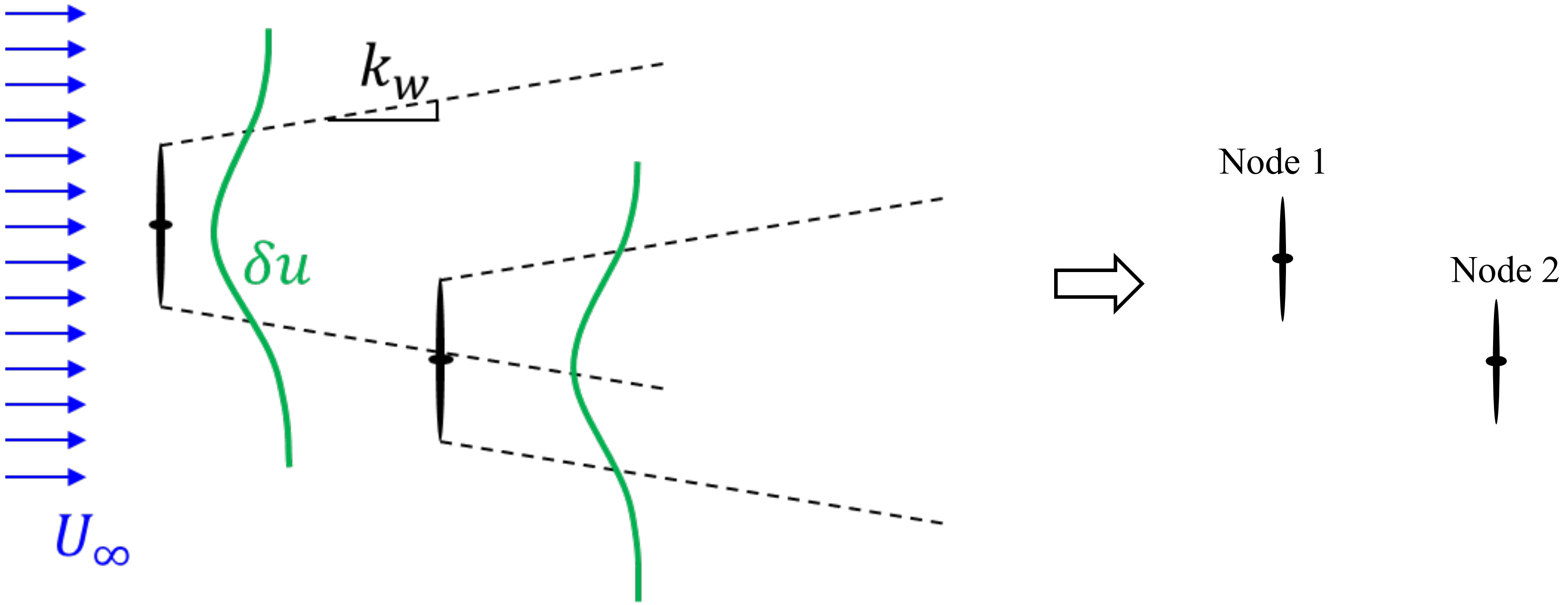


Figure adapted from Gebraad et al. 2016

Want an efficient means to predict the behavior of the farm under these types of dynamic changes

Graph model of a wind farm

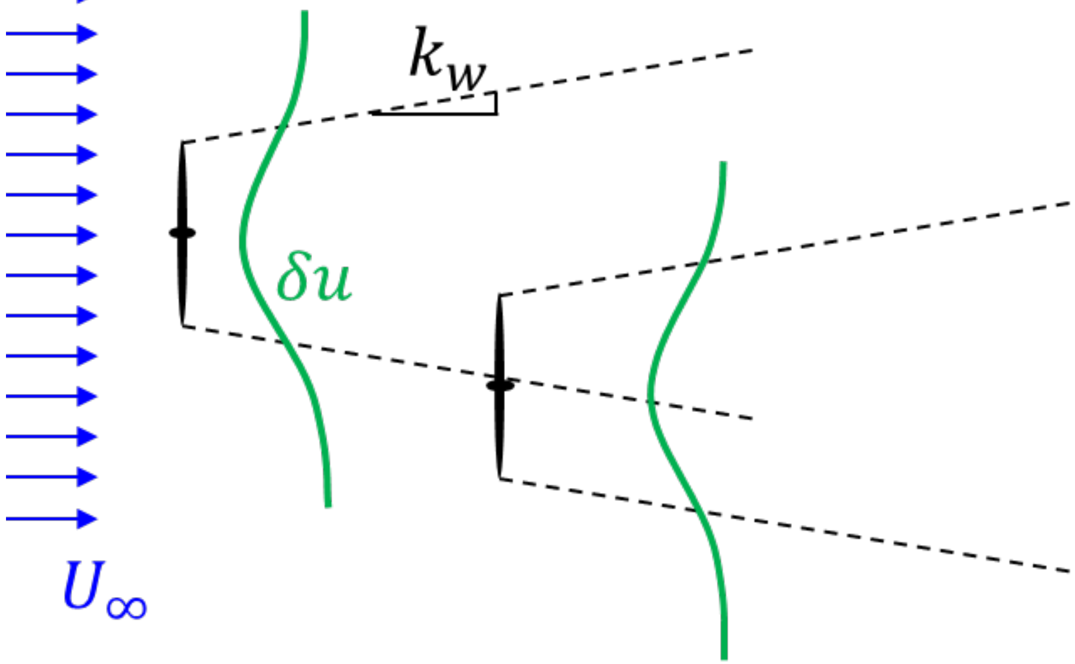
- Each turbine is a node



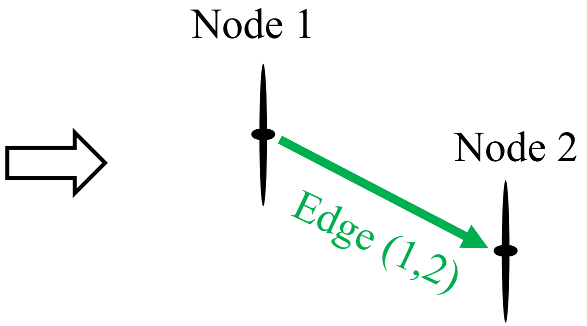
- Extension of the approach in Annoni et al. 2019a, 2019b

Graph model of a wind farm

- Each turbine is a node



- If a turbine is in the wake of another turbine, a directed edge is added to the graph



$\mathcal{G}(\mathcal{N},\mathcal{E})$

$\mathcal{N}$: Nodes (turbines)

$\mathcal{E}$: Edges (wake interactions)

- Extension of the approach in Annoni et al. 2019a, 2019b

Wind farm subgraphs

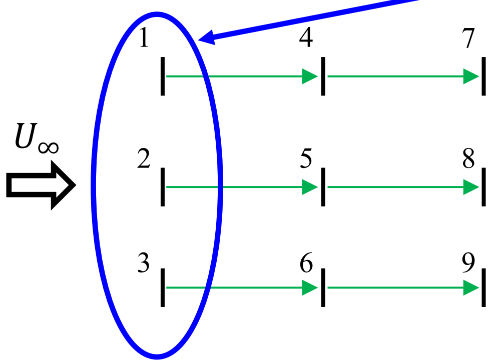
- Divide the farm into weakly-connected subgraphs based on a leader (node) turbine

$\mathcal{G}(\mathcal{N},\mathcal{E})$

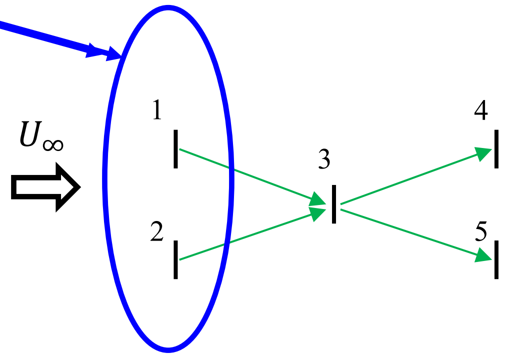
$\mathcal{N}$: Nodes (turbines)

$\mathcal{E}$: Edges (wake interactions)

Lead turbines



Aligned wind farm graph



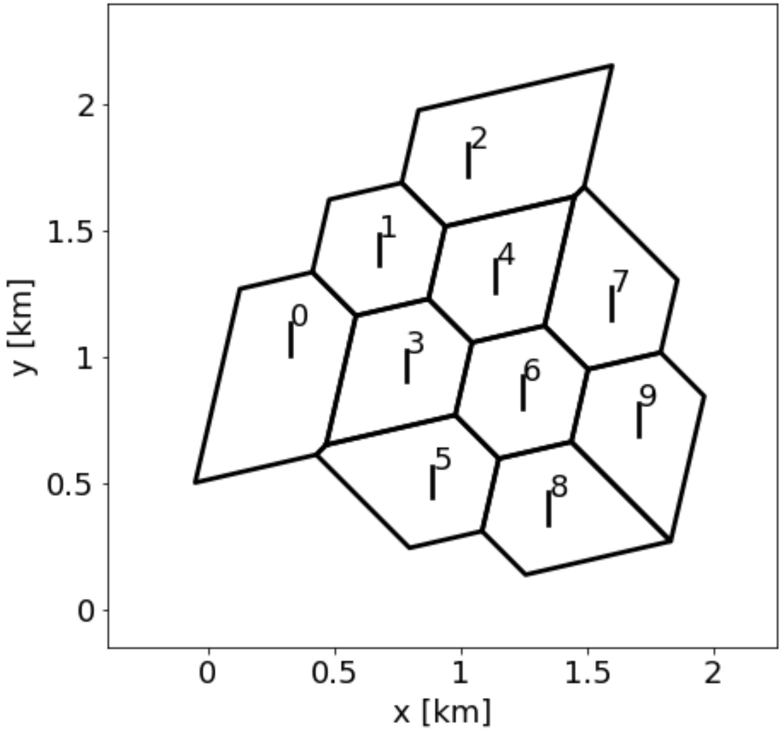
Staggered wind farm graph

$$\mathcal{G}(\mathcal{N},\mathcal{E}) = \{g_1, g_2, \cdots, g_m\}$$

Set of subgraphs

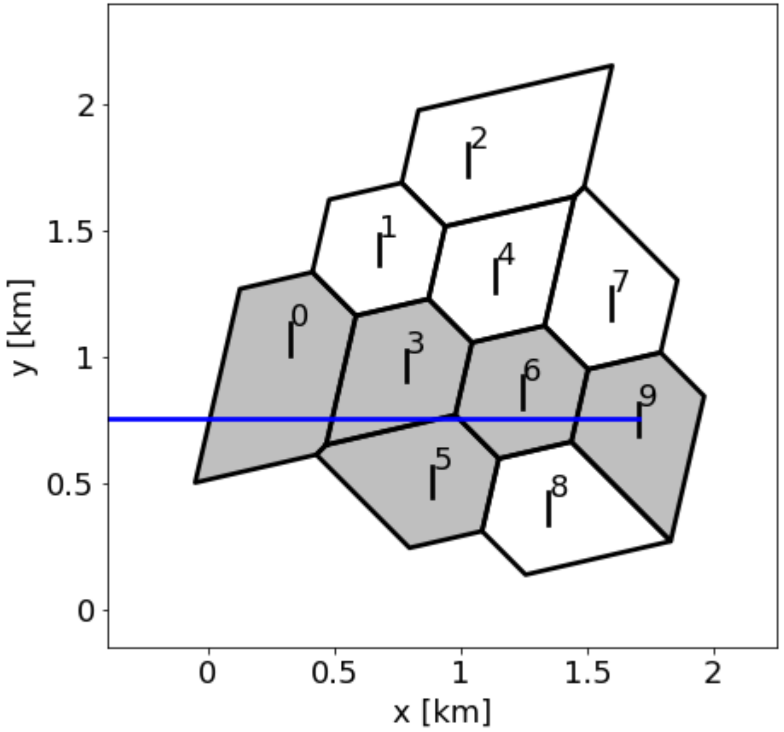
Generating a graph of an arbitrary wind farm geometry

- Define local turbine areas using Voronoi tessellation



Generating a graph of an arbitrary wind farm geometry

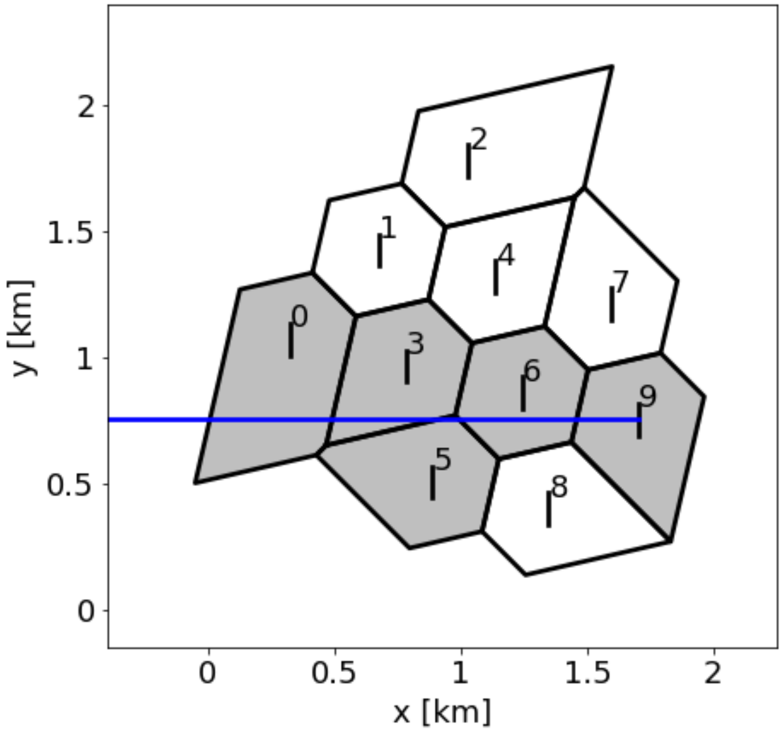
- Define local turbine areas using Voronoi tessellation

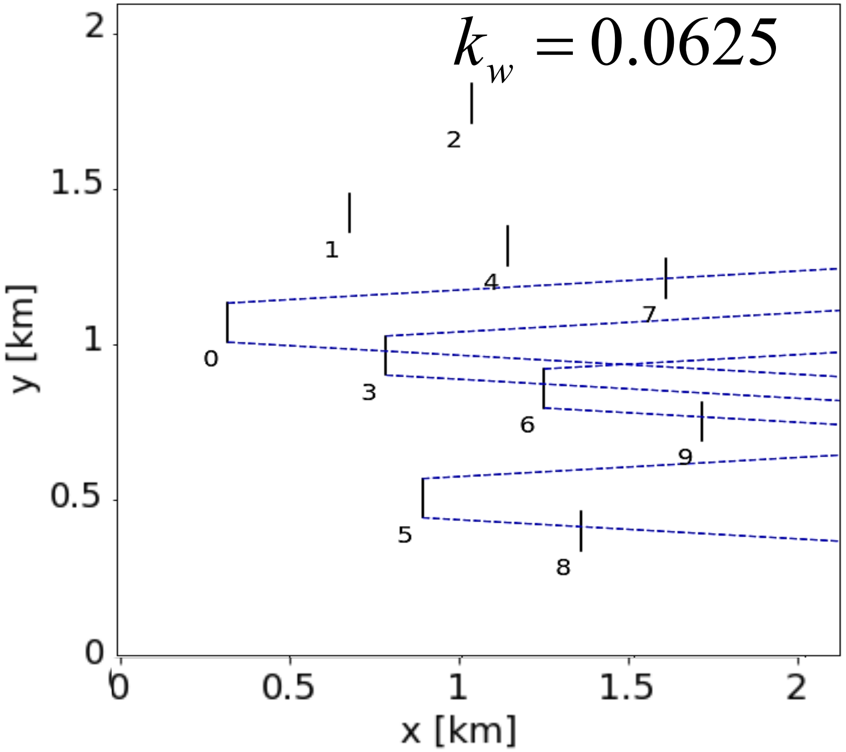


- Given an initial wind direction
  - Lead turbines and interconnections are defined based on the cells crossed as one traverses to the front of the farm
  - The wakes are defined using a linear wake growth (e.g. Jensen 1983 model)

Generating a graph of an arbitrary wind farm geometry

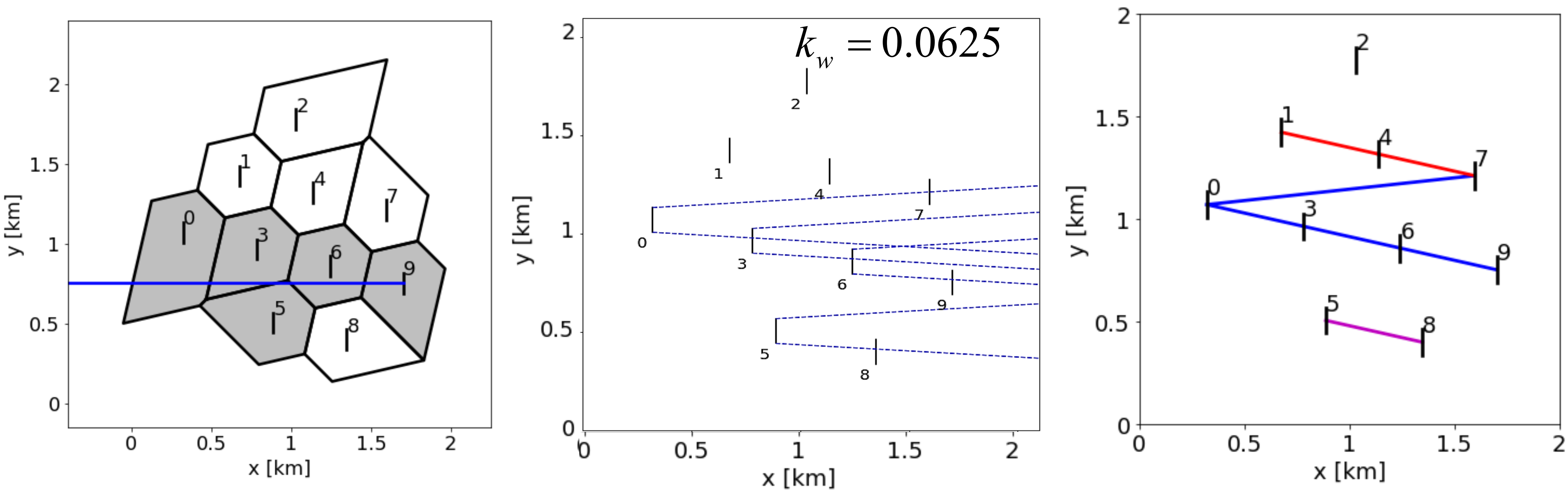
- The turbine wakes are described using linear wake growth





Generating a graph of an arbitrary wind farm geometry

- The turbine wakes are described using linear wake growth

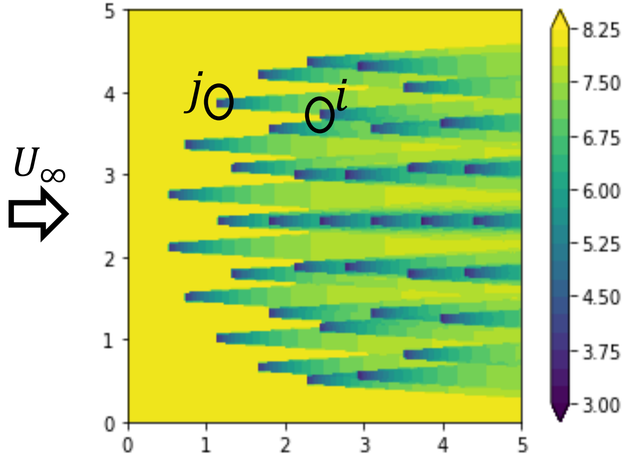


Building the dynamic graph model

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

$\Phi_k \in {}^{\sim N^2}$ has elements $\phi_i^j = \dfrac{2a}{\left(d_{w,n}(\Delta d_i^j)\right)^2} W_i^j$

- state vector of deficits between each turbine pair



Normalized deficits at turbine i due to turbine j

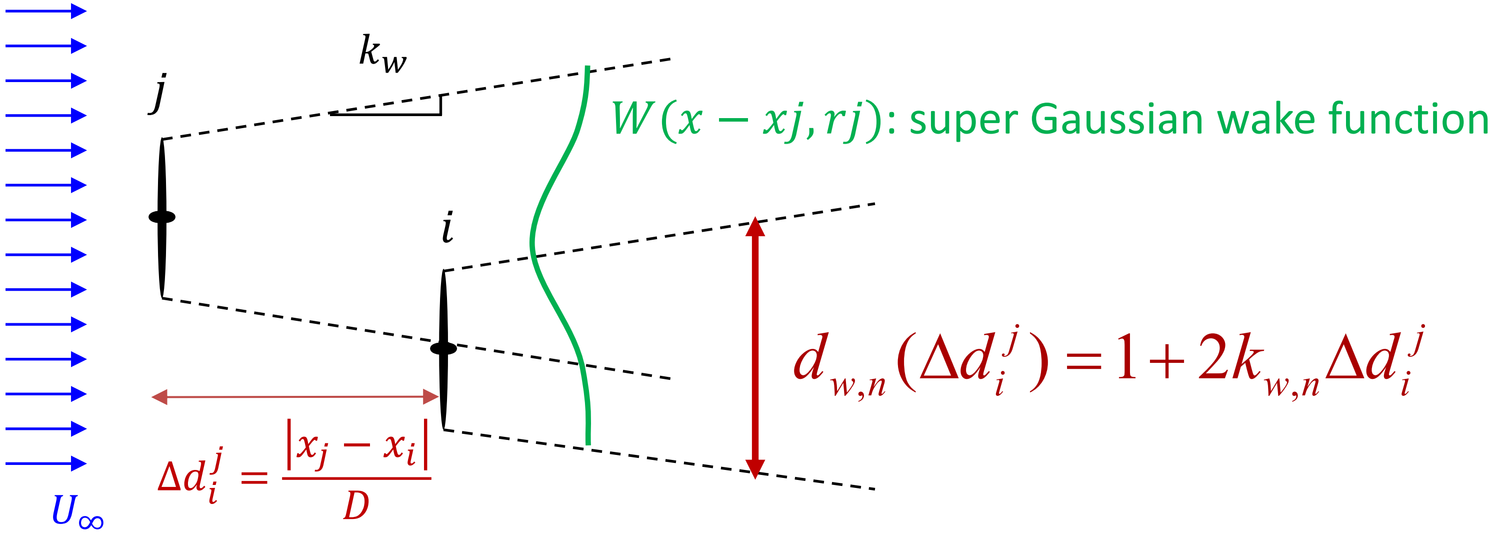
- Based on wake deficit coefficient formulation of Shapiro et al. 2019

Building the dynamic graph model

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

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

$\Phi_k \in \sim^{N^2}$ has elements $\phi_i^j = \dfrac{2a}{\left(d_{w,n}(\Delta d_i^j)\right)^2} W_i^j$



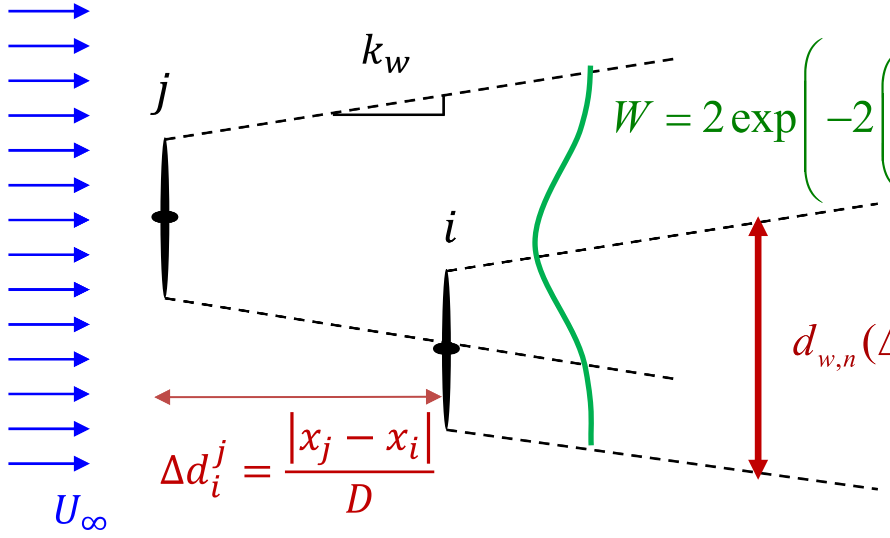
Building the dynamic graph model

$$\phi_i^j = \frac{2a}{\left(d_{w,n}(\Delta d_i^j)\right)^2} W_i^j$$

The wake function from turbine j is projected over turbine i

$$W_i^j = \frac{1}{\pi R_i^2} \int_0^{R_i} \int_0^{2\pi} W(x_i - x_j, r_{ij})\, r_i \, d\theta \, dr_i$$

$W(x,r)$: super Gaussian wake function for linear superposition

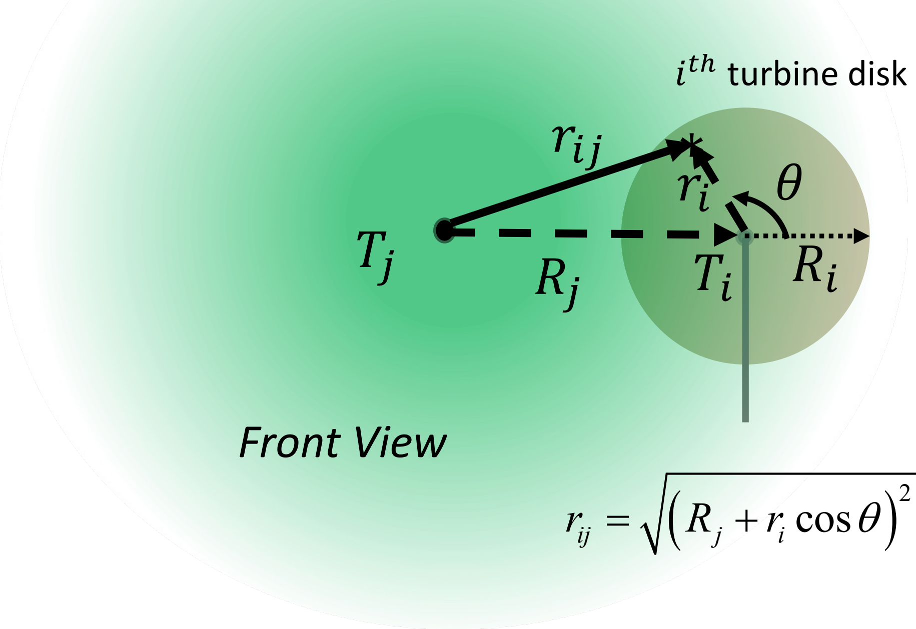


$$W = 2\exp\left(-2\left(\frac{2r_j}{Dd_w(x-x_j)}\right)^2\right)$$

$$d_{w,n}(\Delta d_i^j) = 1 + 2k_{w,n}\Delta d_i^j$$

$$\Delta d_i^j = \frac{|x_j - x_i|}{D}$$

Wake of the j^{th} turbine at streamwise location of Turbine i (at x_i) (Gaussian shape)



$$r_{ij} = \sqrt{\left(R_j + r_i\cos\theta\right)^2 + \left(r_i \sin\theta\right)^2}$$

- Use boundary layer theory to get wake expansion $k_{w,n}$ coefficient for each local turbine

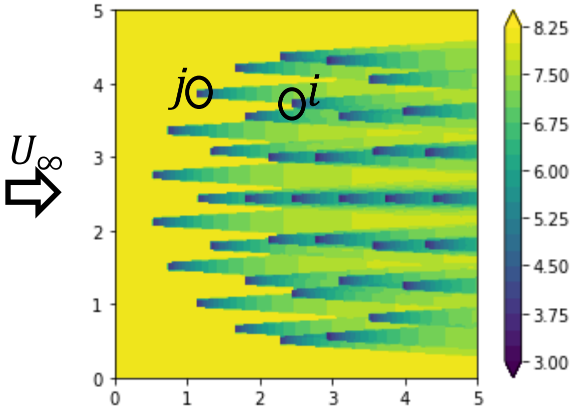
State update map

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

- state vector comprised of deficits between each turbine pair

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

- Event driven input $E_k(\Phi_{e,k}, \tau_{e,k}, \Delta\mathrm{E}_{e,k})$



State update map

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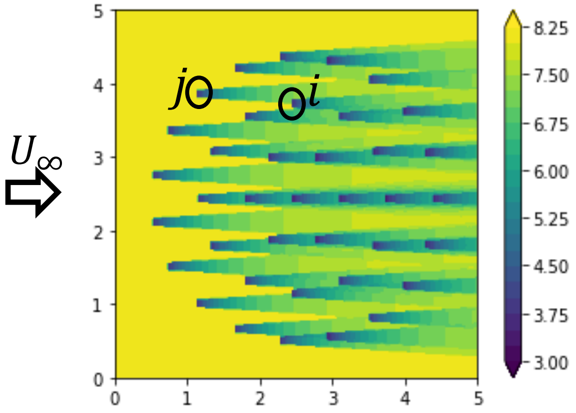
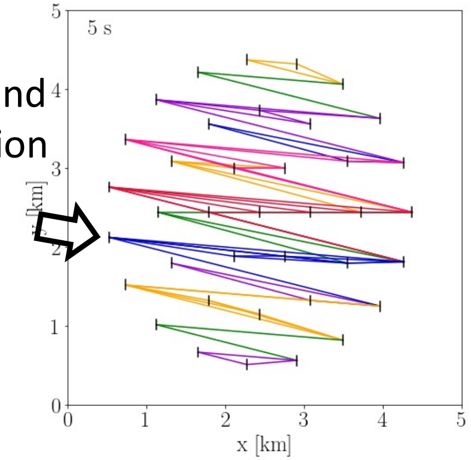


$$\Phi_k = \left[\phi_1^1 \quad \phi_1^2 \quad \phi_1^3 \quad \ldots \quad \phi_1^N \quad \phi_2^1 \quad \ldots \quad \phi_N^{N-1} \quad \phi_N^N \right]^T$$

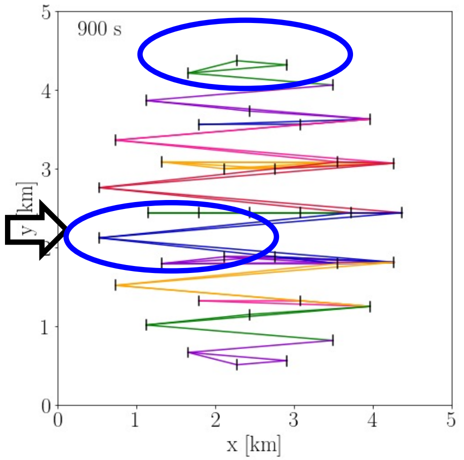
- Event driven input $E_k(\Phi_{e,k}, \tau_{e,k}, \Delta \mathrm{E}_{e,k})$
- System graph changes each timestep k (wind direction change occurs over some # of timesteps)
  - the changes to the state ($\phi_{e,i}$), the updated time delays ($\tau_{e,i}$), and a list of the edge changes ($\Delta \mathbf{E}_{e,i}$)

Initial wind direction



Wind direction change

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



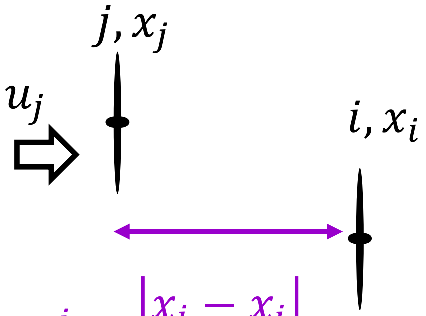
System of equations: Output

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

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

$\Lambda(\tau_k)$: delay dependent weighted adjacency matrix

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



$$\Delta d_i^j = \frac{|x_j - x_i|}{D}$$

System of equations

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

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

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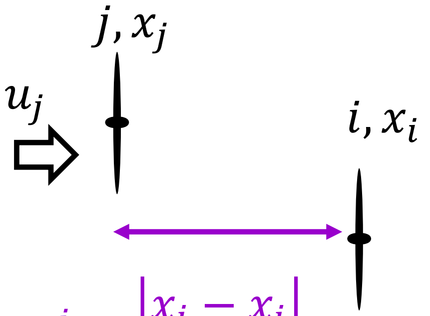


$$\Delta d^j_i = \frac{|x_j - x_i|}{D}$$

Velocity at each turbine (disk velocity)

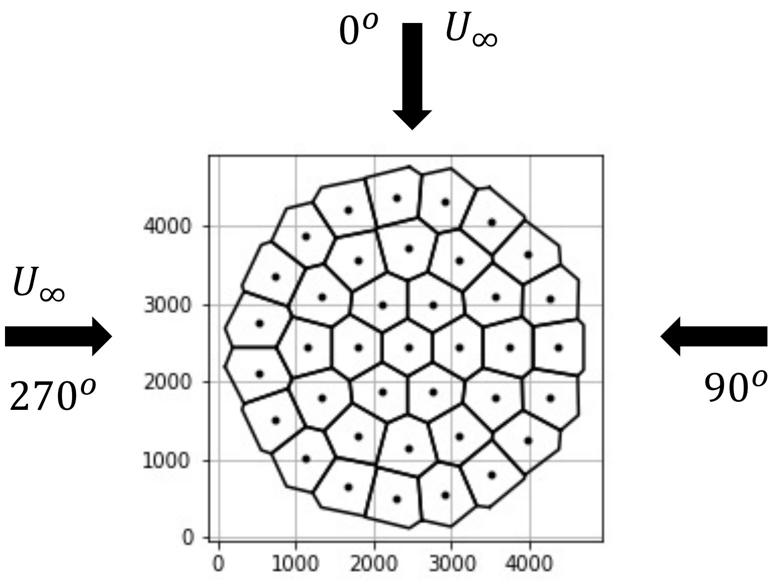
$$U_{d,k+1} = U_\infty(1-\alpha_{k+1})\left(1 - \frac{C_T{}'}{4+C_T{}'}\right)$$

Linear wake superposition

Turbine power output

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

Validation: Circular wind farm



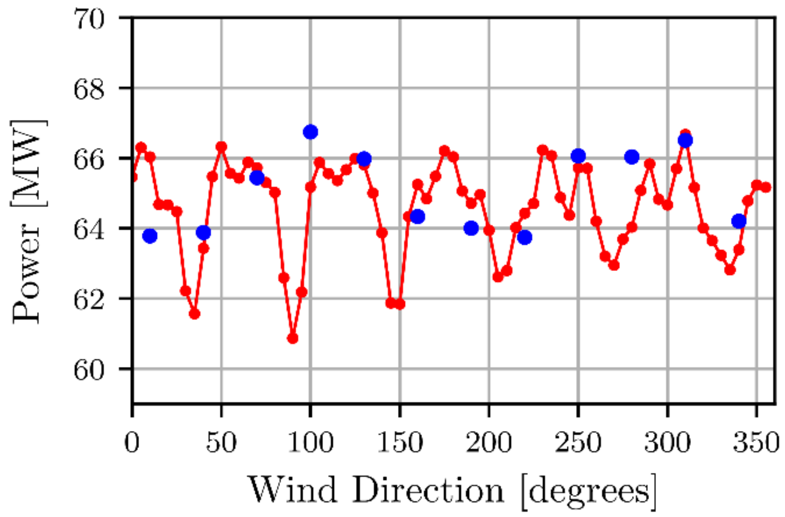
NREL 5 MW Reference Turbine:

- Diameter: $D = 126\ m$
- Hub Height: $z_h = 90\ m$

Flow Conditions:

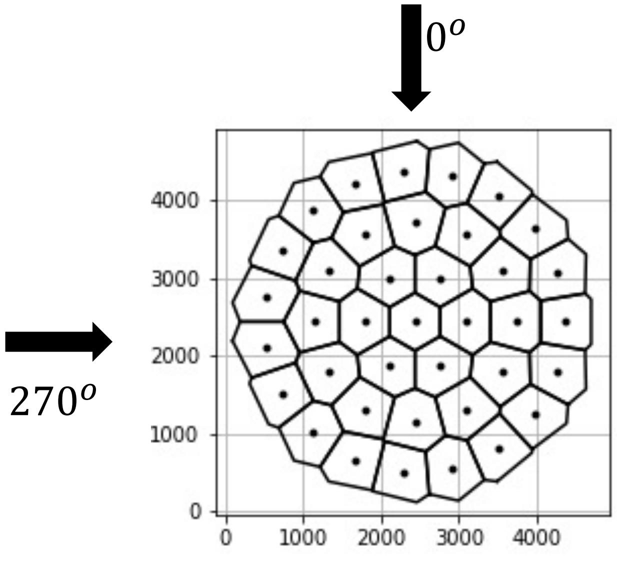
- Lower roughness: $z_0 = 0.15$
- Inversion layer height: $\delta_{max} = 750\ m$

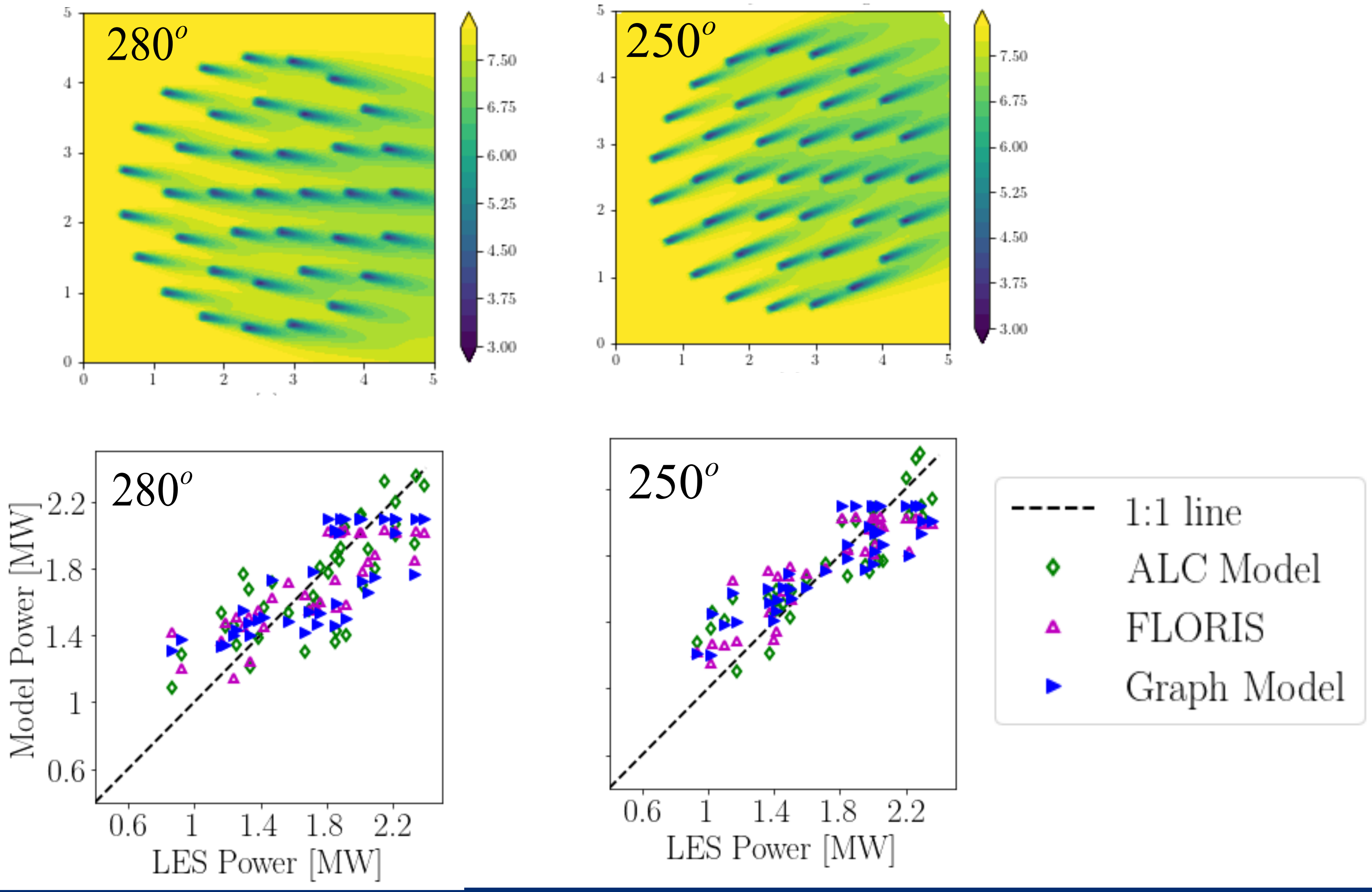
- Data Comparisons
  - SOWFA LES (Churchfield & Lee 2013) data from NREL (data every 30 degrees)
  - Area Localized Model (Starke et al preprint) run every 5 degrees



  - FLORIS static (NREL/floris: v2.2.0) and dynamic (Gebraad et al. 2015) simulations

Steady state behavior

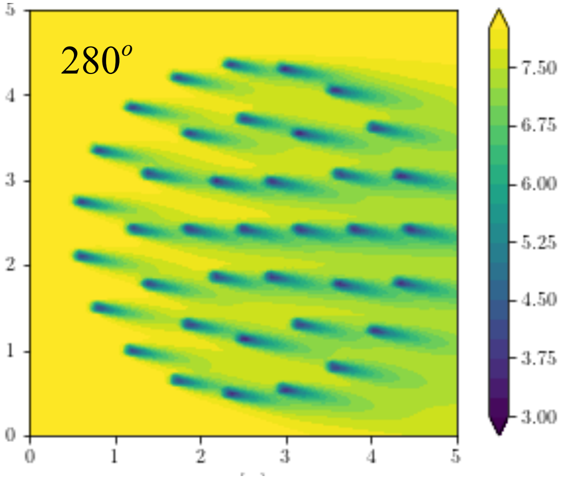


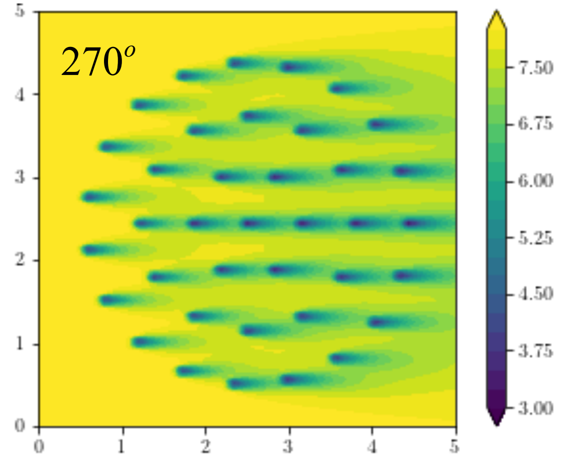


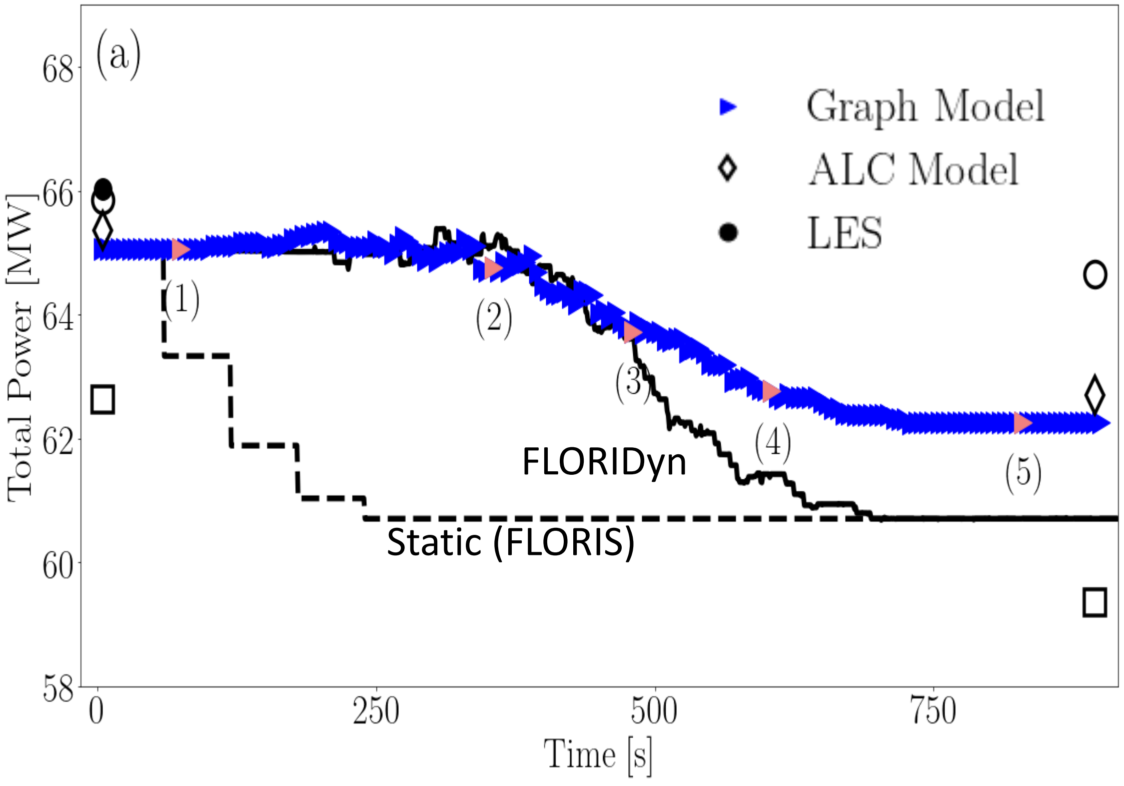
[Starke et al (ACC 2021)]

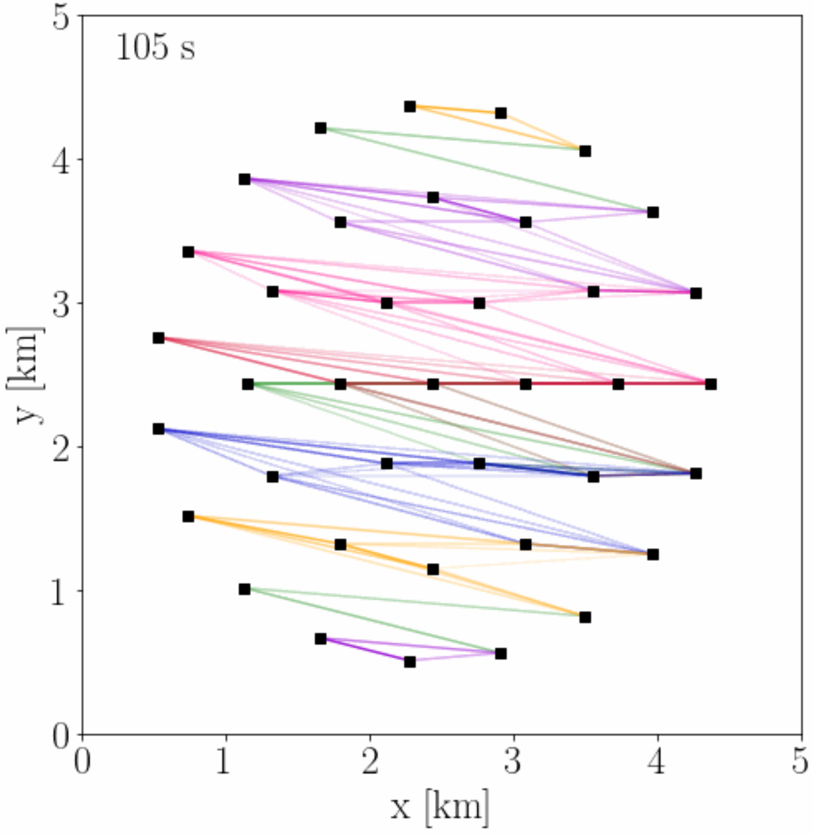
Results: Small angle changes

- 280^o wind direction to 270^o wind direction



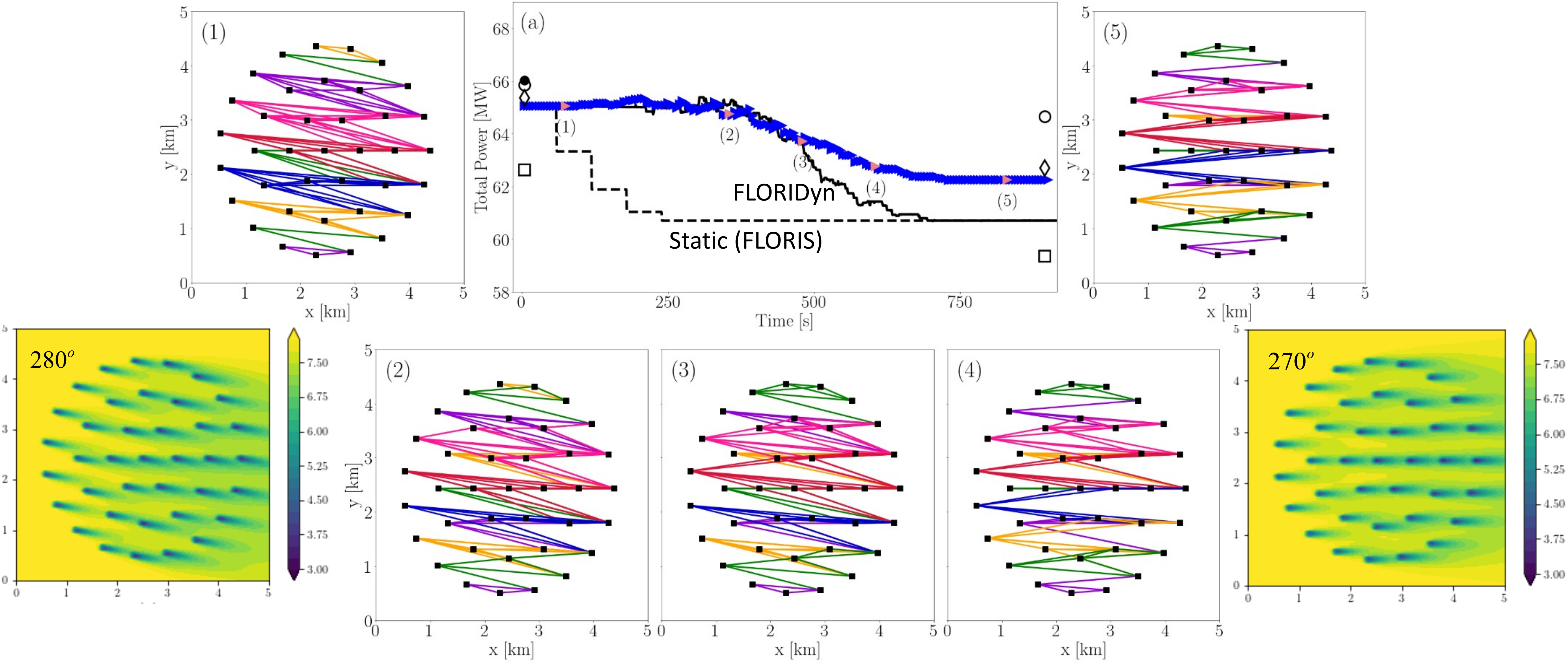






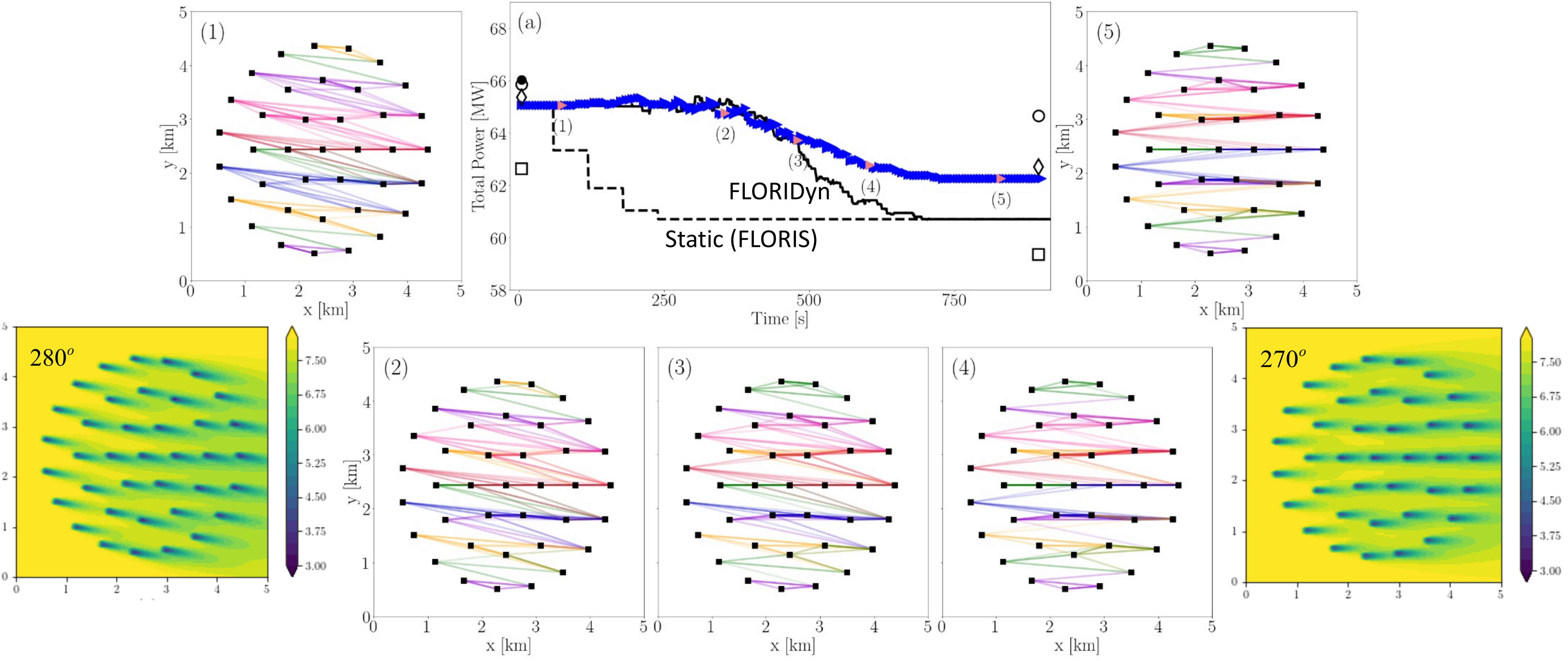
[Starke et al (ACC 2021)]

Results: Small angle changes (graph structure)



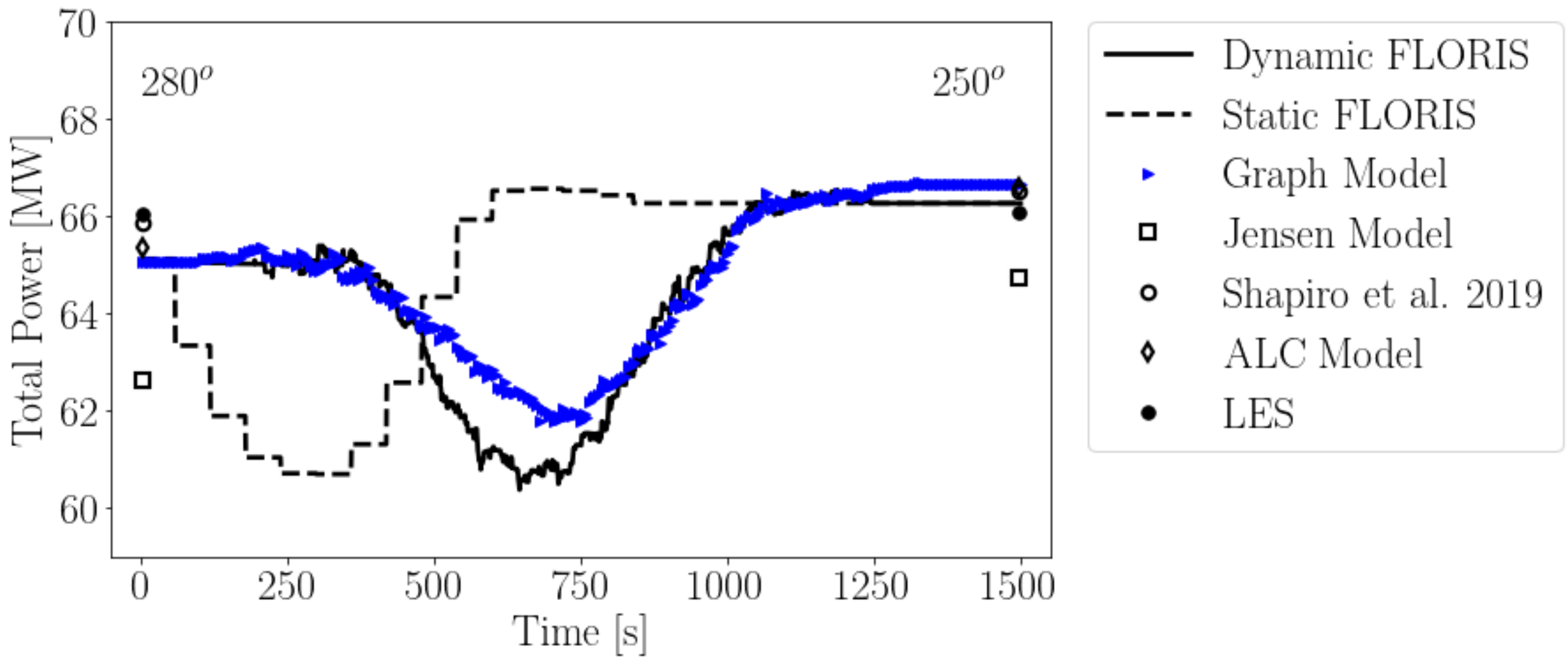
[Starke et al (ACC 2021)]

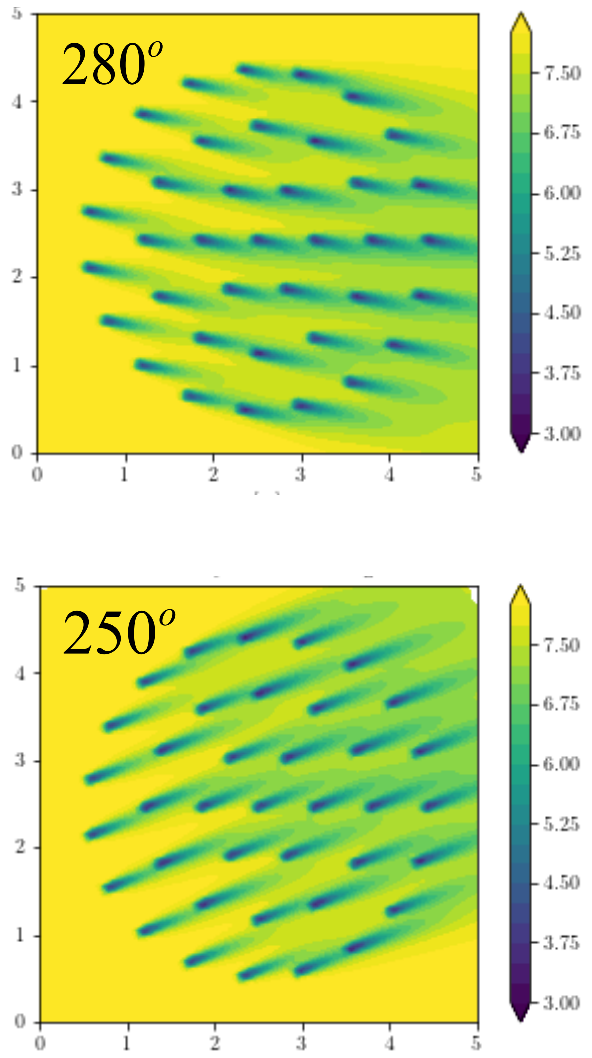
Results: Small angle changes (edge weights/delays)



[Starke et al (ACC 2021)]

Results: Large angle change





- Similar initial increase in power in LES with direction changes (Munters et al. 2016)
  - Further validation needed

[Starke et al (ACC 2021)]

Extending the graph model to turbine yawing

- 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]*

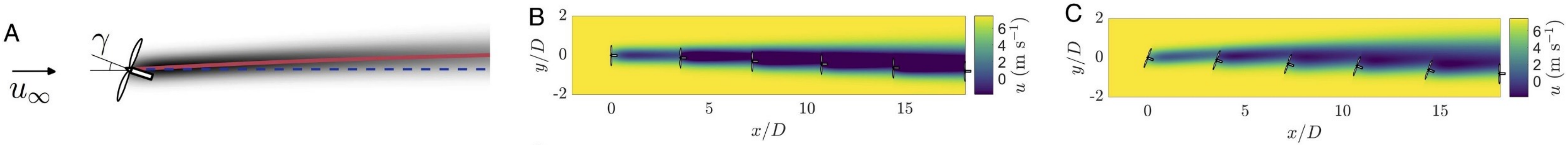
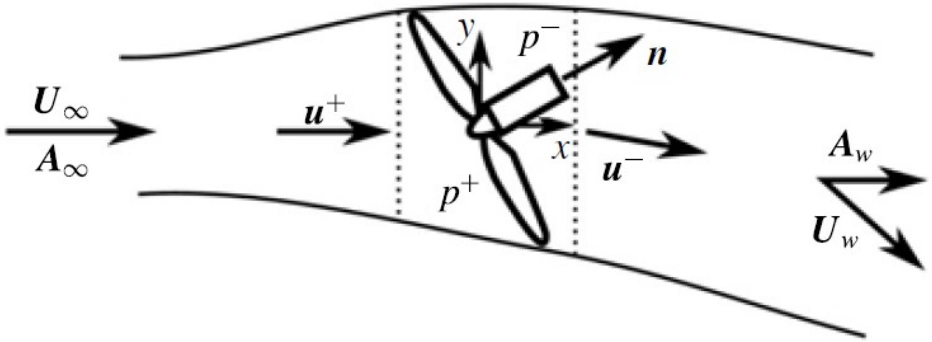


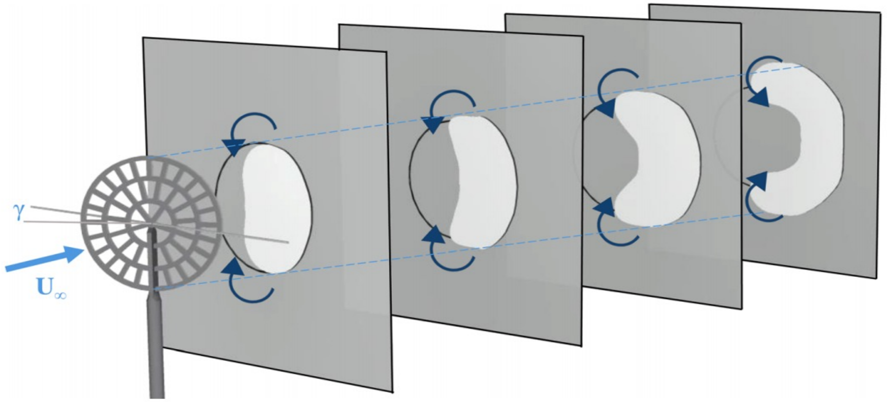
Figure adapted from Howland et al. 2019 demonstrating yaw optimization for power maximization

- Yawing leads deflection and curling of the wake

Wind turbine yaw

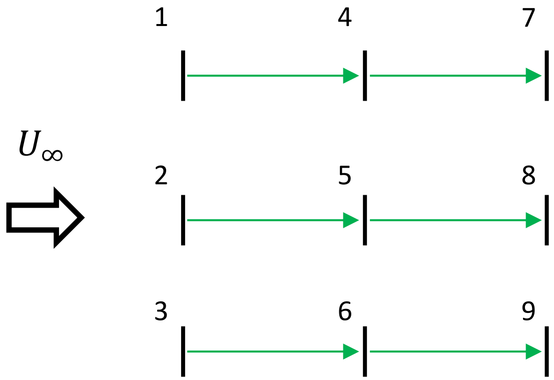


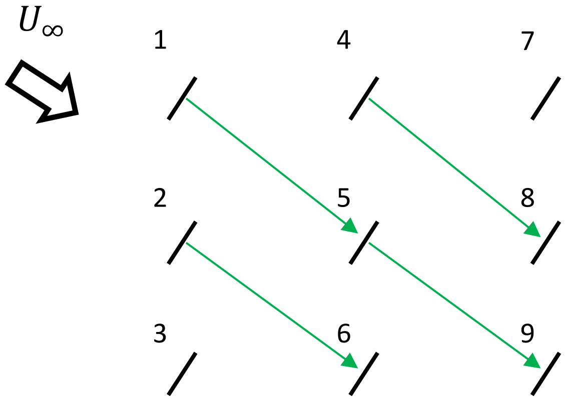
(c) Howland et al (2016)



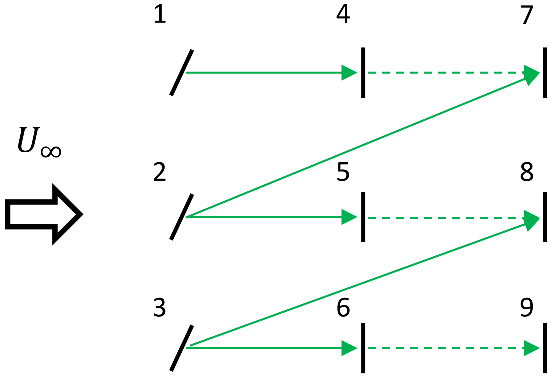
Incorporating wake shape changes due to yaw

- Deflection of the wake captured through changes to the wind graph





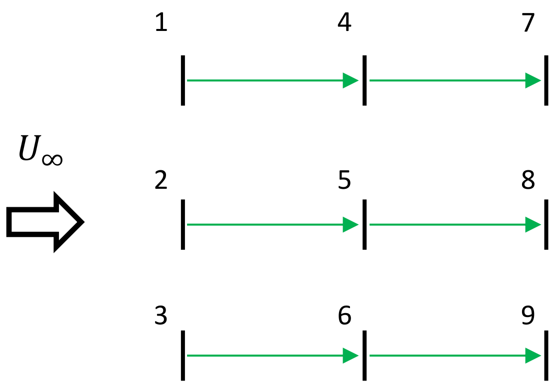
A wind direction change

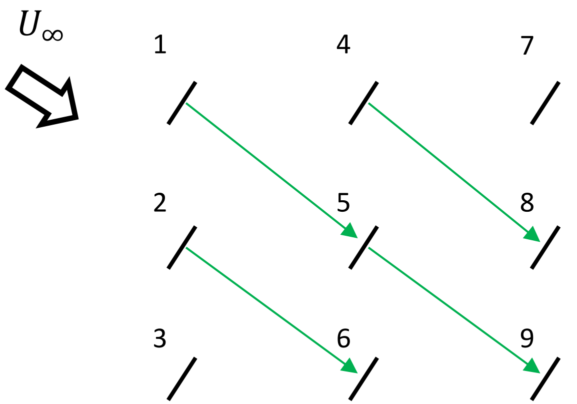


A dynamic yaw change

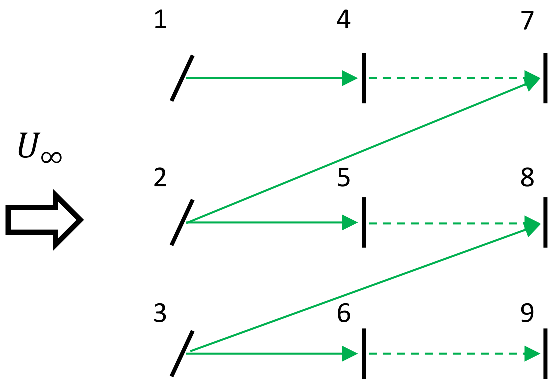
Incorporating wake shape changes due to yaw

- Deflection of the wake captured through changes to the wind graph





A wind direction change



A dynamic yaw change

- Changes in wake shape and propagation need to be accounted for

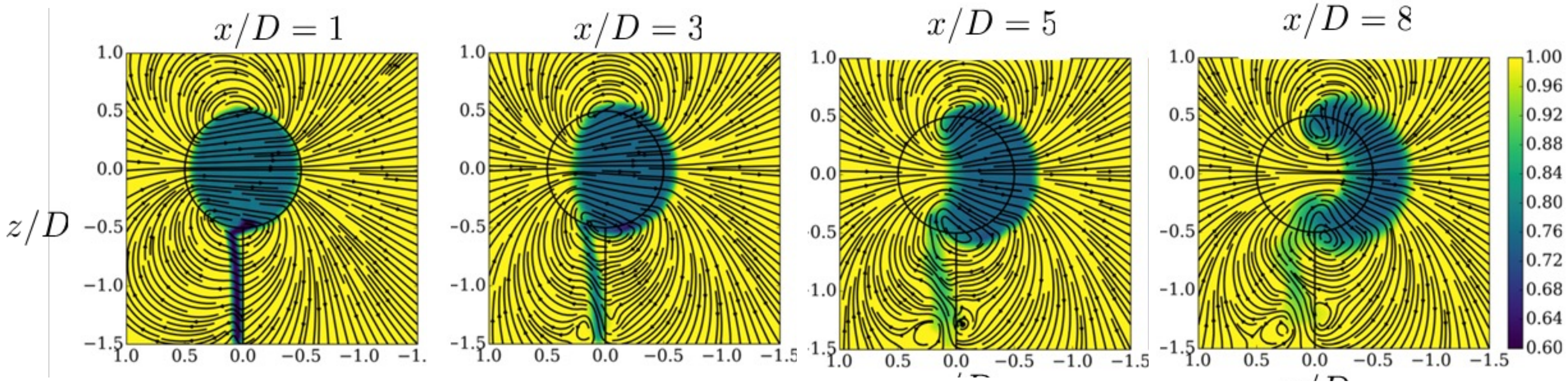


Figure adapted from Howland et al 2016

Velocity deficit model for yawing turbines

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

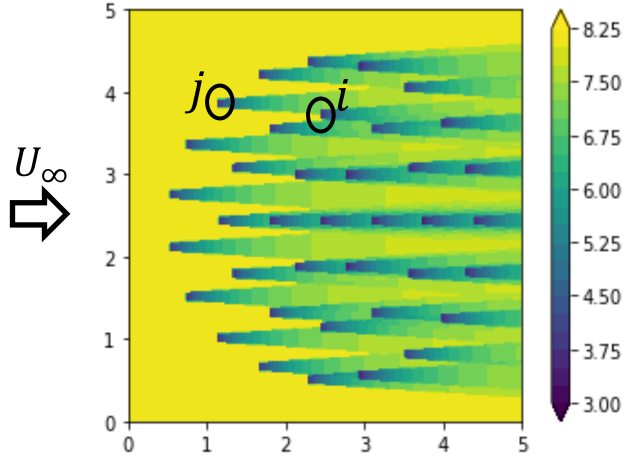
Elements: Normalized deficits at turbine i due to turbine j

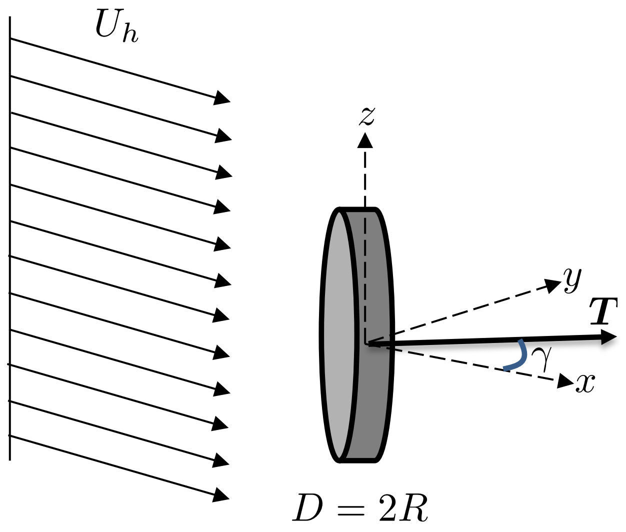
$$\phi_i^j = \frac{1}{Area_{j^{th}\,disk}} \int_{Area_{j^{th}\,disk}} \underbrace{C(\Delta x_{i,j}) \exp\left[-\frac{(y-y_c)^2 + (z-z_h)^2}{2\sigma(\Delta x_{i,j},\theta)^2} \right]}_{\text{Normalized Deficit } \delta u / U_h} dy\, dz$$

$$C(x) = 1 - \sqrt{1 - \frac{C_T \cos^3 \gamma}{2\tilde{\sigma}^2(x)/R^2}}$$

$$\sigma(x,\theta) = k\,x + 0.4\xi(x,\theta)$$

Captures changes in wake shape due to yawing

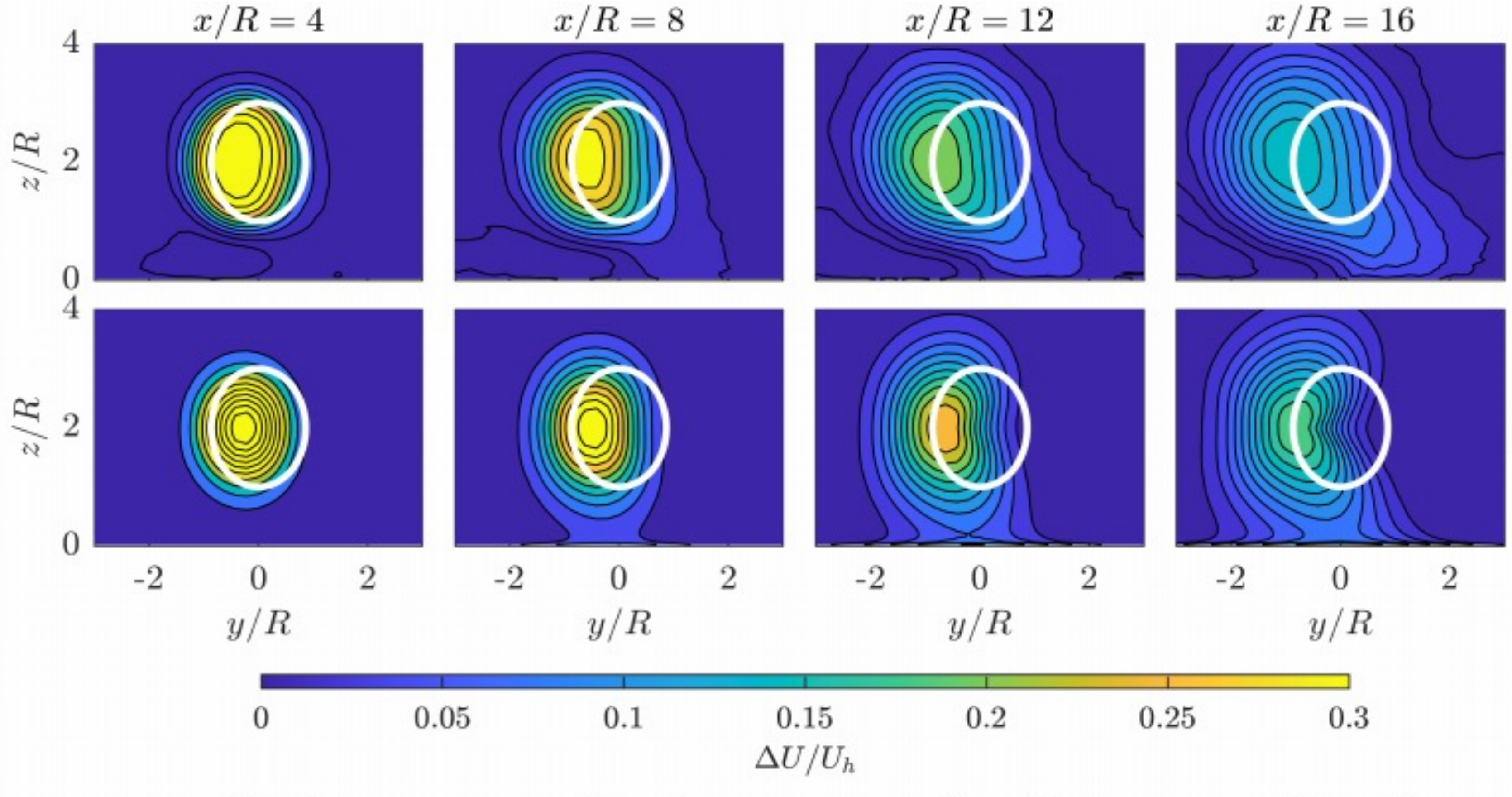




Analytical curled wake model evolution

$$\frac{\delta u}{U_h} = C(x)\exp\left[-\frac{(y-y_c)^2+(z-z_h)^2}{2\sigma(x,\theta)^2}\right] \qquad \sigma(x,\theta) = k\,x + 0.4\xi(x,\theta)$$

(yaw angle $\beta = 25°$)



LES

Analytical

Bastankhah et al. 2021

Yaw model validation: static case

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

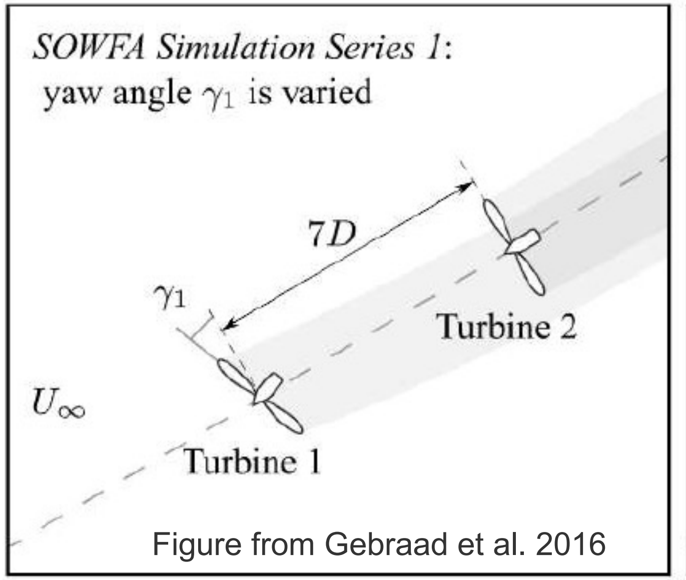
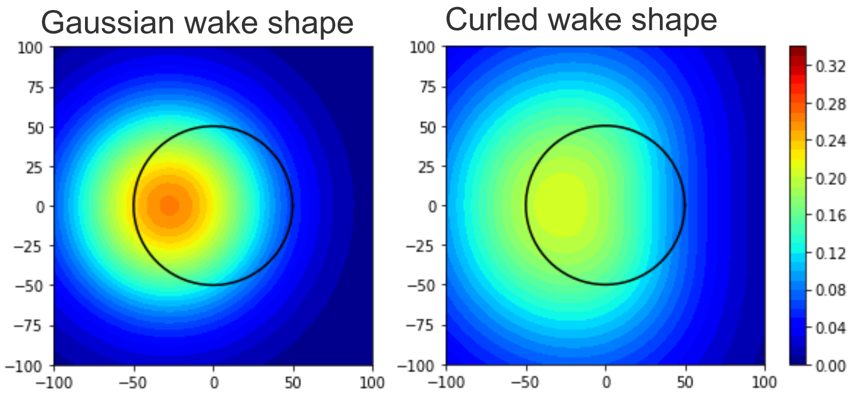
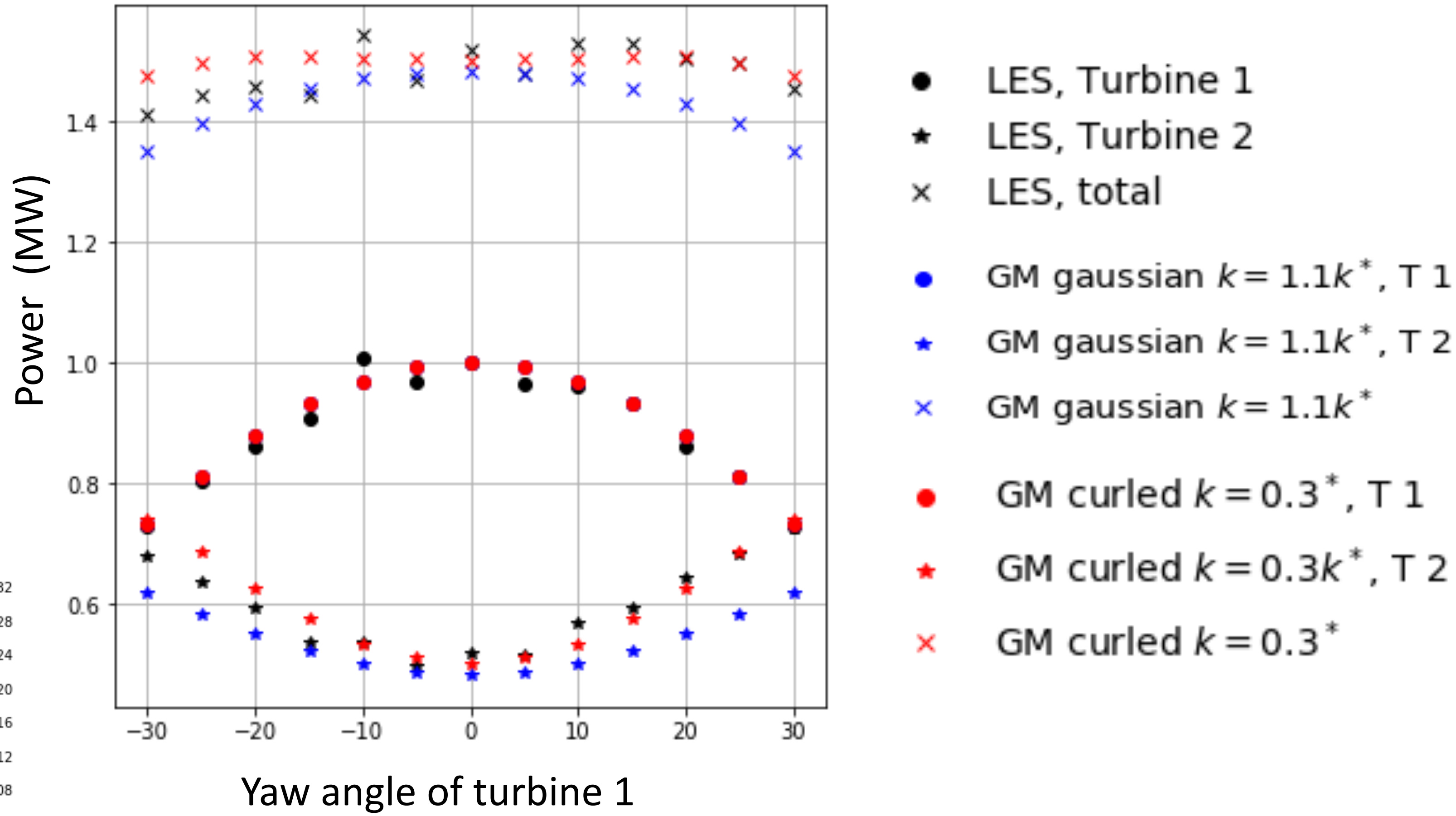


Figure from Gebraad et al. 2016

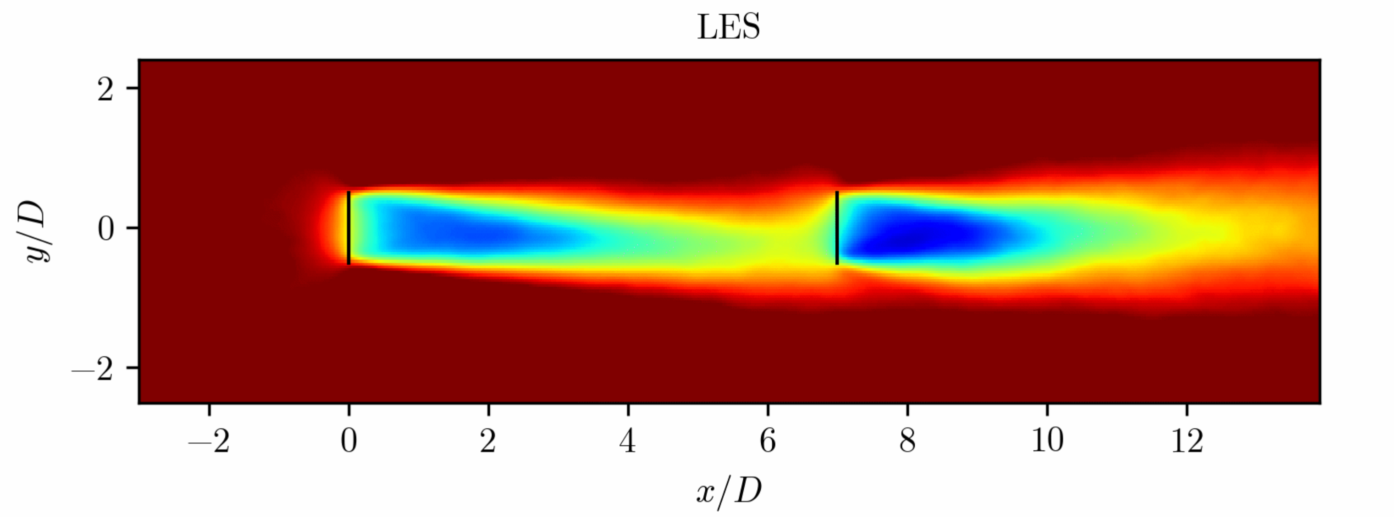




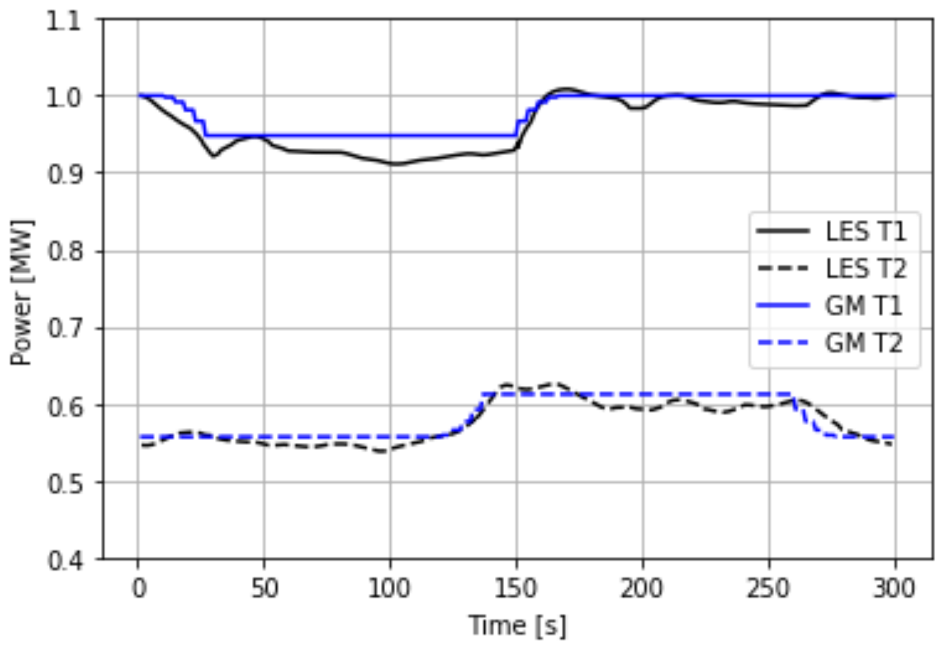
[Starke et al. Preprint]

Yaw model validation: dynamic case

- Dynamically yaw the first turbine 15 degrees at 150 s



JHU LESGO code phase-averaged over 120 realizations

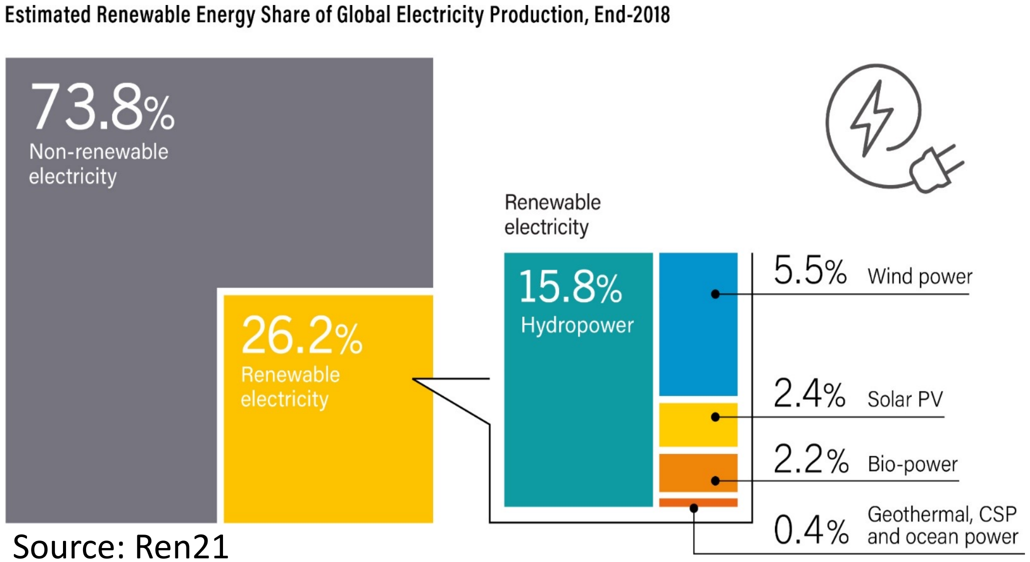


[Starke et al. Preprint]

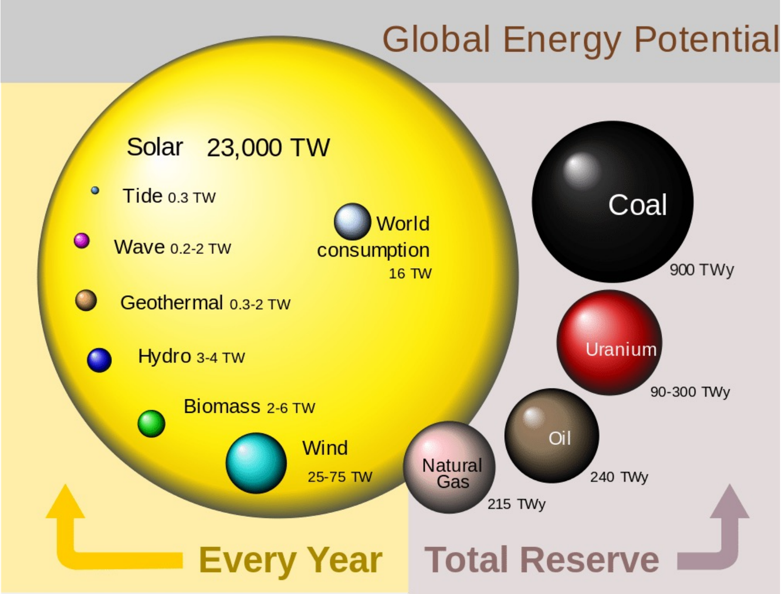
Summary

- Wide range of wake modeling approaches
  - Static models for layout optimization
  - Graph models that can account for wind direction changes and control actions

Most important question, how do we exploit these techniques to reach the full potential of wind energy

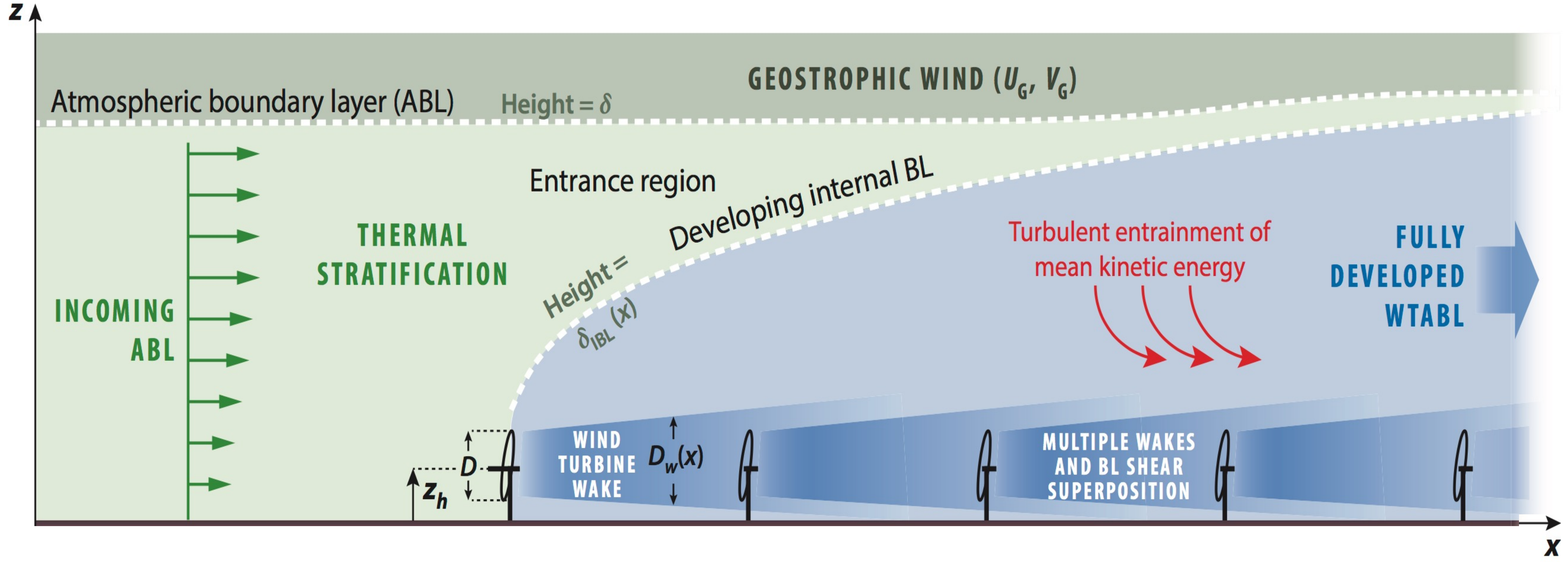


Source: Ren21



Things I did not have time to talk about

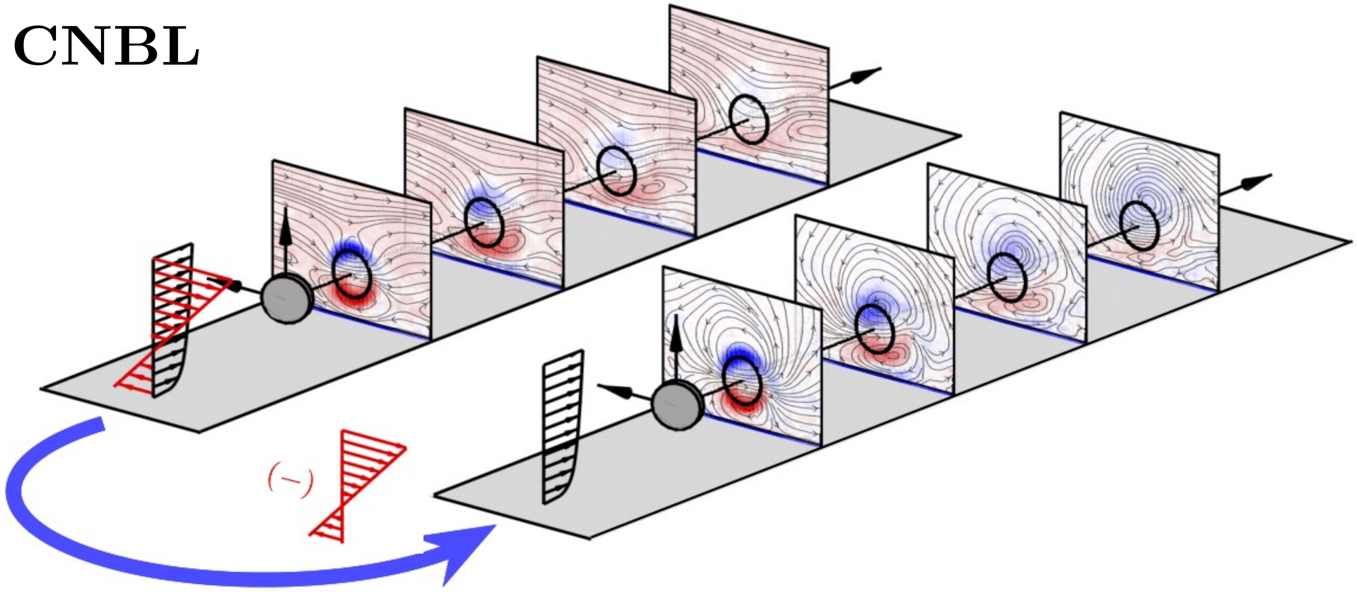
- Accounting for more realistic atmospheric conditions



From: R.J.A.M. Stevens & C.M., “Flow structure and turbulence in wind farms”, (2017), Annu. Rev. Fluid Mech. 49, 311-339.

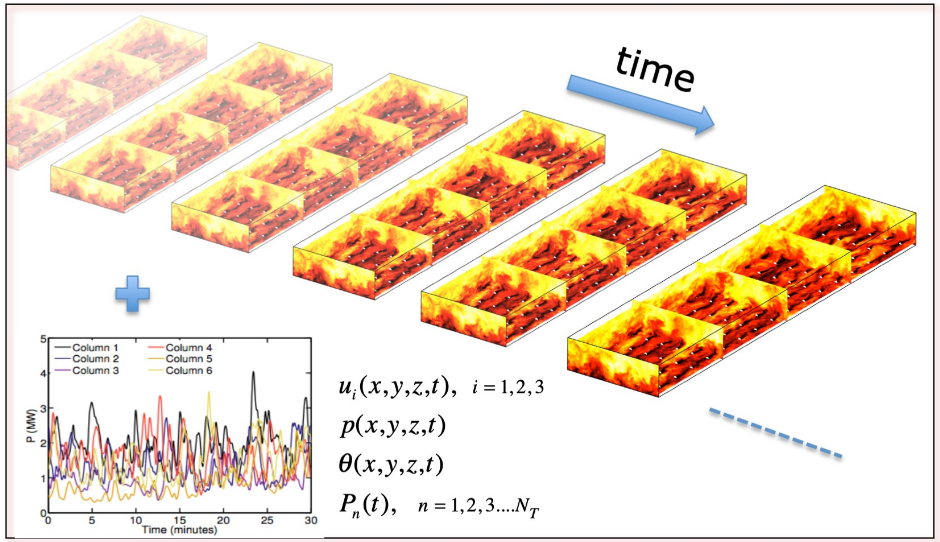
Things I did not have time to talk about

- Accounting for more realistic atmospheric conditions
  - Conventionally neutral (with veer) [Narasimhan et al. PRF 2022]
  - Stably stratified



Things I did not have time to talk about

- Accounting for more realistic atmospheric conditions
  - Conventionally neutral (with veer) [Narasimhan et al. PRF 2022]
  - Stably stratified
- LES model for flow over waves (Ayala)
- Farm level control (power tracking)
  - Using pitch and/or yaw actions
- Coming soon
  - Johns Hopkins Wind farm database



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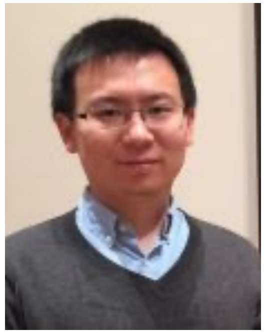

Special thanks to Charles Meneveau for publically sharing the JHU LES code

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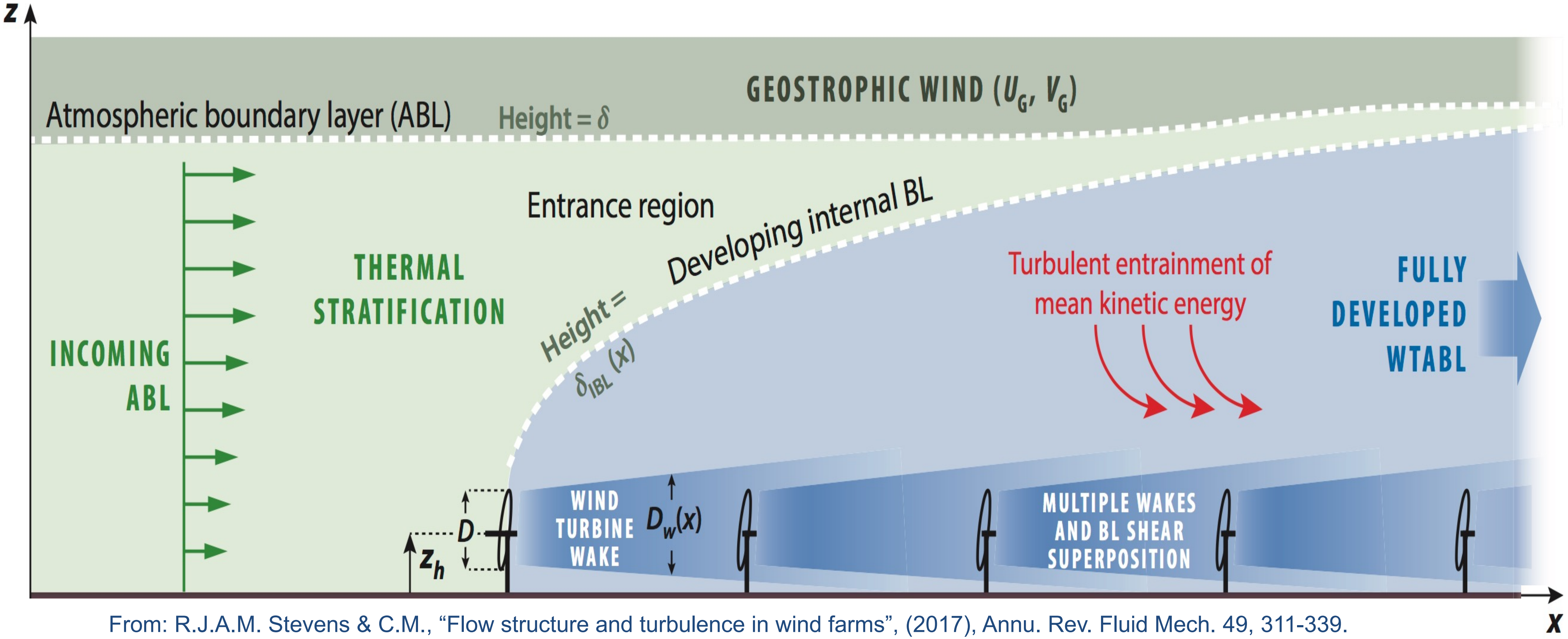
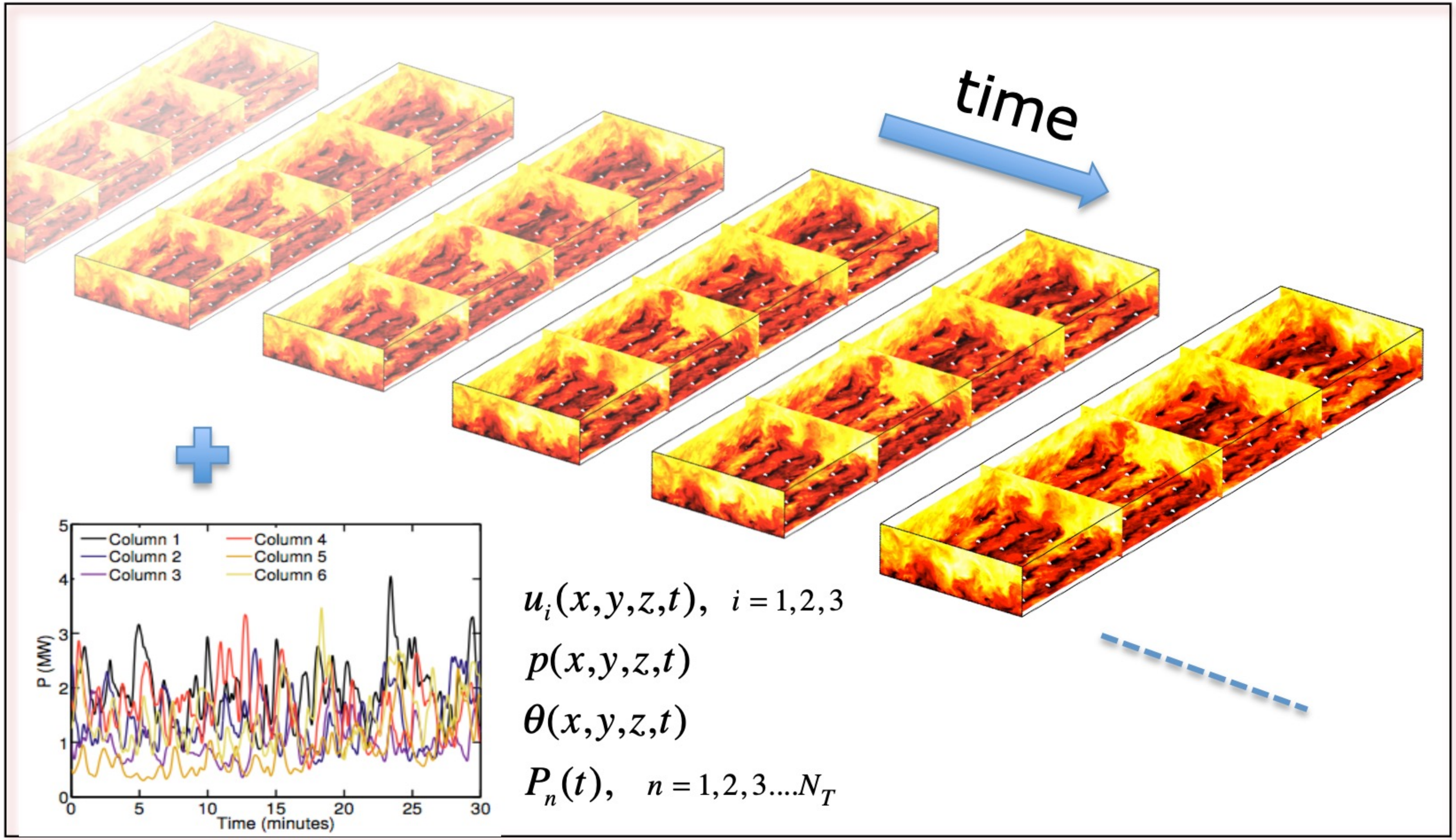
Wind turbine array interactions with the ABL



From: R.J.A.M. Stevens & C.M., “Flow structure and turbulence in wind farms”, (2017), Annu. Rev. Fluid Mech. 49, 311-339.

Wind Farm DB: wind farm turbulence data set



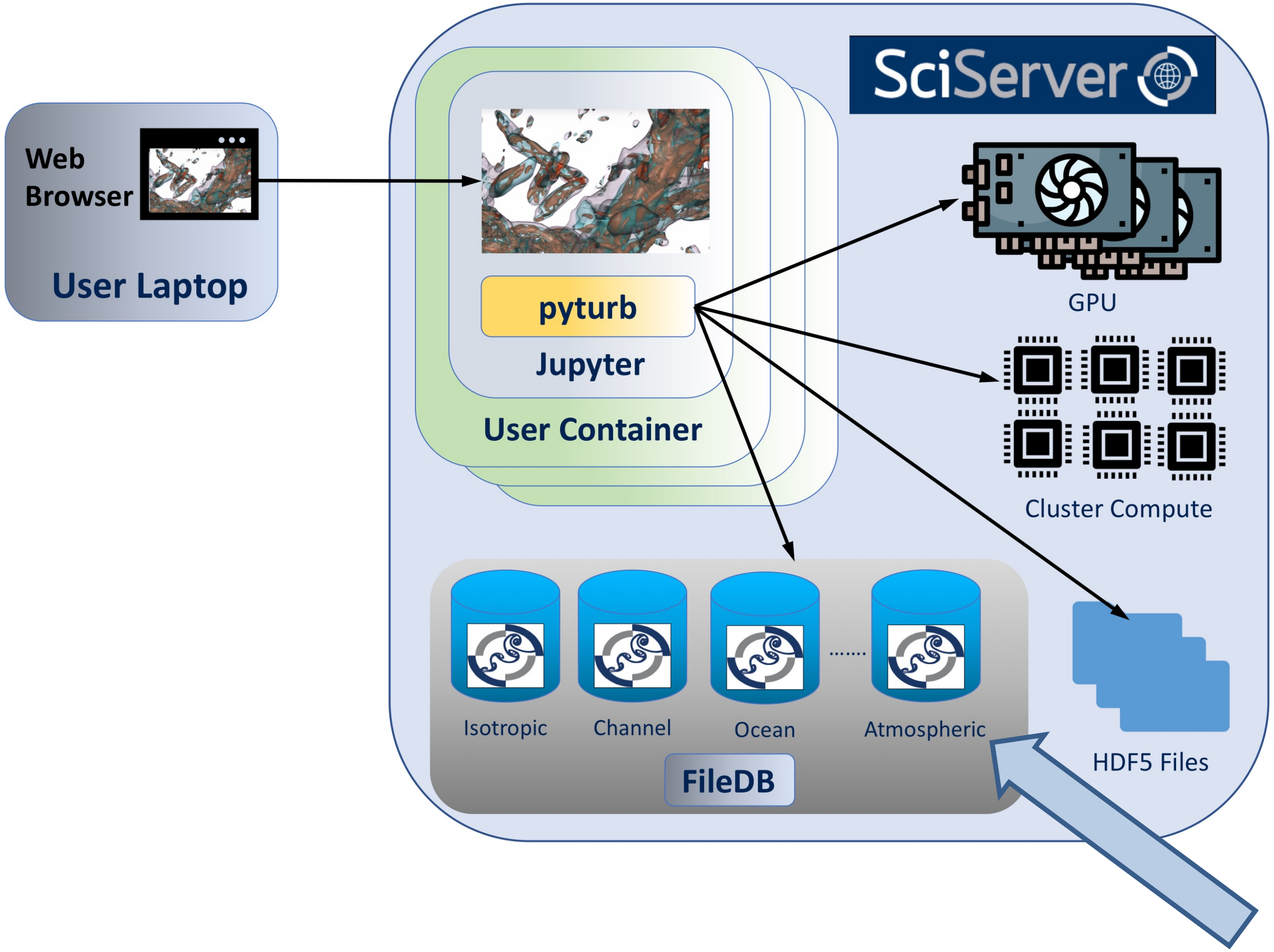
$u_i(x,y,z,t), \quad i=1,2,3$

$p(x,y,z,t)$

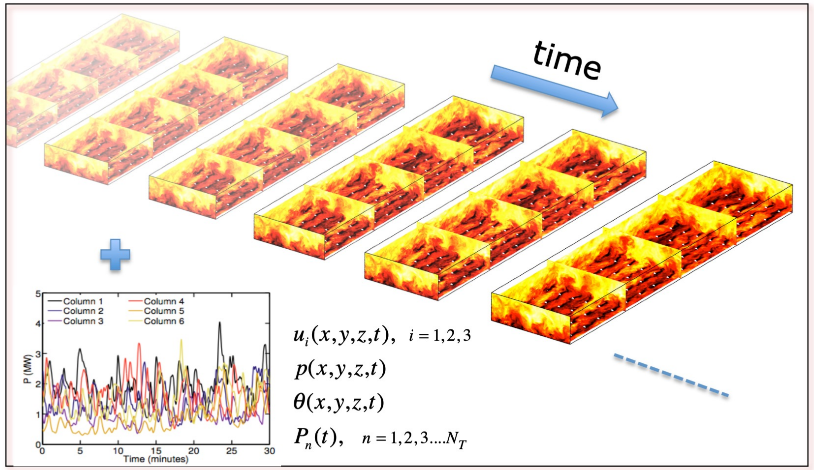
$\theta(x,y,z,t)$

$P_n(t), \quad n=1,2,3....N_T$

Wind Farm DB: wind farm turbulence data set

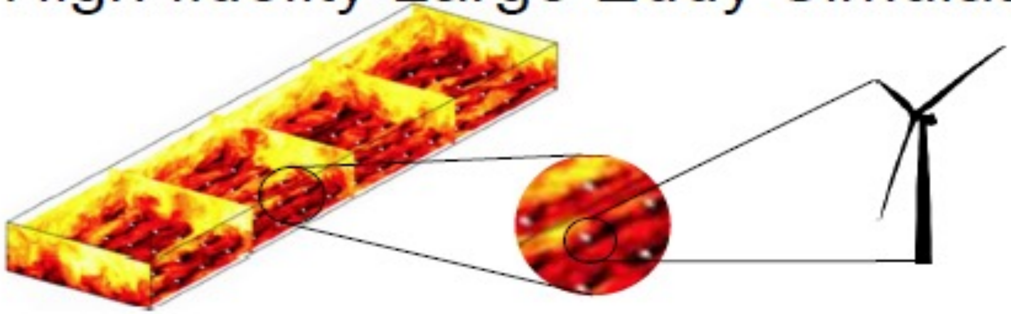


- Store full 4-D fluids data (velocity, pressure, temperature
- Store full actuator line information along each of the rotating blades (structural loading, power, etc).
- Rich metadata



Wind turbine blade representation for Wind Farm DB:

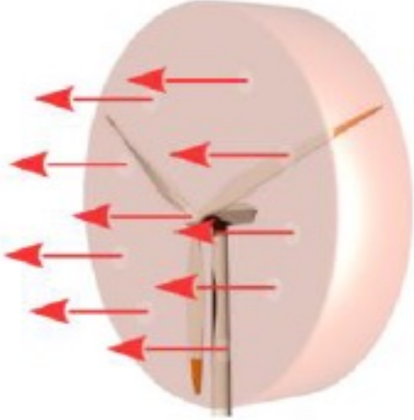
- High fidelity Large Eddy Simulations (LES) of wind farms



[1]Stevens, R.J., Graham, J. and Meneveau, C., (2014).

[2]Stevens, R.J., Gayme, D.F. and Meneveau, C., (2016).

- Modeling wind turbines
  - Actuator disk model (ADM)



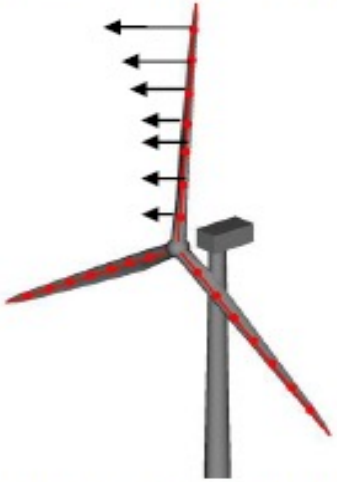
  - Power output & wake structure
  - Typically used for LES of wind farms

[3]Calaf M, Meneveau C, and Meyers J. (2010).

[4]Meyers J and Meneveau C. (2010).

[5]A. Jimenez, A. Crespo, E. Migoya, and J. Garcia.(2008)

- Actuator line model (ALM)



  - Provides more detailed forces
  - Requires finer grid resolutions

[5] Sorensen, J.N. and Shen, W.Z. (2002).

ADM Figure from [6] Hansen, Réthoré, Sorensen, Bechmann, Port-Agel et al.

ALM Figure from [7] M. Ravensbergen, A. Bayram Mohamed, A. Korobenko. (2020)

Cases and expected utility of Wind Farm DB:

- 2 turbine spacings, $s_x=x_y=5,8$ and aligned and staggered (4 cases)
- Stably stratified and convective cases
- Windfarm in a daily cycle
- Total of 140 Terabytes of data

- ROM testing on detailed data
- Calibration of empirical model constants
- Training data for machine learning
- Canonical reference cases for benchmarking

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