BeFORECAST

Deliverable: Data assimilation into microscale LES and wake models

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1 Introduction

The current document describes the research efforts on the microscale data assimilation performed within the BeFORECAST project in the context of Tasks 3.2 and 3.5: "Extending LES-based reconstruction methodology for wind turbine wakes based on weakly constrained 4DVar" and "Development of operational data-assimilation based on TFT hypothesis and wake models".

Data assimilation (DA) enhances state estimation by integrating available measurements with information from various sources within a Bayesian inference framework. This process can be applied at different scales (e.g., macroscale, microscale, etc.). Tasks 3.3 and 3.5 focus on microscale data assimilation, since analyzing small-scale phenomena is crucial for optimizing power output in wind farms. Our goal is to develop a practical framework for reconstructing these small scales within wind farms and the surrounding atmospheric boundary layer (ABL) flow. To this end, we rely on a large-eddy simulation (LES) model to simulate the flow to build a 4D-Var DA framework. In Bauweraerts & Meyers (2020), a strongly constrained 4D-Var method was used leading to an LES optimization problem. Here, we aim to improve on this method, by developing a weakly constrained 4D-Var method, in which we characterize subgrid-scale model error using approximations based on a spectral-tensor for boundary-layer turbulence.

In Task 3.5, the original goal was to develop data-assimilation methods using fast dynamic models that can be used in an operational setting. In this task, the aim was to use the 4D-Var approach in combination with a simple Taylor Frozen Turbulence (TFT) model for the background flow. However, due to recent scientific insights, this task was slightly redefined as will be further elaborated below.

The current report is structured as follows. In section (2), the scientific results related to Task 3.3 are briefly introduced. This is followed then by a discussion of Task 3.5 in section (3). Finally, the report is concluded with an overview dissemination related to the current deliverable.

2 T3.3: Extending LES-based reconstruction methodology for wind turbine wakes based on weakly constrained 4D-Var

In this work, we start from the strong 4D-Var method of Bauweraerts and Meyers (2020), with the goal to develop a practical weakly constrained 4D-Var algorithm that incorporates the model error associated with sub-grid scales in the LES model. We achieve this in two stages. In the first stage, we address the computational challenges in the work of Bauweraerts and Meyers (2020) associated with the expensive prior statistics, which form a significant bottleneck and render the algorithm impractical. In the second stage, we extend the model developed in the first stage to account for model errors arising from unresolved scales in the LES framework, further improving the accuracy and robustness of the algorithm, especially for long time horizons where the accumulated model error plays a dominant role. In the following, these two steps are elaborated.

2.1 Practical strong 4D-Var method for ABL flow reconstruction

We propose an efficient method to reconstruct the turbulent flow field in a neutrally stratified atmospheric boundary layer using LES and a series of lidar measurements. The reconstruction is formulated as a strong four-dimensional variational data assimilation problem, which involves optimizing two competing terms that contribute in the objective functional. The first term is a likelihood term, while the second contains the prior statistics of the initial velocity fluctuations and works as a regularization term. Typically, these priors are computed offline by averaging over a long historical LES simulation. While the resulting statistics are typically accurate and representative for the flow under consideration, they require prohibitively expensive prior simulations. Although this forms a bottleneck in any practical application, it remains valuable for benchmarking purposes (see figure 1). In this subtask, we substitute the numerically obtained statistics with analytical approximations based on turbulence theory, aiming to reduce computational complexity while preserving key physical characteristics. To this end, we implement two models: the Hunt–Graham–Wilson (HGW) model and the Mann model.

The HGW model is a fully analytical spectral model that was introduced long ago by Hunt & Graham (1978) in the context of studying the effect of introducing a moving rigid surface suddenly at time $t = 0$ to a free-shear flow. Later, Wilson (1997) used these ideas to derive an analytical model for the vertically inhomogeneous spectral tensor in the atmospheric convective boundary layer. Herein, we further exploit this approximated model to provide a fast and physical-based regularization of our 4D-Var problem. The HGW model is fully isotropic. However, it captures the wall effect, and therefore, it is inhomogeneous only in the vertical direction. Figure (2-a) illustrates the two-point correlation function obtained using the HGW model at $z = 100\ m$, which is the lidar elevation in our experiment. The Mann model, on the other hand, is another analytical model that was proposed by Mann (1994) in the context of studying ABL statistics. Unlike the HGW model, the Mann model is anisotropic and homogeneous. That is, the model is able to capture inclinations in the correlation function due to the mean shear. Figure (2-b) shows the obtained correlation function for the streamwise velocity component, where the inclination in the vertical direction can be observed. While the analytical models above do not exactly lead to the numerically obtained statistics Bauweraerts and Meyers (2020) in figure (1), it remains useful as will be shown below.

Figure (3) shows a comparison between the reconstructed turbulent fields using the analytical models above verse the reference fine simulation, from which the virtual lidar measurements were collected. As seen from the figure, employing either of the two models above leads to accurate reconstruction inside the lidar area. However, the Mann model exclusively shows the ability to capture the inclination of the large vertical structures in the vertical direction due to its anisotropic nature. The accuracy of the reconstruction is further assessed by considering the relative error defined inside the scanning area. Figure (4) shows that our analytically regularized strong 4D-Var method provides very good reconstruction accuracy, while maintaining a cost-effective algorithm. <u>This work was published in the Journal of Fluid Mechanics (see desimination below).</u>

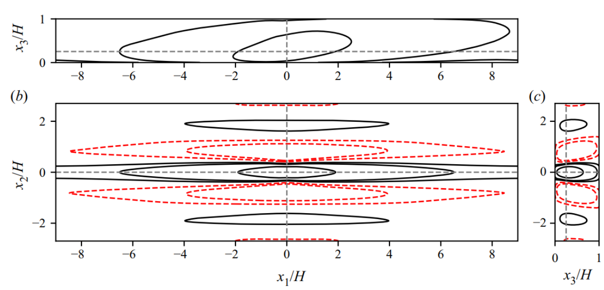

Figure 1: Two-point correlation function for the streamwise velocity component at the lidar height. The black lobes represent positive correlations, while the red ones correspond to negative correlation. These results were obtained by Bauweraerts and Meyers (2020) using long historical LES simulations.

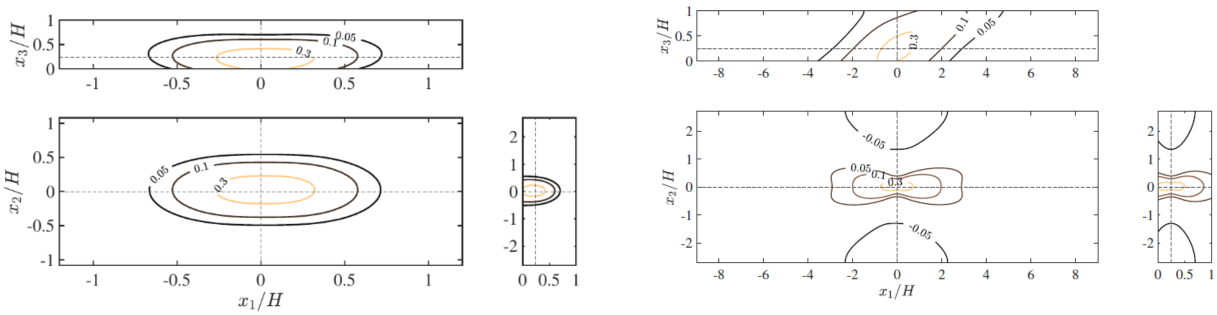

Figure 2: The two-point correlation function similar to figure 1, as obtained using the HGW model (left), and the Mann model (right).

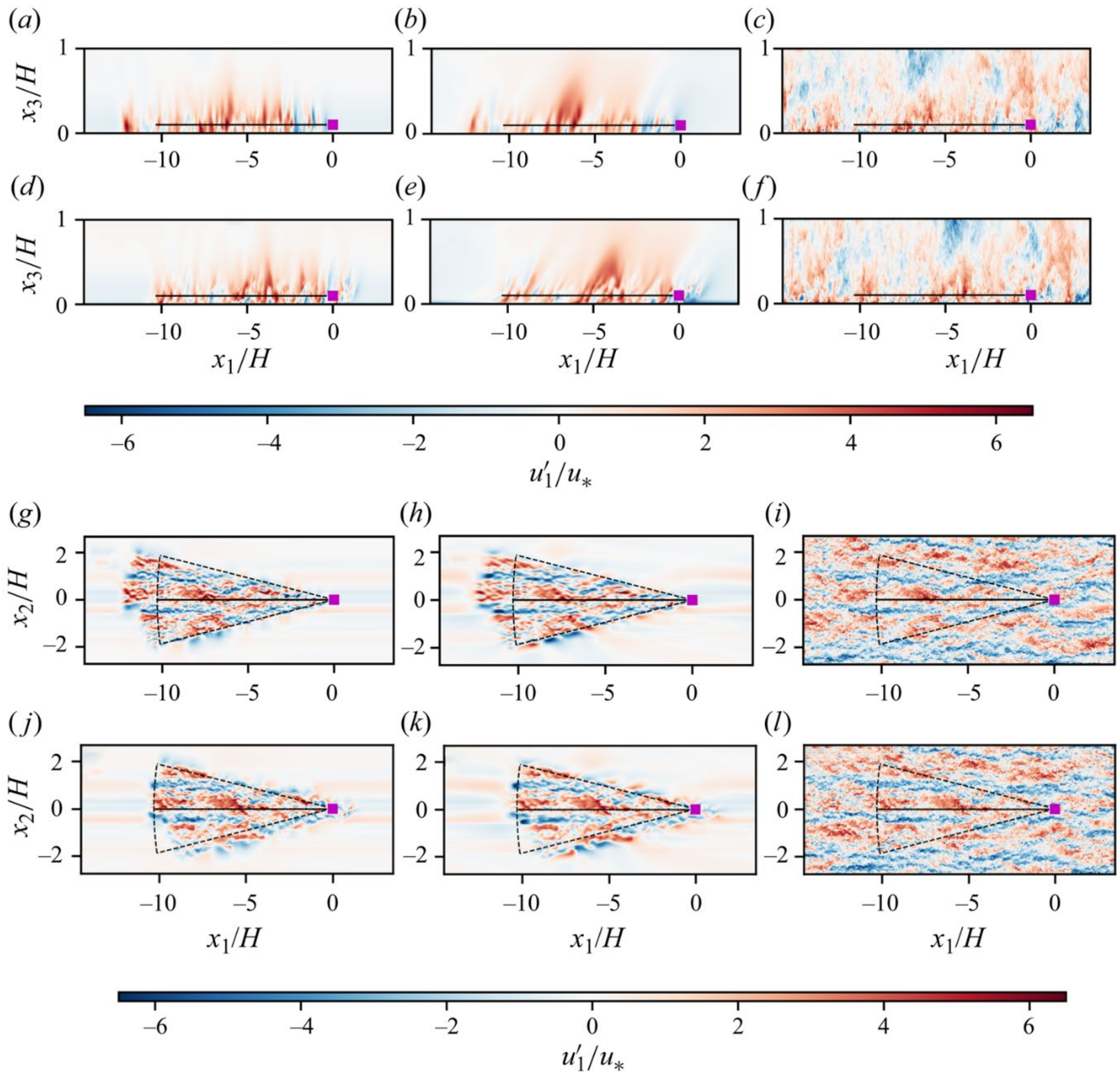

Figure 3: The streamwise velocity fluctuation component at the $x_2 = 0$ (a–f) and $x_3 = 0.1H$ (g–l) planes. The right column is the reference velocity and the left two columns are the reconstructed velocities using the HGW model and the Mann model, respectively.

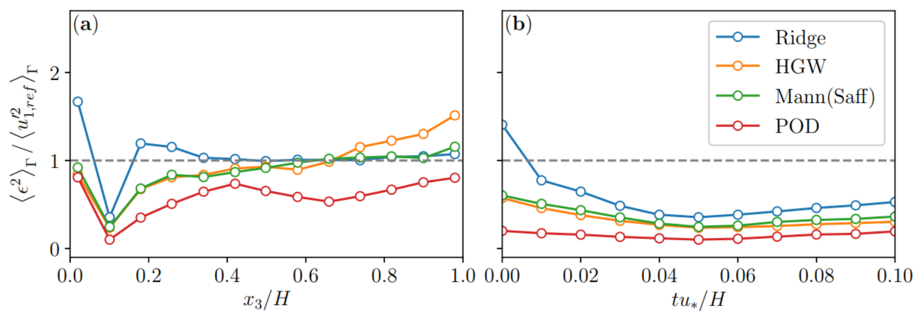

Figure 4: The normalized spatially averaged error inside the scanning area for the ridge, HGW and Mann models and the POD-based regularization in Bauweraerts & Meyers (2020). Panel (a) shows the errors at $t = 0.05u_*/H$, while (b) shows the results at $x3 = 0.1H$.

2.2 Weakly constrained 4D-Var algorithm using LES

Here, we consider the second step of our methodology, which involves extending the algorithm in the previous section to address the model error associated with the SGS term in the LES equation. Unlike the more common strong formulation, the weak version is usually avoided in practice since it requires considering the state equation as a weak constraint to the optimization problem, resulting in a space-time control vector (instead of space only in the strong version). However, it is also expected to give better reconstruction accuracy since it allows for more degrees of freedom in addition to the initial state as before. In the following, we start from the algorithm presented in the previous section and replace the SGS term in the LES with a space-time forcing term. Afterwards, we employ insights from the turbulence theory to describe the statistics of this forcing term. In the case of the ABL flows as considered here, the latter (2nd order) statistics can easily reach a size of 10^8. This leads to a massive two-point-two-time correlation tensor that is impossible to handle or model with the current resources. To proceed, we assumed that the model error in hand is decorrelated in time and focus on providing the correlation in space only. We investigated two different options for the space correlation, namely, the HGW model from above, and another isotropic model that features a spectral behavior $\sim k^2$.

Thanks to the efficient parallelization in our LES solver, and the time decorrelation assumption, the weak formulation is efficiently solved after proper scaling and preconditioning. Figure (5) shows the updated error plot after adding the weak formulation results. As seen from the figure, the weak reconstruction consistently outperforms the strong version presented in the previous section. The k^2 model shows 40% improvement in the reconstruction accuracy at the beginning of the window, and 12% and the middle using the k^2 model. This result is very close to the results of Bauweraerts, P., & Meyers, J. (2020). However, the results here are achieved using much less computational resources.

<u>The work presented in this section was documented in a jouranl article that will be submitted to the Journal of Computational Physics.</u>

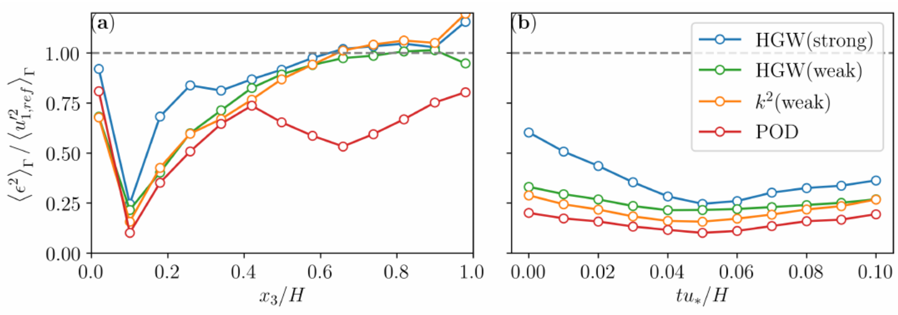

Figure 5: The normalized spatially-averaged error inside the scanning area for the strong HGW in in figure (4), HGW (weak), k2 (weak), and the POD case in Bauweraerts and Meyers (2020). The left figure shows the errors at t = 0.05u∗/H, while the right figure shows the results at x3 = 0.1H.

3 T3.5: Development of operational data-assimilation based on TFT hypothesis and wake models

In this task, the original goal was to develop data-assimilation methods including fast dynamic models that can be used in an operational setting. These models include the simple Taylor Frozen Turbulence (TFT) model alongside a dynamic extension of the static wake model by Lanzilao & Meyers (2020). The investigation of using coarse LES in such practical setup was also planned.

In Year 1 of the project, we focused on replacing the LES model in our 4D-Var algorithm with the TFT simplification, enabling a faster reconstruction process. Additionally, static wake models were successfully applied as a background for 4D-Var wind farm reconstructions (see figure (6)). These results were published in Journal of Physics: Conference Series (see below). Concurrently, the use of coarse-grid LES was also explored at KU Leuven, with a potential goal of replacing the 'heuristic engineering wake models'. This revealed that using coarse grid LES in an MPC framework for wind farm control could lead to a faster than real-time algorithm, which can effectively control wind farm power in real time. These results were published in Wind Energy Science (Janssens & Meyers, 2024, https://doi.org/10.5194/wes-9-65-2024). Therefore, we believe that coarse grid LES models may be integrated in an operational wind-farm setting as an alternative for more heuristic dynamic engineering wake models.

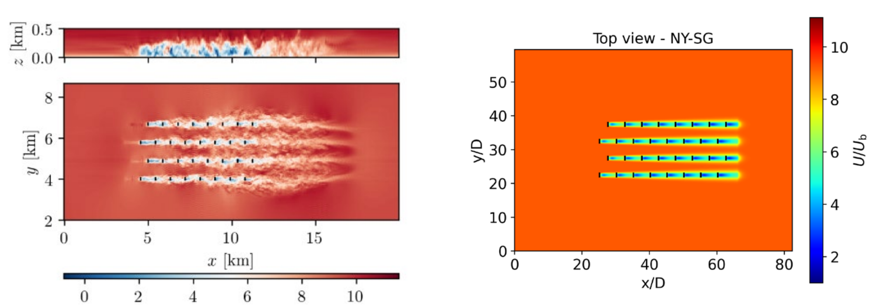

Figure 6: Example of employing wake models (right), to regularize 4D-Var problem (left), involving wind farms.

4 Dissemination

The work above was published/presented in several occasions as follows:

- **Articles**

  - Alreweny, A., Vandewalle, S., & Meyers, J. (2024). Large-eddy simulation-based reconstruction of turbulence in a neutral boundary layer using spectral-tensor regularization. Journal of Fluid Mechanics, 981, A28. doi:10.1017/jfm.2024.92

  - Alreweny, A., Vandewalle, S. & Meyers, J. (2024). Turbulent flow field reconstruction in wind farms using power measurements. Journal of Physics: Conference Series 2767 (9), 092032

- **Conferences/meetings**

  - Alreweny, A., Vandewalle, S., Meyers, J. (2024). Weakly constrained 4D-Var data assimilation in ABL using LES. ECCOMAS2024, Lisbon, Portugal, 3-7 Jun 2024

  - Alreweny, A., Vandewalle, S., Meyers, J. (2023). Preconditioned 4D-VAR data-assimilation of turbulent flow fields with the aid of atmospheric analytical models. UNCECOMP2023, Athens, Greece, 12-14 Jun 2023

  - Alreweny, A., Vandewalle, S., Meyers, J. (2023). LES-based reconstruction of turbulence in the ABL using Mann spectral-tensor regularization. Wind Energy Science Conference 2023, Glasgow, UK, 23-26 May 2023

5 References

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- Wilson, D. K. (1997). A three-dimensional correlation/spectral model for turbulent velocities in a convective boundary layer. Boundary-Layer Meteorology, 85(1), 35–52.
- Hunt, J. C. R., & Graham, J. M. R. (1978). Free-stream turbulence near plane boundaries. *Journal of Fluid Mechanics, 84(2)*, 209–235.
- Alreweny, A., Vandewalle, S., & Meyers, J. (2024). Large-eddy simulation-based reconstruction of turbulence in a neutral boundary layer using spectral-tensor regularization. *Journal of Fluid Mechanics, 981*, A28.`
- Lanzilao L, Meyers J. A new wake-merging method for wind-farm power prediction in the presence of heterogeneous background velocity fields. Wind Energy. 2022; 25(2): 237-259.
- Janssens, N. and Meyers, J.: Towards real-time optimal control of wind farms using large-eddy simulations, Wind Energ. Sci., 9, 65–95.