Estimation of annual energy production using dynamic wake meandering in combination with ambient CFD solutions

S. Hahn, E. Machefaux, Y. V. Hristov, M. Albano and R. Threadgill
Vestas Wind Systems A/S, Hedeager 42, 8200 Aarhus N, Denmark
E-mail: sehah@vestas.com

Abstract. In the present study, combination of the standalone dynamic wake meandering (DWM) model with Reynolds-averaged Navier–Stokes (RANS) CFD solutions for ambient ABL flows is introduced, and its predictive performance for annual energy production (AEP) is evaluated against Vestas’ SCADA data for six operating wind farms over semi-complex terrains under neutral conditions. The performances of conventional linear and quadratic wake superposition techniques are also compared, together with the in-house implementation of successive hierarchical merging approaches. As compared to our standard procedure based on the Jensen model in WindPRO, the overall results are promising, leading to a significant improvement in AEP accuracy for four of the six sites. While the conventional linear superposition shows the best performance for the improved four sites, the hierarchical square superposition shows the least deteriorated result for the other two sites.

1. Introduction
As investments on large-scale wind farms grow, precise estimation of annual energy production (AEP) is becoming increasingly important, especially during the planning phase of a project, in order to guarantee business case certainty. The challenge of AEP evaluation mainly originates from its multi-disciplinary nature, where prediction uncertainties from various elementary sources such as ambient ABLs, wakes, power curves and risk mitigation strategies are all blended together. Preliminary uncertainty analyses suggest that no single uncertainty source plays a dominant role but rather the most limiting factor varies case by case [1]. Therefore, integration of most advanced models for all individual elementary physics would be a key step towards improved AEP accuracy.

Vestas has devoted substantial efforts to ensure most up-to-date CFD capabilities, including high-fidelity simulation techniques as well as steady/unsteady Reynolds-averaged Navier–Stokes (RANS) models. In our standard micro-siting approach, AEP is estimated by combining a wind resource file (RSF) from RANS simulation with the Jensen model within the software WindPRO. The objective of the present study is to introduce the dynamic wake meandering (DWM) model to our process in order to account for wake physics of higher complexity at an affordable cost, and validate its predictive performance for AEP against Vestas’ SCADA data for various operating wind farms.
2. Methodology

2.1. Dynamic wake meandering

Based on the concept of scale separation and the passive-tracer assumption, the DWM wake model combines the conventional Ainslie-type eddy-viscosity model with large-scale unsteadiness by meandering of the wake trajectory, which is deduced from turbulence characteristics of the ambient ABL. Since the prototype was first proposed by Larsen et al. [2], DWM has been constantly extended for a wider range of application. In the present study for AEP estimation, we adopt the standalone version of DWM, where a lookup table about the mean wake-deficit profile is pre-calculated for a range of operating conditions [3, 4].

2.2. CFD solution for ambient flow

The CFD software employed in the present study is named “VestasFOAM”. It is composed of a chain of streamlined processes in which users can perform low- or high-fidelity CFD simulations simply by specifying several parameters in a couple of input OpenFOAM dictionary files. Main emphasis is put on full automation from pre- to post-processing in order to minimize any need for users’ intervention. Pre-processing includes basic sanity check and format conversion for input data, mesh generation and partitioning, whereas post-processing includes data generation for subsequent load calculations, figure plotting and report generation. Using VestasFOAM, Vestas currently provides six different levels of CFD support for our routine siting projects. For the most basic level-1 and 2 CFD supports, on which the present study is based, VestasFOAM solves the incompressible steady RANS equations under the isothermal condition, where turbulence closure is achieved by the $k-\epsilon$ model with the default model constants readjusted for atmospheric boundary layer (ABL) simulation [5] with the addition of the Durbin limiter [6]. This approach is the state-of-the-art industry standard for analysis of flow over complex terrain [7]. Meanwhile, for sites with considerable atmospheric or terrain complexity, higher-level CFD supports are provided using unsteady RANS (URANS), DES or LES technique with or without stability consideration. The highest-level support includes direct simulation of turbine wakes using the actuator line model (ALM).

2.3. Scaling of CFD solution

In siting applications, CFD and mast measurements work in a mutually complementary manner to offer the most reliable prediction of the entire wind field over a site of interest. By scaling the CFD solution with measured values at multiple discrete masts, one can minimize any potential uncertainties that can be caused by incomplete specification of simulation conditions such as inflow boundary condition.
Figure 3. Mean wind speeds at the hub height for six sites.

Figure 4. Error difference between WindPRO Jensen and DWM models $|e_J| - |e_D|$.

Normally the final velocity field is stored in the WAsP RSF format to estimate AEP using the software WindPRO, which requires spatial distribution of Weibull parameters and wind frequency, too. With measurements available at $N$ masts, our scaling and RSF generation procedure can be summarized as follows:

(i) A long-term correction (LTC) [8] is applied to the raw data from mast measurements using sectorwise linear regression against 14-year time series from WRF mesoscale simulation. The linear regression is based on 36 sectors and the resultant LTC time series are once again binned into 36 sectors to tabulate sectorwise Weibull scale and shape parameters $A_W, k_W$ and wind frequency $f$.

(ii) From the 3D RANS CFD solution, the flow field on the hub-height surface is extracted. The hub-height surface is constructed on $25\times25$ square grids for convenience of subsequent processing.

(iii) For each of the 36 sectors at each mast $i (1 \leq i \leq N)$, the mean wind speed at the hub height $U_{M_i}$ is estimated by shearing the measured wind speed to the hub height using the standard power law
and the wind-shear exponent $\alpha_i$ calculated from CFD:

$$U_{M_i} = A_{W_i} \Gamma \left( 1 + \frac{1}{k_{W_i}} \right) \left( \frac{z_h}{z_{M_i}} \right)^{\alpha_i},$$

where $z_{M_i}$ and $z_h$ are measurement and hub heights, respectively. Note that several different approaches can be considered for the shearing process, depending on the choice for an LTC method (e.g. linear regression or matrix method) and the source for wind-shear exponent (e.g. from CFD, mesoscale simulation or from masts with multiple measurement heights). Our current choice provided the optimal AEP prediction in our earlier parametric study over thirty operating wind farms against Vestas’ SCADA data. The scaling factor at each mast $S_i$ is then calculated by:

$$S_i = U_{M_i}/U_{CFD_i},$$

where $U_{CFD_i}$ is the hub-height wind speed from CFD at the $i$-th mast location. (iv) Reconstruct the scaling factor on the entire hub-height surface $S(x, y)$ by inverse distance weighting (IDW) interpolation:

$$S(x, y) = \sum_{i=1}^{N} w_i(x, y) S_i,$$

$$w_i(x, y) = \frac{1/d_i(x, y)^p}{\sum_{j=1}^{N} 1/d_j(x, y)^p},$$

where $w_i(x, y)$ are the interpolation weights given by IDW, $d_i(x, y)$ is a distance function between $(x, y)$ and the $i$-th mast and $p$ is the IDW exponent. In the present study, a fixed value of $p = 2$ is used for all cases, but it is also possible to use this exponent as a free control parameter for case-dependent optimization. The final ambient velocity field $U(x, y)$ on the hub-height surface is then given by scaling with $S(x, y)$:

$$U(x, y) = U_{CFD}(x, y) S(x, y).$$

(v) The same IDW technique (3) is applied to reconstruct the Weibull shape parameter $k_W(x, y)$ and wind frequency $f(x, y)$, viz.

$$k_W(x, y) = \sum_{i=1}^{N} w_i(x, y) k_{W_i},$$

$$f(x, y) = \sum_{i=1}^{N} w_i(x, y) f_i.$$ 

On the other hand, instead of applying IDW, we evaluate the Weibull scale parameter $A_W(x, y)$ from the following Weibull relation in order to correctly preserve the scaled velocity field (4):

$$A_W(x, y) = \frac{U(x, y)}{\Gamma(1 + 1/k_W(x, y))}.$$ 

These variables are written to an RSF file for a given hub height with 25m×25m horizontal resolution.

In addition to the local wind speeds, local turbulence intensities and wind directions are also retrieved from the CFD solution in order to search the lookup table and propagate the wake deficit properly.
2.4. Wake calculation in non-uniform ambient flow field

In most wake models, calculation of the wake velocity field is derived on the assumption that the ambient wind speed $U$ is constant. With the nomenclature for wake coordinates shown in figure 1, the wake calculation is normally based on the dimensionless wake-deficit profile $F$:

$$\frac{U - u_w(x, y)}{U} = F(\xi, \eta),$$
$$u_w(x, y) = U - UF(\xi, \eta),$$

(8)

where $\xi \equiv l_i/R$ and $\eta \equiv r_i/R$ are dimensionless axial and radial coordinates in the wake from the $i$-th turbine, respectively. It is not straightforward how to generalize this conventional procedure for a spatially non-uniform ambient flow field $U(x, y)$ as is considered in the present study. We adopt one of the simplest extensions in this study:

$$u_w(x, y) = U(x, y) - U(x_i, y_i)F(\xi, \eta),$$

(9)

based on the intuition that the velocity recovery and deficit would be mainly characterized by wind speeds at the local observation and turbine locations, respectively.

2.5. Superposition of multiple wakes

One of the key sources of uncertainties in wake modelling comes from empirical superposition methods for multiple wakes, which lack the physical justification. As was investigated in depth by [9], the performances of the conventional linear and square superposition techniques are also compared in the present study. In addition to these conventional methods, an in-house implementation of successive hierarchical merging approaches is also examined, which is illustrated in figure 2. In this approach, the rotor wind speed is sequentially calculated from the most upstream turbines to the most downstream ones. For this purpose, a table of all-to-all containment relationship (top right of figure 2) is established first. In order to expedite the sequential wake calculation process, a tree structure (bottom right of figure 2) is then constructed from the all-to-all table. Note that, in contrast to the conventional tree data structure, this tree structure should allow duplicate entries (the turbine 6 in figure 2, for example). However, lateral wake coalescence cannot be handled by this sequential procedure and hence an empirical model is still needed. Therefore, two different types of hierarchical methods, with linear and square lateral superpositions, respectively, are also considered in the present study.

3. Results

Six operating wind farms over semi-complex terrains, which are subject to neutral stratification, are chosen from Vestas’ SCADA database for the present study, which are labelled from S1 to S6 hereinafter. For these six sites, the mean wind speed from mast measurements varies from 5.9 to 9.2 m/s, as is shown in figure 3. Figure 4 shows the error difference $|e_J| - |e_D|$ for all six sites, where $e_J$ and $e_D$ are the percentage errors with Jensen and standalone DWM models, respectively. Positive and negative $|e_J| - |e_D|$ indicate the improvement and degradation of the present DWM model as compared to the Jensen model, respectively. A promising enhancement is obtained for the sites S1–S4, whereas deterioration is observed for S5 and S6. It is also found that the conventional linear superposition shows the best performance for the improved four sites, whereas the hierarchical square superposition shows the least deteriorated result for S5 and S6. Figure 5 shows contours of the wind speed at the hub-height surface for S4 in the 300° sector with all four superposition techniques. This figure elaborates on figure 4 and visually illustrates how much the wake calculations are affected by superposition techniques. Although the dependence of superposition results on the wind-speed regime is not so clearly identified as in [9], the slower wake recovery with linear superposition is prominent in the central row of six turbines. In particular, lateral wake coalescence does not seem to be a dominant factor because lateral spacing between turbines is sufficiently large, which is also the case for the other five sites and explains why the two hierarchical superposition techniques make only a marginal difference for all considered cases.
Figure 5. Contours of the wind speed at the hub-height surface for S4 in the 300° sector with linear (top left), square (top right), hierarchical linear (bottom left) and square (bottom right) wake superpositions.

4. Summary and future plan

With the aim of enhancing the overall accuracy and performance of power prediction, a methodology of combining the standalone DWM model with RANS CFD solutions for ambient ABL flows was presented in the present study. The predictive performance of the proposed procedure was evaluated against Vestas' SCADA data for six operating wind farms over semi-complex terrains under neutral conditions, and four different wake superposition techniques were also compared. A promising improvement in AEP accuracy was observed for four of the six sites as compared to our standard procedure based on the Jensen model in WindPRO. While the conventional linear superposition showed the best performance for the improved four sites, the hierarchical square superposition showed the least deteriorated result for the other two sites. In general, performance of a wake model is affected by many different factors and thus the root cause for the deterioration of the DWM results for the two sites is rather unclear. Since the two sites without improvement have higher terrain complexity than the other four sites, one plausible hypothesis is that the performance of standalone DWM is more sensitive to terrain complexity or vertical variations of turbine locations because of the continuous wake-deficit profile from the Ainslie-type eddy viscosity model in contrast to a boxcar-type one from the Jensen model. From this scenario, a full three-dimensional extension which also takes the vertical dimension into account would
be a natural next step to further refine the predictive capability of the present method. Regarding the
wake superposition, it would be more reasonable to apply sectorwise different superposition techniques
depending on the wind regime for each sector. These two extensions are currently under development.
For statistically more meaningful conclusions, the present comparative study is also planned to be
extended to more wind farms in our SCADA production database. On the other hand, implementation
of the full DWM is also underway in addition to the standalone version considered in the present paper.
In combination with an aeroelastic solver, it will be applied to more refined load analyses with a higher
degree of accuracy.

References
[1] Istchenko R 2015 Re-examining uncertainty and bias Presented at AWEA Wind Resource & Project Energy Assessment Seminar 2015 www.awea.org
[2] Larsen G C, Madsen H A, Thomsen K and Larsen T J 2008 Wind Energy 11 377–395
[3] Keck R E 2015 Wind Energy 18 1579–1591
[4] Keck R E and Undheim O 2015 Wind Energy 18 1671–1682
[5] Richards P J and Hoxey R P 1993 Journal of Wind Engineering and Industrial Aerodynamics 46-47 145–153
[6] Durbin P A 1996 International Journal of Heat and Fluid Flow 17 89–90
[7] Sumner J and Masson C 2012 International Journal for Numerical Methods in Fluids 70 724–741
[8] Thøgersen M L, Motta M, Sørensen T and Nielsen P 2007 Measure-correlate-predict methods: case studies and software implementation http://www.emd.dk/files/windpro/Thoegersen_MCP_EWEC-2007.pdf
[9] Machefaux E, Larsen G C and Leon J P M 2015 Proceedings of Wake Conference 2015, June 09–11, 2015, Visby, Sweden (Journal of Physics: Conference Series vol 625)