BeFORECAST

Deliverable: Dynamic Fast Wake models

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1 Introduction

The current document describes the research efforts on fast dynamic wake models performed within the BeFORECAST project in the context of Task 4.1: "Development of fast dynamic wake models for wind turbines and wind farms".

Wake effects constitute the dominant power loss in large wind farms such as the Belgian offshore wind farm cluster. As such, quantifying these losses is an important aspect of both wind farm development and operations. A wide range of numerical wake models exist, ranging from low-fidelity fast engineering wake models (both physics-based and data-driven) to high-fidelity computational fluid dynamics models such as large-eddy simulations (which are typically to expensive to run for operational usage). In industry, wake effects are mostly quantified using steady-state fast engineering wake models. Although these models can reasonably predict wake losses on an annual basis, e.g. for planning purposes, their steady-state nature fails to capture any important dynamics which might occur during wind farm operations, e.g. due to a frontal passage, wind ramps, etc. Although a multitude of commercial and research software suites exist for steady modeling, dynamic solutions are much scarcer. For this reason, Task 4.1 has focused on the development and validation of fast-running dynamic wake models.

Due to new scientific and strategic insights, the focus of this task has shifted slightly since the inception of the project. More specifically, at the VKI side, instead of developing a new parabolized unsteady Reynolds-averaged Navier-Stokes model from scratch, focus was shifted towards a comparative study of an in-house dynamic low-fidelity model with an open-source mid-fidelity solution instead. At the KU Leuven side, this document mostly reports on fast-running coarse large-eddy simulations which are seen as a potential alternative for fast dynamic wake models. In particular, when considering the windfarm at a larger scale, additional effects such as wind-farm blockage are not trivially included in existing dynamic wake models, whereas such effects are in principle directly included in large-eddy simulations.

The remainder of this document is structured as follows. Section 2, 3, and 4 respectively describe research efforts on the VKI, KU Leuven, and VUB side. Finally, Section 5 provides a brief summary and conclusion of the manuscript.

2 VKI: Intercomparison of dynamic wake modeling frameworks for offshore wind farms

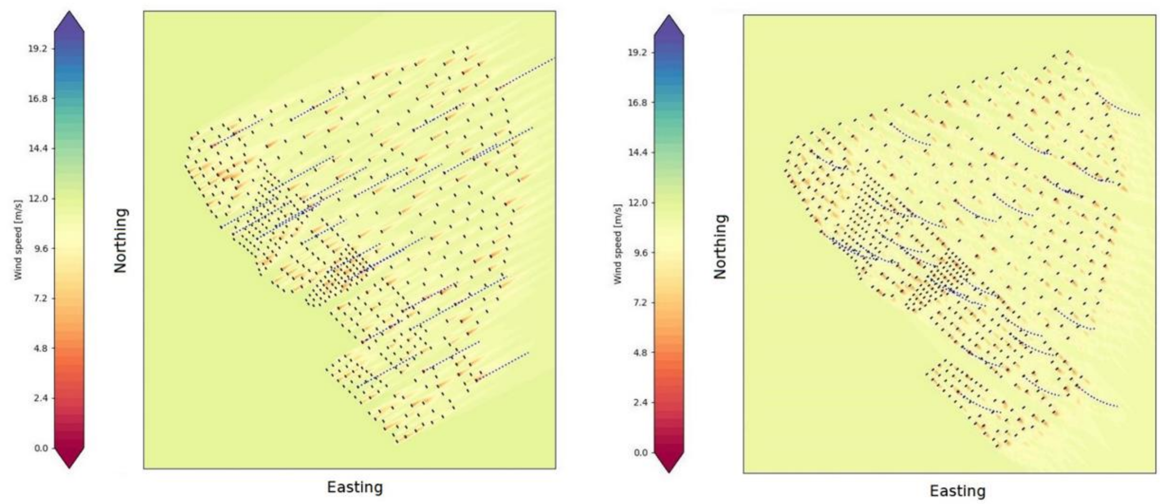
At the VKI, an intercomparison of dynamic wake modeling frameworks was performed in the context of the VKI internship of Domenico Ruotolo under supervision of prof. Sandra Pieraccini (Politecnico di Torino, IT) and dr. Simone Gremmo & dr. Wim Munters (VKI). Here below, an executive summary of this research is presented. The full thesis report is included as an Appendix to this report.

This study compares various wake simulation models of different fidelities, ranging from analytical steady to multi-body unsteady, to investigate how these models relate to each other and underlying physical phenomena. The study focuses on the low-fidelity wake modeling frameworks UFLORIS (developed at VKI) and FLORIDyn (developed at TU Delft), which are an extension of the steady wake framework FLORIS. The comparison also involves the medium-fidelity FAST.Farm framework which is a multi-physics engineering tool for modeling power performance and structural loads.

First, the intercomparison is carried out on a simplified wind turbine layout which consists of three turbines in a row with yaw control for the upstream turbine to assess the routine, accuracy, and flexibility of each model. Secondly, an analysis in detail of the unsteady VKI solver, UFLORIS, is carried out and some improvements are proposed. The effects of these changes are illustrated in a simple simulation, yet retaining all physics of interest. Finally, this solver is used to simulate a low-pressure system in the North Sea considering the full Belgian-Dutch offshore cluster.

The comparison between the low-fidelity unsteady solvers UFLORIS and FLORIDyn, both capable of simulating wake dynamics with low computational costs, reveals differences mainly related to the wake deficit models and the strategy used for the convection of wake tracking points in the wake field. UFLORIS benefits from improvements made in the steady solver's models due to its foundation on the open-source FLORIS source code; whereas FLORIDyn lacks the ability to account for secondary steering effects and yaw-added recovery, which could enhance result fidelity in misaligned turbine scenarios. Both unsteady solvers show good agreement with higher-fidelity FAST.Farm results, and discrepancies in power output could potentially be solved through parameter tuning, a task not addressed in this study. Furthermore, both UFLORIS and FLORIDyn exhibit errors in wake advection delay due to the convection velocity of wake tracking points in the flow field. While the VKI solver aligns closely with the higher-fidelity model, an optimal tracking point convection strategy remains undetermined. Nonetheless, both engineering models are of significant interest due to their low computational costs, despite simplifications in the problem's physics. The modifications applied to UFLORIS address issues such as incorrect calculation of the wake deficit and differences with FLORIS in the prediction of the wake centerline in steady conditions. These issues stem from ground effects in transversal wake velocities and incorrect interpolation of turbine settings convected by tracking points. In addition, the novel tracking point deletion strategy, based on the selection of the maximum number of tracking points in the chains, reduces CPU time without significantly compromising accuracy. Finally, simulating the low pressure event for the full Belgian-Dutch offshore cluster exposes a weakness in the UFLORIS framework. When dealing with a large number of turbines (hundreds), computational costs escalate significantly, especially in the "corrected" version of the solver. Implementing a different tracking point deletion strategy helps to reduce simulation CPU time, although not enough to make this engineering model viable for such applications. Despite computational costs and discrepancies between UFLORIS models and real data when turbine operational states are unknown, the overall power trend captures rapid wind condition changes effectively.

Here below, a sample result of the unsteady UFLORIS framework for the Belgian-Dutch offshore wind farm cluster is presented during the passage of a low-pressure system on 24 December 2020. Figure 1 illustrates 2 snapshots of the wake field during the event, indicating a shift in wind direction from the Southwest to Northwest direction. Figure 2 shows the timeseries of ambient wind speed and wind direction during the event, along with the simulated and observed (black) power production. It is shown that, although a significant offset between simulated and observed values exists, the model successfully captures the trend in power production. Further model improvements including, among other, a detailed state estimation of the spatial heterogeneity of the flow field, are expected to further improve these results. Furthermore, note that significant uncertainty remains in the operational state of the turbines, as we do not have insights into turbine controller dynamics. As such, the model predictions are to be interpreted as "potential power" that can be extracted by the turbines.



(a) Wake field at 01:00 on 24 December 2020 (b) Wake field at 02:50 on 24 December 2020

Figure 1: Wake field as simulated by UFLORIS for the low pressure event.

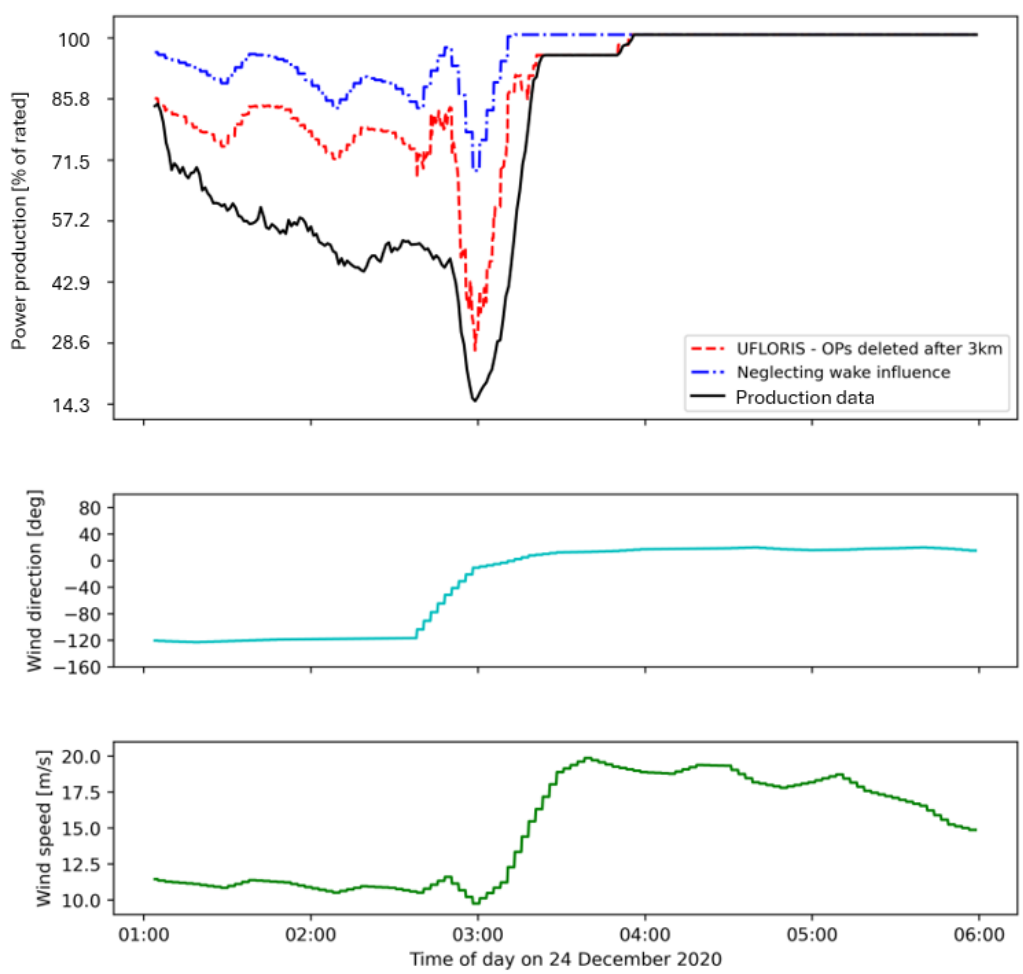


Figure 2: Power production (top), wind direction (middle), and ambient wind speed (bottom) during the low-pressure event on 24 December 2020. Power production data is non-dimensionalized for confidentiality of the production data.

3 KU Leuven: fast-running coarse-grid large-eddy simulations

With the insight that windfarms excite atmospheric meso-scales systems such as gravity waves and related blockage, the realization has grown that conventional wake models need to be augmented to include these additional effects. At KULeuven we have been working towards static models for resource assessment that combines a linearized gravity-wave feedback model with classical wake models (see the open-source software package WAYVE – https://gitlab.kuleuven.be/TFSO-software/wayve). To work towards future generation dynamic wake models, not only the wake description needs to be adapted (e.g. using approaches such as in the DMW model or FLORIDyn), but also the gravity-wave component needs to be adapted. Unfortunately, this is not straightforwardly possible in WAYVE, as the time-dependent gravity-wave equations are hyperbolic, requiring a significant rethinking of also the spatial discretization (e.g. using flux limiters or essentially non-oscillatory schemes). This added complexity poses a significant challenge to the development of fast and accurate dynamic engineering models for wind farms.

At KU Leuven, we have been recently exploring a different approach, that seems currently very promising. Rather than using dynamic 'heuristic engineering wake models' we aim at directly using large-eddy simulations, but using a sufficiently coarse mesh, so that they become sufficiently fast. Obviously, on coarse meshes, larger simulation errors emerge, so that the feasibility of such an approach depends on the trade-off between computational speed (when coarsening the mesh) versus accuracy. In order to quantify the latter, we have set up a study in which coarse-grid LES was used as a control model in a wind-farm MPC, driving a fine-grid wind-farm emulator. In such a set-up, 'accuracy' can be simply associated with control effectiveness, i.e. will an MPC based on a coarse grid model still be effective in increasing the windfarm control objective (in this case energy extraction)? We found that MPC based on coarse grid LES can be faster than real time while still increasing wind-farm energy extraction (which serves as the figure of merit for accuracy). Results were published in Wind Energy Science (Janssens & Meyers, 2024, https://doi.org/10.5194/wes-9-65-2024). This strongly indicates that in the near future, coarse grid LES models may be integrated in an operational wind-farm setting as an alternative for more heuristic dynamic engineering wake models.

4 VUB: Development of fast data-driven dynamic farm power model

Data-driven models are typically significantly faster than physics-based models. However, state-of-the-art data-driven models work typically with SCADA data averaged over 15-minutes or 1-hour time steps. Naturally, such models cannot model fast real-world events that occur in shorter time periods, such as fast wind speed transients. In order to capture the dynamics of a varying wind propagating through the wind farm, the time resolution of the model has to be shorter than the duration needed by the wind to cross the entire wind farm. For example, for an offshore wind farm with a cross-section length of 10 km, with wind speeds between turbine cut-in and cut-out wind speeds of respectively 4 m/s and 30 m/s, this duration is between 6 to 42 minutes. Therefore, a data-driven farm power model has been developed based on 1-minute SCADA data [Ally, Stijn, et al. "Modular deep learning approach for wind farm power forecasting and wake loss prediction." *Wind Energy Science Discussions* 2024 (2024): 1-33.].

It can be noted in Figure 3 and Figure 4 that the developed farm power model does indeed capture the influence of dynamic wind speed variations on the farm power.

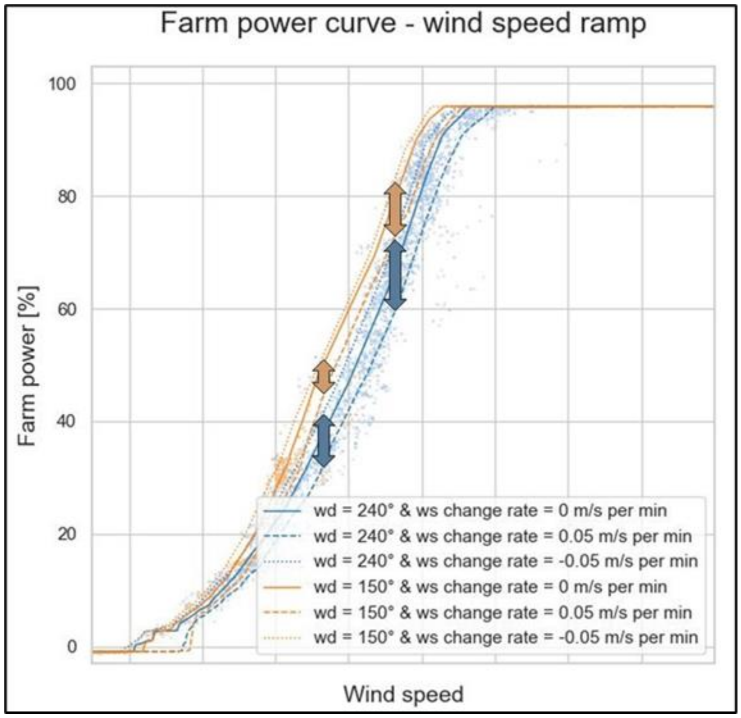


Figure 3: Predicted farm power by the wind farm power model in function of inflow wind speed with a linearly increasing and decreasing speed with a change rate of 0.05 m/s per minute, for wind directions 240° and 150°.

Figure 3 shows the wind farm power predictions for an offshore wind farm in the Belgian North Sea for wind directions 150° (with low farm-internal wake) and 240° (with high farm-internal wake). In addition to the two power curves for constant wind speeds, the power predictions are shown for the cases with a linear wind speed increase and decrease with a change rate of 0.05 m/s per minute. It can be seen that in case of increasing wind speed, the predicted farm power is lower than for steady-state wind speed. In contrast, for decreasing wind speed, the predicted power is higher. Indeed, if at the inflow side of the wind farm the wind speed is increasing, this means that downstream in the wind farm the wind speed is still lower than at the inflow side, which results in a lower total farm power. As can be seen on this plot as well, this effect is larger for wind direction 240° (blue arrows) than for wind direction 180° (orange arrows). This is because the cross-section of the wind farm in direction 240° is longer than in wind direction 180°. Consequently, changed wind speeds need more time to reach the downstream turbines. In addition, on the figure it can be seen that there is a hysteresis for the start-up and shut-down of the turbines around the cut-in wind speed.

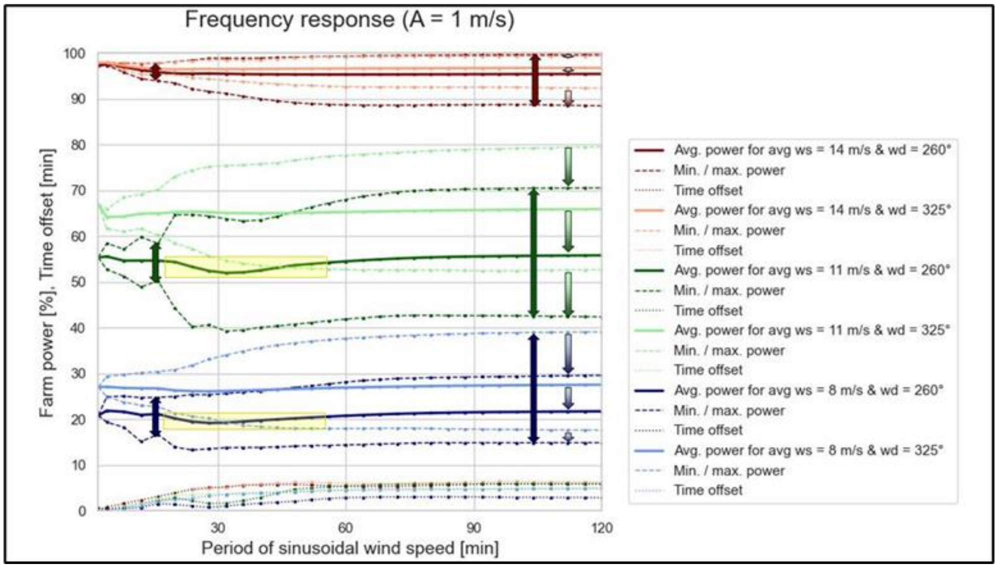


Figure 4: Frequency response of predicted farm power in case of a wind inflow with a sinusoidal oscillating wind speed component with an amplitude of 1 m/s. The plots show the average, maximum and minimum power of the predicted oscillating farm power in function of the period of the sinusoidal component of the wind speed. In addition, also the time offset between the oscillating farm power and wind speed is shown. The colors of the curves indicate the average wind speed (resp. 14 m/s, 11 m/s and 8 m/s) and the wind direction (260° and 325°).

Figure 4 shows the frequency response of the power model for another offshore wind farm in the Belgian North Sea. The wind speed is simulated as a constant average speed superposed with a sinusoidal component with an amplitude of 1 m/s. Simulations were run for a period *T* of the sinusoidal component equal to 2 minutes up to 120 minutes (*T* = 2, 4, 8, 12, 16, 20, ..., 120 minutes). This has been done for different average wind speeds (14 m/s, 11 m/s and 8 m/s) and wind directions (260° and 325°). The curves show the average, maximum and minimum values of the resulting oscillating farm power, as well as the time delay between the sinusoidal wind speed component and the oscillating farm power.

As a period of 120 minutes is much longer than the time needed for the wind to cross the complete wind farm, this is a quasi-static wind condition. If the period is smaller, the frequency of the wind oscillation is higher. However, for *T* = 2 minutes, taking into account the 1-minute time step of the model, the wind speed is again constant.

Furthermore, Figure 4 shows that the average, maximum and minimum farm power for wind direction 260° (with high wake) is always lower than for wind direction 325° (with less wake at a given specific wind speed and oscillation frequency. For faster fluctuating wind speeds, the amplitude of the farm power fluctuation decreases (see bidirectional arrows). In addition, in case of wind conditions with a high farm-internal wake, there appears to be a decrease of the average farm power, as indicated by the yellow markings. For small oscillation periods below 15 minutes, the average power increases again, converging back to the same value as for quasi-static wind conditions.

For short oscillation periods and consequently small wavelengths of the spatial wind speed distribution, the time delay of the farm power is converging to zero. Indeed, the time delay cannot be longer than the oscillation period of the sinusoidal wind speed component. For longer oscillation periods, the time offset converges to a constant value. Logically, the time delay will never be higher than the time needed by the wind to cross the complete farm.