Mesoscale modeling applied to wind energy offshore at DTU Wind Energy

Extremes
Tall profiles & Resources
wake investigations

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Outline

- Modeling for wind energy resource mapping
  - method
  - verification
  - coupling to micro-scale models
  - issues
- Long-term stability and wind profile from mesoscale models
- Wind variability occurs at variety of time scales
- Mesoscale modeling applied to extreme winds estimation
- Some comments on Wake measurements and Modelling offshore
- Other uses; final remarks
Typical downscaling steps

Global

Mesoscale modeling
KAMM, MM5, WRF, etc.

Regional

Microscale modeling
(WAsP, CFD, etc) or statistical technique

Local

WAsP: Wind Atlas Analysis and Application Program
http://www.wasp.dk
Dynamical downscaling for wind energy resource estimation

For estimating wind energy resources, mesoscale model simulations are:

- Not weather forecasting, spin-up may be an issue
- Not regional climate simulations, model drift may be an issue

For this application:

- We “trust” the large-scale reanalysis that drives the downscaling
- We need to resolve smaller scales not present in the reanalysis

Downscaling from large-scale to Mesoscale (statistical method)

wind classes from large pressure field
wind profiles atmos stab.
terrain elevation surface roughness

wind maps for each wind class
+ frequency distributions of wind classes

wind resource map

Simple/Fast/Cheap
Interpolation
Risø Wind Atlas

Complex/Slow/Expensive
Statistical-dynamical
Fully dynamical
Assumptions used in statistical downscaling

- Climate can be adequately represented by the combination of a finite number of weather “states”
- There is a one-to-one relationship between each of these states and the local wind conditions
WRF set up (dynamical runs)

• Technique based on Hahmann et al. (2010)*
• 15 km x 15 km; 5 km x 5 km grid spacing, WRF version 3.2.1;
• 5 years, 2006-2010
• 41 vertical levels with model top at 50 hPa; 12 within 1000 m of the surface; the first level ~14 meters AGL.

• Forcing:
  – USA NOAA (CFSR) reanalysis at 0.5° × 0.5° horizontal grid spacing
  – SST and sea-ice fractions come from the dataset of Reynolds et al. (2002) with 0.25° × 0.25° resolution, updated daily.

• 11-day long overlapping simulations (first day ignored) - nudging model solution towards reanalysis on large domain above boundary layer
Spin-up and resolution effects

Downscaling run 5 km horizontal resolution grid over Northern Europe

Time required to build up mesoscale structures: ~24 hours

This length depends on domain size, wind regime, topographic complexity and resolution of the reanalysis used.

Effective resolution ~7 x grid spacing, depends on model numerical algorithms
Mesoscale modeling for generating wind atlases: The South Baltic Wind Atlas

Mean Wind Speed: Jan 2006 - Dec 2010

Height: 100 meters

Mesoscale wind speed climatology
Sensitivity study – PBL scheme, October 2009

Table 2: Summary of PBL schemes used the model sensitivity study.

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Reference</th>
<th>Closure type</th>
<th>Surface scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>YSU</td>
<td>Hong et al. (2006)</td>
<td>1st order</td>
<td>M-O scheme</td>
</tr>
<tr>
<td>MYJ</td>
<td>Janjic (2001)</td>
<td>TKE 1.5 order</td>
<td>M-O scheme</td>
</tr>
<tr>
<td>QNSE</td>
<td>Sukoriansky et al. (2006)</td>
<td>TKE 1.5 order</td>
<td>QNSE</td>
</tr>
<tr>
<td>MYNN2</td>
<td>Nakanishi and Niino (2006)</td>
<td>TKE 1.5 order</td>
<td>MYNN</td>
</tr>
<tr>
<td>MYNN3</td>
<td>Nakanishi and Niino (2006)</td>
<td>TKE 2.5 order</td>
<td>MYNN</td>
</tr>
<tr>
<td>BouLac</td>
<td>Bougeault and Lacarrère (1989)</td>
<td>TKE 1.5 order</td>
<td>M-O scheme</td>
</tr>
</tbody>
</table>
Offshore masts

FINO1

FINO2

Høvsøre

NORSEWIND
Validation of downscaling wind profiles, October 2009

6 boundary layer schemes
Same model setup
Diagnosis of the wind shear

Høvsøre test center, Denmark

The parameter $\alpha$ is often used to diagnose the shape of the wind profile. It comes from the expression

$$\frac{u(z_1)}{u(z_2)} = \left(\frac{z_1}{z_2}\right)^\alpha$$

where $u(z_1)$ and $u(z_2)$ are the wind speeds at heights $z_1$ and $z_2$, respectively. $\alpha$ varies with height, surface roughness length, and atmospheric stability. Using similarity theory, for neutral conditions, surface roughness length of 5 cm, and $z_1=10$ and $z_2=60$ m, $\alpha=0.162$. Smaller (larger) values represent unstable (stable) atmospheric BL conditions.
Wind profiles grouped according to observed stability at Høvsøre, Denmark, October 2009

Stability classes according to the observed Obukhov length $L$ (Gryning et al. 2007)

<table>
<thead>
<tr>
<th>Monin-Obukhov Length</th>
<th>stability class</th>
</tr>
</thead>
<tbody>
<tr>
<td>-500 &lt; $L$ &lt; -50</td>
<td>unstable</td>
</tr>
<tr>
<td>$L &lt; -500; L &gt; 500$</td>
<td>neutral</td>
</tr>
<tr>
<td>200 &lt; $L$ &lt; 500</td>
<td>near-stable</td>
</tr>
<tr>
<td>50 &lt; $L$ &lt; 200</td>
<td>stable</td>
</tr>
<tr>
<td>10 &lt; $L$ &lt; 50</td>
<td>very stable</td>
</tr>
</tbody>
</table>

Draxl et al (2011) submitted to Wind Energy
Choice of parameterizations is important

\[ \frac{u_1}{u_2} = \left( \frac{z_1}{z_2} \right)^{\alpha} \]; shear exponent; 10-60 m
Verification at Høvsøre

\[ U = 9.46 \text{ m s}^{-1} \]
\[ A_w = 10.11 \text{ m s}^{-1} \]
\[ k_w = 2.18 \]
\[ U_d = 8.95 \text{ m s}^{-1} \]
\[ (P/A)_w = 773 \text{ W m}^{-2} \]
\[ (P/A)_d = 802 \text{ W m}^{-2} \]

\[ U = 9.22 \text{ m s}^{-1} \]
\[ A_w = 9.75 \text{ m s}^{-1} \]
\[ k_w = 2.41 \]
\[ U_d = 8.71 \text{ m s}^{-1} \]
\[ (P/A)_w = 643 \text{ W m}^{-2} \]
\[ (P/A)_d = 701 \text{ W m}^{-2} \]
Based on these (and other) statistics – choose MYJ PBL scheme
Tall measurements at Høvsøre and Verification WRF (weibull k profile)

WRF model under predicts the shape parameter parameter.

New parametrization for the shape parameter in the Weibull distribution
New model of $k$ to in Wasp 11
Measurements on Wind veer

Based on one year of measurements at Høvsøre within the sea sector (200 to 340 degrees and a wind speed higher than 4 m/s)

- **Lidar measurements**
- **Mast measurements**
- **WRF modelling**
However, simulations can also be sensitive to the choice of boundary conditions.

Mean sea surface temperature: October 2009

SST, 0.25°

SST, 1/12°

SST diff
Determination of long-term stability by mesoscale model data

• For most applications, estimates of wind and wind shear at 100 m are required. At this level the effect of atmospheric stability is important.

• Most offshore measurement sites (e.g., Lidar) do not have means to estimate stability.

• Long-term stability is required for:
  – input to micro-scale models (e.g., WAsP)
  – “Lift” satellite-derived wind measurements (QuikSCAT, SAR) to hub height.

• It could be possible to use mesoscale models output (like WRF) to derive stability.

Long-term stability at M2: Kelly and Gryning (2010)

\[
P = n \pm \frac{C_{\pm}}{\sigma_{\pm}} \exp \left[ - \left( \frac{C_{+} |1/L| / \sigma_{+}}{\sigma_{+}} \right)^{2/3} \right]
\]

\[
\sigma_{\pm} = \frac{g}{\langle T \rangle} \left( \frac{\langle w' \theta'_{v} \rangle - \langle w' \theta'_{v} \rangle_{\pm}}{\langle u_{3}^{2} \rangle} \right)^{1/2}
\]

Theoretical formulation of the distribution of atmospheric stability (1/L) at Horns Rev M2.

Long-term stability correction

\[ \langle \frac{\kappa u(z)}{u_*} \rangle = \ln \left( \frac{z}{z_o} \right) \langle \psi_m(z/L) \rangle \text{ where } \langle \psi_m(z/L) \rangle \neq \psi_m(z/\langle L \rangle) \]

\[ \langle \psi_m(z/L) \rangle = -n_+ \frac{3\sigma_+}{C_+} b' z + n_- f_-(\sigma_-, C_-, \beta, z) \]

Parameters that can be derived from WRF simulation

Peña and Hahmann (2011)
Wind Energy
Severe wind variability - time scales and definitions

- Abrupt changes in statistical properties of the time series
- Need an objective way to describe hour-scale wind fluctuations

*Thanks to Dong Energy and Vattenfall for the observations
Satellite, SAR and time series observations

Open cellular Convection

Cell centre

Cell wall

Cell diameter ~10–80 km
Open cellular convection in WRF

WRF simulation hour 24 for domain 4

Output from model simulations can be used to generate a “variability” atlas of the North Sea.

Vincent, Hahmann and Kelly, 2011: Idealized Mesoscale Model Simulations of Open Cellular Convection Over the Sea, Boundary Layer Meteorology, online

Vincent et al (2011)
Extreme winds

The spectral correction method

- To prepare long term time series from modelling
- To examine the spectral behavior of the time series
- To apply the spectral correction
- To obtain the corrected extreme wind estimation

\[ k_p = \sqrt{2 \ln \left( \frac{1}{2\pi} \sqrt{\frac{m_2}{m_0}} T_0 \right)} \]

and

\[ k_p = \frac{\overline{U} \max - \overline{U}}{\sigma} \]

\[ m_j = 2 \int_0^\infty \varphi(\omega) \omega^j S(\omega) d\omega \]

Larsén, Ott, Badger, Hahmann, Mann 2011: Recipes for correcting the impact of effective mesoscale resolution on the extreme wind estimation. Journal of Applied Meteorological Meteorology, Published online, DOI:10.1175/JAMC-D-11-090.1
Extreme winds

The selective dynamical downscaling method

- To identify the storms from a selected region from global data
- To model the storms through the years using high resolution mesoscale modeling, here we use WRF
- To apply the post-processing procedure to convert the mesoscale winds to a standard condition, which is prepared for data validation and the further microscale modeling
- To use WAsP Engineering or other microscale models to obtain the site-specific extreme winds

Fig.: Example of the U50 at standard conditions (z=10 m, z0=5 cm) over Denmark and surroundings

Higher uncertainty for offshore sites at least partly because of missing wave dynamics in the current WRF simulation.

Table: U50 at standard conditions, simulated and observed

<table>
<thead>
<tr>
<th>Stations</th>
<th>WRF</th>
<th>OBS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sprogø</td>
<td>24.2±4.4</td>
<td>23.9±2.0 *</td>
</tr>
<tr>
<td>Tystofte</td>
<td>25.0±5.4</td>
<td>25.7±2.9 *</td>
</tr>
<tr>
<td>Kegnæs</td>
<td>25.8±5.5</td>
<td>26.3±3.8 *</td>
</tr>
<tr>
<td>Jylæx</td>
<td>27.4±5.4</td>
<td>29.1±2.9 *</td>
</tr>
<tr>
<td>Risø</td>
<td>25.6±5.3</td>
<td>23.7±4.7</td>
</tr>
<tr>
<td>Høvsøre</td>
<td>29.7±5.8</td>
<td>29.8±9.4</td>
</tr>
<tr>
<td>Horns Rev</td>
<td>29.0±5.3</td>
<td>31.6±8.5</td>
</tr>
<tr>
<td>FINO</td>
<td>27.8±4.3</td>
<td>30.3±7.6</td>
</tr>
</tbody>
</table>

Main features of FUGA a Lin. Wake model

- Solves linearized RANS equations
- Closure: mixing length, $k-\varepsilon$ or 'simple' ($v_t = \kappa u_z$)
- Fast, mixed-spectral solver using pre-calculated look-up tables (LUTs)
- No computational grid, no numerical diffusion, no spurious mean pressure gradients
- Integration with WAsP: import of wind climate and turbine data.
- $10^6$ times faster than conventional CFD!

Validation

[Graph showing data points and a curve labeled 'FUGA']

GUI
Meandering of Wakes and the application to wake deficit

• In DWM meandering is modelled as if the wake was a passive scalar diffusing Mann turbulence. This approach will be tried, but we expect it to seriously slow down computation time.

• As an alternative we will try a simpler model and adjust it to the Mann turbulence model and/or to data (how?). The simple model follows a fluid particle backwards in time and from a rotor to see how many upwind rotors it has passed through. From this the accumulated velocity deficit can be estimated.

• The simple model is based on a Langevin equation. The model has two parameters: a turbulence velocity $\sigma_v$ and a Lagrangian time scale $T_L$.

• The slowest part of the meandering will only causes a general trend during 10 minutes. This part can be estimated from data...
Non-stationarity and trend

• Conventional wisdom says: Data from a 10 minute sampling period is representative for a stationary time series and average values define one single CFD flow case.

• Is it better to regard it as a non-stationary time series covering a range of CFD flow calculations?

• What is the typical 10 minutes drift of the wind direction?
Drift

- Definitions:
  - Wind direction: $\theta$
  - 10 minutes average of $\theta$: $\theta_a$
  - Drift of $\theta_a$ during 10 minutes:
    \[
    \Delta \theta_a = \theta_a(t+10\text{min}) - \theta_a(t)
    \]
  - Rms value of $\Delta \theta_a$: $\sigma_{\Delta \theta_a} = \sqrt{\langle (\Delta \theta_a)^2 \rangle}$

- $\sigma_{\Delta \theta_a}$ is a measure of the linear drift of the average wind direction during 10 minutes.

- $\sigma_{\Delta \theta_a}$ can be obtained from 10 minutes average wind vane data.

$\sigma_{\Delta \theta_a} = 4.7$ degrees
Effect of mean value drift (a sort of meandering)

Nysted  278°+/-2.5° bin
Spectra

Universal range

$\theta_a$ filter

$\sigma_{\Delta \theta a}$ filter

meandering

scrambling

eddy viscosity and RANS

Larsén, Vincent & Larsen 2011

Courtney & Troen 1990
The Egmond aan Zee wind farm
The result is 29.30MW, 29.56MW and 29.26MW for measurements, FUGA and DWM, respectively.

FULL SCALE VERIFICATION OF WIND FARM PRODUCTION PREDICTIONS

Summary of applications of mesoscale modeling activities

Meso-scale modeling offshore have proven to be very useful according the following list:

- Wind power resources and forecasting
  - power distribution modeling
  - combination of dynamical and statistical methods
  - Wind atlas applications (extremes, variability, correlations etc)
  - assimilation of wind farm data (nacelle winds and yaw angles)
  - Prediction of the meandering characteristic for wake deficit
    - used for optimizing windfarm layout
- Forecasting icing occurrence and ice amount on turbine blades in cold climate
- External design parameters for wind farm design (extremes, shear, veer not turbulence -sofar)
Dynamical downscaling applications

Average wind conditions

Spatial correlation and variability

Time series: diurnal, seasonal and interannual variability

Studies of other wind-related atmospheric conditions: icing, severe temporal variability, predictability, etc.