Turbulence, wakes and wind farm control

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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

- 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

\[
\frac{1400 \text{ m}}{10 \text{ m/s}} = 140 \text{ seconds}
\]

- 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
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)

“WindPark” by Philipp Hertzog is licensed under CC BY-SA 3.0
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

Grid: $128 \times 128 \times 128 \approx 2.1$ million grid points
Time: 1 hour at 0.1 second steps = 36000 time steps

• 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

Meneveau group simulation Visualization courtesy of D. Bock (Extended Services XSEDE)
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 each turbine $U_{turb} = \langle U \rangle_T(x_T, y_T, z_h)$
  - Associated forces/moments
  - Power output

$$P_{turb} = \frac{1}{2} C_p \rho \frac{\pi}{4} D^2 U_{turb}^3$$
Design oriented wind farm models


• 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
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

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

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

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

Power in the wind
$$P = \frac{1}{2} C_p \rho \frac{\pi}{4} D^2 U_{turb}^3$$
Modeling wake behavior: Jensen model

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

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

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

  Wake deficit function

$U_{\infty}$

$u_{\infty}(1 - a)$

$U_{\infty}(1 - 2a)$

$x = x_j$
Jensen model wake interactions

- Calculate velocity deficit of each turbine $\delta u_j$ using $U_\infty$
- Superpose kinetic energy deficits (idea Lissaman 1979)

$$k.e. \text{ deficit in farm} = \text{sum of } k.e. \text{ deficit of isolated wakes}$$

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

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 $\delta u_j$ using $u_d$ e.g., Zong and Porté Agel 2020

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

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

\[
U(z) = \langle \bar{u}(x,y,z) \rangle_{xy}
\]

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

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

2 log layers in wind farm ABL
Calaf et al 2010
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

\[ u(x,t) = U_\infty(x,t) - \sum_n \delta u_n(x,t)W_n(x) \]

**Wake shape function**

![Diagram of wake growth and shape](image)
ALC wake model parameter

- Fully specified wake model except for the parameter $\alpha$

[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;
  \[
  \frac{\partial \langle \vec{u} \rangle}{\partial z} = \frac{1}{\kappa u_* z_h + \nu_w} u_*^2
  \]
  - turbine effects incorporated through an added eddy viscosity \( \nu_w \)

Planar average momentum balance \[ u_{*,hi}^2 = u_{*,lo}^2 + \frac{1}{2} C_{fi} \bar{u}_h^2 \]

\( C_{fi} \) : planform thrust coefficient
ALC model: defining local turbine areas

- Define area associated with each turbine using Voronoi tessellation

Friction velocity for cell n

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

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

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

- Top-down model planar-averaged hub-height velocity in each cell
  \[
  \bar{u}_{h,n} = \frac{u_{*,hi,n}}{K} \ln \left( \frac{z_h}{z_{0,hi,n}} \left[ 1 + \frac{R}{z_h} \right]^{\frac{v_{w*}}{(1 + v_{w*})}} \right)
  \]
  \[v_{w*} \approx 28 \sqrt{\frac{1}{2} c_{fT}}\]  Added eddy viscosity due to turbines

- Average of the wake model velocity field in each cell \(\bar{u}_{n}^{wm}\)
  \[
  k_{w,n} = \frac{\alpha}{2} \left( \frac{u_{*,lo} + u_{*,hi}}{\bar{u}_h} \right)_{n}
  \]
  \[
  P_{n} = \frac{1}{2} \rho \pi R_{T}^2 C_T \bar{u}_{d,n}^3
  \]

Planform thrust coefficient in each cell (determines velocity)
Validation: circular wind farm

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

NREL 5 MW Reference Turbine:
- Diameter: $D = 126 \text{ m}$
- Hub Height: $z_h = 90 \text{ m}$

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

[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

**Turbine power comparison**

**LES very well converged**
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

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

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

\[ G(\mathcal{N}, \mathcal{E}) \]

\( \mathcal{N} \): 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

\[ \mathcal{G} \left( \mathcal{N}, \mathcal{E} \right) \]

- \( \mathcal{N} \): Nodes (turbines)
- \( \mathcal{E} \): Edges (wake interactions)

\[ \mathcal{G} \left( \mathcal{N}, \mathcal{E} \right) = \left\{ g_1, g_2, \cdots, g_m \right\} \]

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

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

- state vector of deficits between each turbine pair

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

Normalized deficits at turbine \( i \) due to turbine \( j \)
Building the dynamic graph model

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

\[ \Phi_k = \begin{bmatrix} \phi_1^1 & \phi_1^2 & \phi_1^3 & \ldots & \phi_1^N \\ \phi_2^1 & \phi_2^2 & \phi_2^3 & \ldots & \phi_2^N \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \phi_k^1 & \phi_k^2 & \phi_k^3 & \ldots & \phi_k^N \end{bmatrix}_{N^2} \]

\[ \Phi_k \in \sim N^2 \]

has elements

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

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

\[ U_{\infty} \]

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

\[ k_w \]

\[ j \]

\[ i \]

\[ W(x - xj, rj) \]: super Gaussian wake function
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 \( i \)

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

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

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

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

- 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

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

- Event driven input \( E_k (\Phi_{e,k}, \tau_{e,k}, \Delta E_{e,k}) \)
State update map

\[ \Phi_{k+1} = \Phi_k + E_k \]

- state vector comprised of deficits between each turbine pair

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

- Event driven input \( E_k (\Phi_{e,k}, \tau_{e,k}, \Delta E_{e,k}) \)

- 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 \( (\Delta E_{e,i}) \)
System of equations: Output

\[ \Phi_{k+1} = A\Phi_k + E_k \]

System output

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

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

\[ \tau_{k,(i)}^j = \frac{D\Delta d_i^j}{u_j} \]: 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

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

\[ \Lambda(\tau_k) : \text{delay dependent weighted adjacency matrix} \]

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

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

\[ P_k = \frac{1}{2} \rho \left(\frac{1}{4} \pi D^2\right) U_{d,k+1}^3 C_P' \]
Validation: Circular wind farm

- 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

NREL 5 MW Reference Turbine:
- Diameter: \( D = 126 \, \text{m} \)
- Hub Height: \( z_h = 90 \, \text{m} \)

Flow Conditions:
- Lower roughness: \( z_0 = 0.15 \)
- Inversion layer height: \( \delta_{max} = 750 \, \text{m} \)

- 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

- $280^\circ$ wind direction to $270^\circ$ wind direction
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
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]

- Yawing leads deflection and curling of the wake

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

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

\[
\begin{align*}
U_\infty & \\
1 & \rightarrow & 4 & \rightarrow & 7 \\
2 & \rightarrow & 5 & \rightarrow & 8 \\
3 & \rightarrow & 6 & \rightarrow & 9
\end{align*}
\]

\[
\begin{align*}
1 & \rightarrow & 4 & \rightarrow & 7 \\
2 & \rightarrow & 5 & \rightarrow & 8 \\
3 & \rightarrow & 6 & \rightarrow & 9
\end{align*}
\]

A wind direction change

\[
\begin{align*}
1 & \rightarrow & 4 & \rightarrow & 7 \\
2 & \rightarrow & 5 & \rightarrow & 8 \\
3 & \rightarrow & 6 & \rightarrow & 9
\end{align*}
\]

A dynamic yaw change
Incorporating wake shape changes due to yaw

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

![Wind direction change](image1)

![Dynamic yaw change](image2)

- 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 \( j \)

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

Captures changes in wake shape due to yawing

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

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

(yaw angle $\beta = 25^\circ$)

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 Gebraud et al. 2016

Gaussian wake shape

Curl wake shape

[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*

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**Estimated Renewable Energy Share of Global Electricity Production, End-2018**

- **73.8%** Non-renewable electricity
- **26.2%** Renewable electricity
  - 15.8% Hydropower
  - 5.5% Wind power
  - 2.4% Solar PV
  - 2.2% Bio-power
  - 0.4% Geothermal, CSP and ocean power

Source: Ren21

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Things I did not have time to talk about

• Accounting for more realistic atmospheric conditions

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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Wind turbine array interactions with the ABL

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

- Modeling wind turbines
  - Actuator disk model (ADM)
  - Power output & wake structure
  - Typically used for LES of wind farms

- Actuator line model (ALM)
  - Provides more detailed forces
  - Requires finer grid resolutions


ADM Figure from [6] Hansen, Réthoré, Sorensen, Bechmann, Port-Agel et al.
ALM Figure from [7] M. Ravensbergen, A. Bavram 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