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Final Report

Wind energy optimization using simulations, measurements and artificial intelligence

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Contents

List of abbreviations

LiDAR	Light Detection and Ranging
LDV	Laser Doppler Velocimetry
LCOE	Levelized Cost Of Energy
LES	Large-eddy simulation
PIV	Particle-image velocimetry
SCADA	Supervisory Control and Data Acquisition
WFLO	Wind farm layout optimization
STWPF	Short term wind power forecasting
WiRE	Wind Engineering and Renewable Energy Laboratory (EPFL)

Project goals

The main goal of this project is to develop accurate prediction tools for optimizing the design, control and forecast of wind farms. That has been achieved using a synergistic combination of computer simulations, experiments, and physics-informed artificial intelligence tools. The new prediction framework is expected to help optimize the use of wind energy within the context of the Swiss Energy Strategy 2050.

Summary

The main aim of this project is to develop and validate a new prediction framework that can be used for the optimization (design and control) and forecast of wind farms. To achieve that, we have used a synergistic combination of computational fluid dynamics (large-eddy simulation), reduced-order models and physics-informed artificial intelligence tools. During the course of the project, substantial progress has been made on all the planned tasks, corresponding to the three main work packages highlighted in the original proposal. The activities and main results for each task are briefly summarized below:

- **Development of analytical wind-turbine wake models:** A new generation of analytical models has been developed that are physics based, simple, fast and accurate enough to be used for optimizing the design and control of wind farms.

- **Validation of numerical models:** Novel wind tunnel experiments and field experiments have been designed and carried out to gain new understanding of wind turbine and wind farm flows, and to provide unique datasets for the validation of numerical models (both LES and the newly developed analytical models).

- **Development of artificial intelligence tools for the optimization and forecasting of wind farm power**: Specifically, genetic algorithms and machine learning (neural networks) have been developed and implemented to optimize the design, control and forecast of wind farms.

Work undertaken and findings obtained

During the duration of the project, substantial progress has been made, as planned, on the three main work packages. The activities and main findings for each Task are summarized below:

Work Package 1: Analytical model development

Analytical wind turbine wake models are widely used in the wind energy community to predict the wind turbine and wind farm performance. Their main weakness is that they often rely on empirical and difficult to interpret and generalize equations. The following tasks have been carried out to develop a new physics-based analytical wake modelling framework for the mean wind speed (and associated turbine power) that is fast and accurate enough to be used for optimizing the design and control of wind farms. Specifically, this projects has led to the following developments:

<u>A new analytical model for wind turbine wake flow expansion</u>

Development of **a new physics-based wake model to predict the wake growth rate downstream of a turbine based on the incoming ambient turbulence and turbine operating conditions**. Note that the wake growth rate is a key parameter that has been, to date, specified using empirical formulations. The performance of the proposed model has been validated using data from large-eddy simulation (LES) of a utility-scale wind turbine wake under neutral atmospheric conditions with a wide range of incoming turbulence levels. **Figure 1** shows the comparison between the profiles of the velocity deficit predicted by the new model and those simulated with our LES code. The results show that the proposed model yields reasonable predictions of the wake width, maximum velocity deficit, and near wake length. Results from this research have been published in the *Journal of Fluid Mechanics* (Vahidi and Porté-Agel, 2022a).

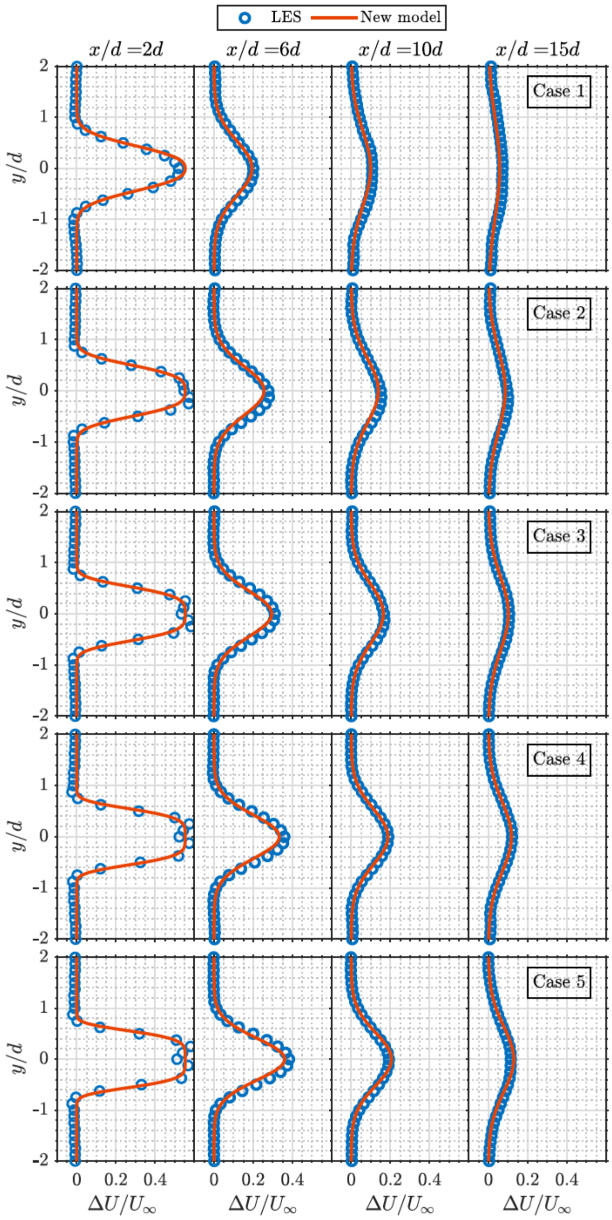


Figure 1: Normalized velocity deficit profiles at different streamwise locations for all the cases under consideration. Cases 1 to 5 are characterized by ambient turbulence intensities that decrease monotonically from 0.140 (Case 1) to 0.053 (Case 5).

A new simple model based on the universal scaling of the normalized wake characteristics

We have proposed a new simple wake model based on the universal behaviour (found in our LES results) of the normalized wake flow characteristics with respect to the streamwise distance when the latter is normalized by the near-wake length (see Figure 2). The performance of the new model is assessed against large-eddy simulation data of a wind turbine wake under neutral atmospheric conditions. Overall, we observe a good agreement between the simulation data and the models' predictions and considerable savings in the models' computational costs. Results from this study have been published in the journal *Energies* (Vahidi and Porté-Agel, 2022b).

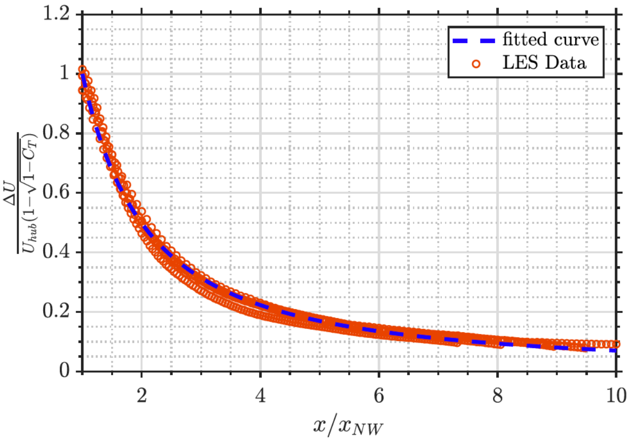


Figure 2. Collapsed profile of the normalized wake velocity deficit for the test cases as a function of the new streamwise scaling. The dashed line corresponds to the fitted function, which is used in the new model.

Extension of the analytical framework to wind farms

The aforementioned simple model based on the universal scaling of the normalized wake velocity has been expanded to account for wake flow superposition inside and downwind of wind farms. The new framework, which is tested against LES of wind farms of different sizes and layouts, outperforms all the existing analytical models. This is mainly due to the fact that the new model, unlike the existing models, does not rely on the assumption of linear wake expansion, which is found be a source of substantial errors at relatively long downstream distances, both inside and downstream of the wind farms. Results from this research have recently been published in the journal *Renewable Energy* (Souaiby and Porté-Agel, 2024).

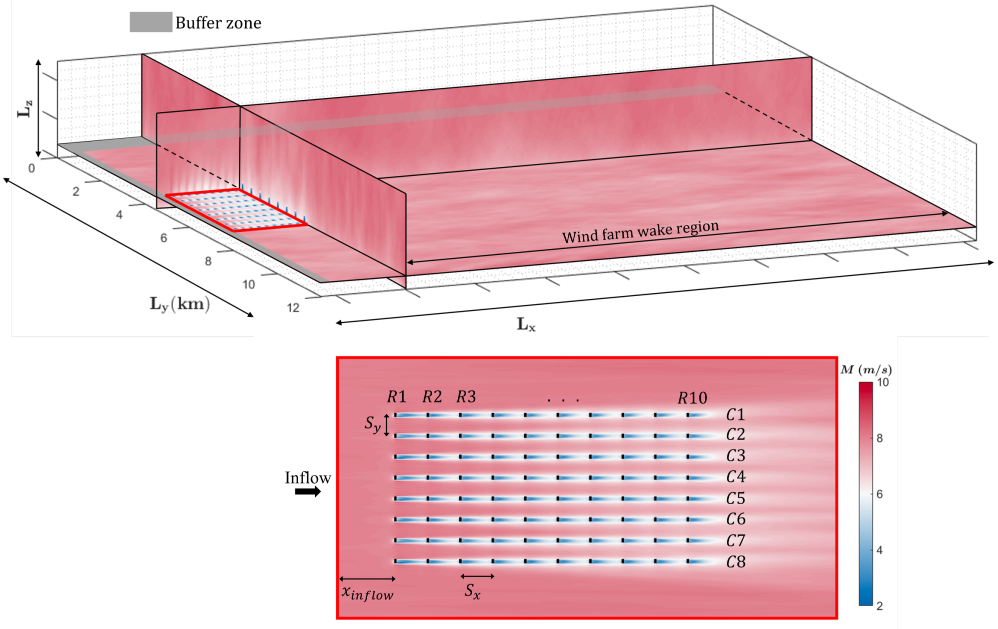


Figure 3: Schematic of the computational domain and mean velocity field simulated with the WiRE LES code in a wind farm of 10 rows. The data is used for validation of the analytical models (see Figures 4 and 5).

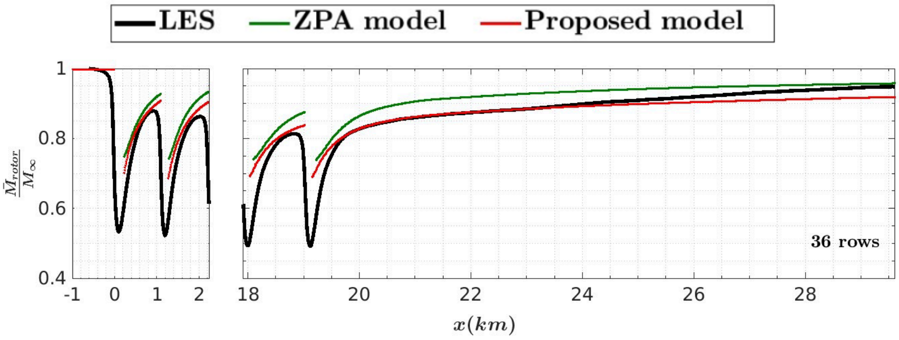


Figure 4: Time- and spanwise-averaged wind speed at different positions inside and downwind of a wind farm with 36 rows and staggered configuration. The high-fidelity LES results are used to validate the state-of-the art analytical model (ZPA model) as well as the newly developed model (Souiaby and Porté-Agel, 2024).

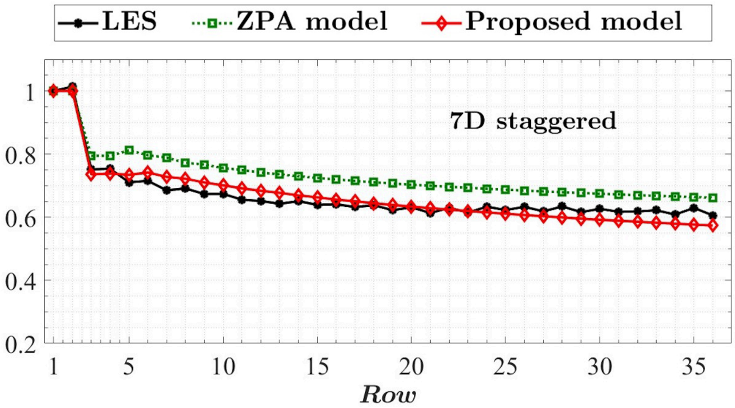


Figure 5: Normalized power output as a function of wind farm row for a wind farm with 36 rows and staggered configuration. The high-fidelity LES results are used to validate the state-of-the art analytical model (ZPA model) as well as the newly developed model (Souiaby and Porté-Agel, 2024).

A new analytical model for wind farm flows that includes yaw control

A new analytical model for wind farm flows, which includes yaw control, has been developed and validated using wind tunnel experiments (see next section for more details on the wind-tunnel experiments and results) as well as power measurements and LES simulations of the Horns Rev wind farm for a wide range of wind angles. The experimental setup is shown in Figure 6. The new analytical model yields good predictions of the flow and wind turbine power, compared with the experiments and LES. A sample of the turbine power validation results is given in Figure 7. Results from this research have been published in the *Journal of Fluid Mechanics* (Zong and Porté-Agel, 2021).

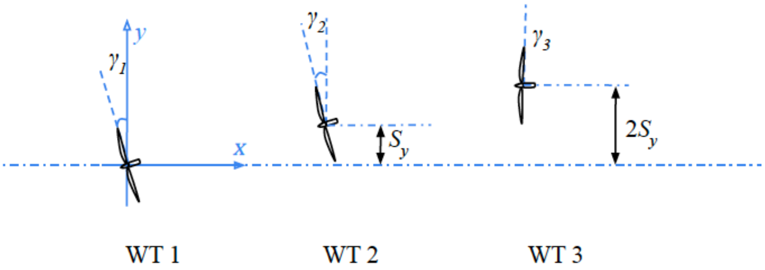


Figure 6: Experimental setup for wind tunnel experiments and analytical model validation.

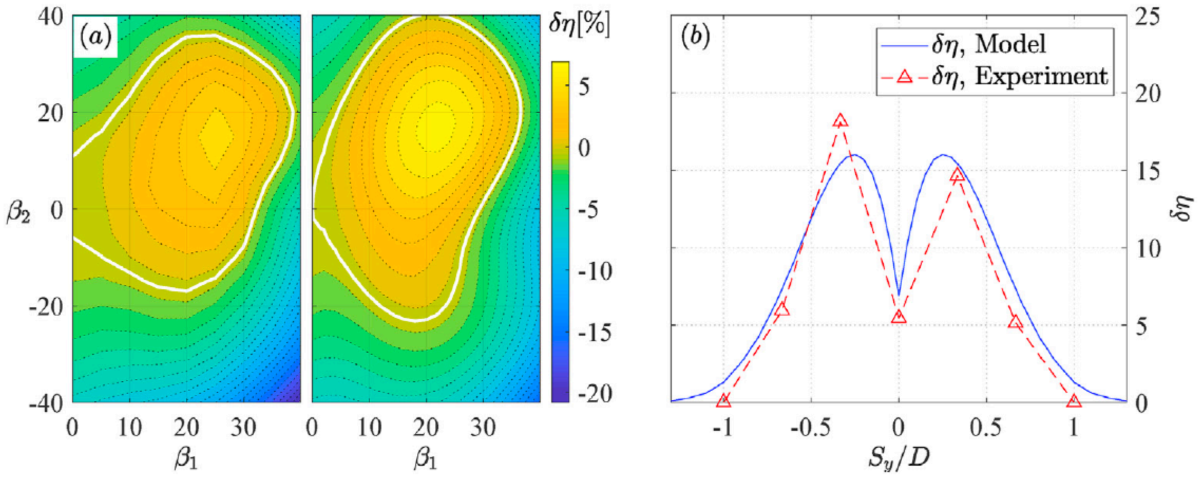


Figure 7: (a) Comparison of the full-wake power maps obtained from the experiments (left half) and the analytical model (right half). The solid white lines are contour lines of dh =0. (b) Model predictions of the relative power improvement at different spanwise offsets (S_y). More details in Zong and Porté-Agel (2021).

A new analytical model for wind turbine wind turbine wake flows over topography

We have developed a new analytical modeling framework for wind turbine wakes under an arbitrary pressure gradient imposed by topography. The model is based on the conservation of the streamwise momentum and self-similarity of the wake velocity deficit. The model is validated against experimental data of wind turbine wakes on escarpments of varying geometries (see Figure 8). The new model is observed to agree well with the experimental data, and it outperforms the other two models tested in the study for all escarpment cases (see Figure 9). Results from this study have been published in the journal *Energies* (Dar and Porté-Agel, 2022).

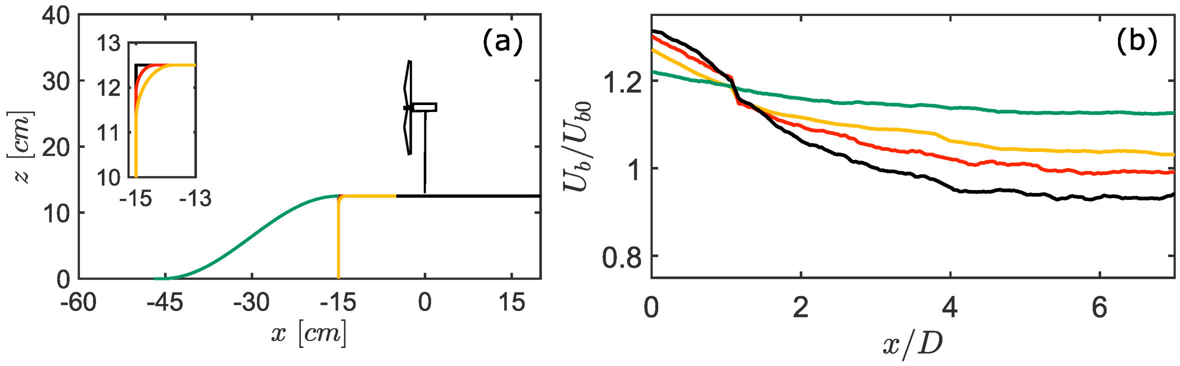


Figure 8: Side view of the escarpment geometry (a) and normalized base flow velocity at the hub height on top of the escarpments (b). Colors represent the respective escarpment shapes. The figure is adapted from Dar and Porté-Agel (2021). *D* is the turbine diameter.

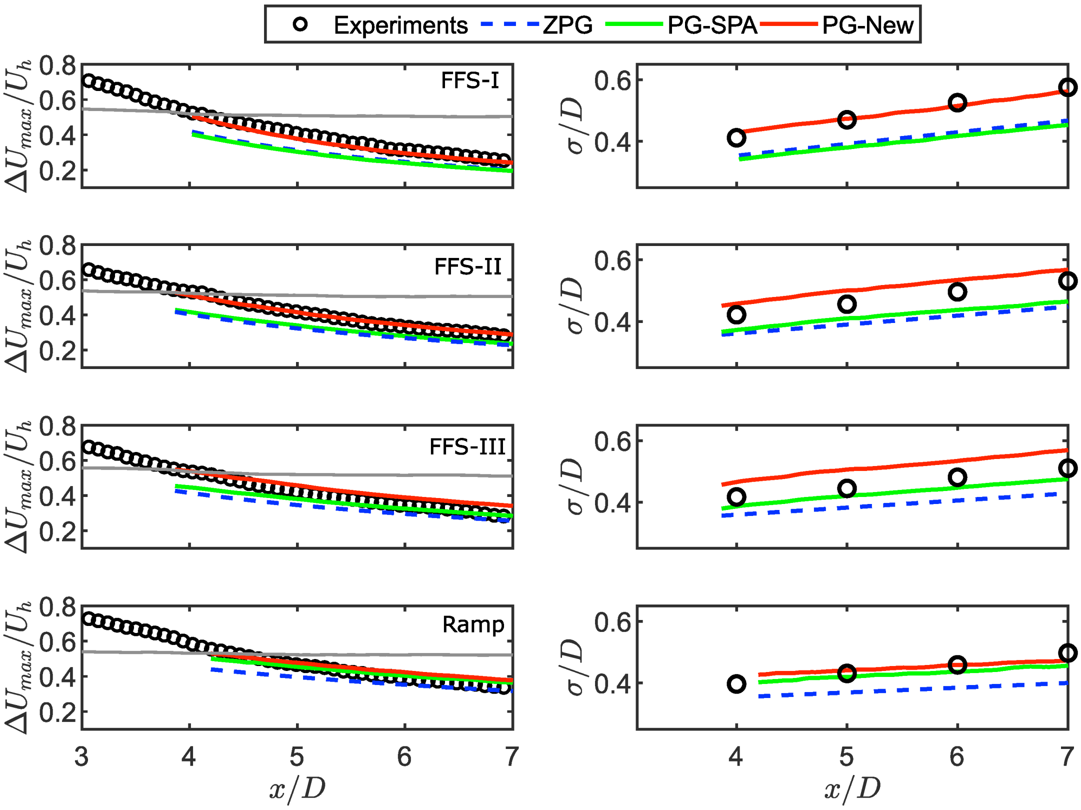


Figure 9: Comparison of the maximum normalized velocity deficit (left) and equivalent wake width (right) between the experiments and the analytical models. The solid gray line shows the theoretical maximum velocity deficit assuming a fixed near wake velocity. **Red: New model**; Green line: Shamsoddin and Porté-Agel model; Blue line: Standard Gaussian model.

Work Package 2: Validation of numerical models

Wind tunnel experiments and field measurements were carried out to investigate wind turbine and wind farm flows over different terrains (topography) as well as wind turbine control strategies such as active yaw control. The results are used for the development and validation of numerical models (e.g., the analytical models developed in WP1). Specifically, the main activities and results in this work package can be summarized as follows:

Wind tunnel studies of the effect of topography on wind turbine flow and performance

Wind tunnel experiments were performed at the EPFL-WiRE wind tunnel to investigate the effect of topography on the wake flow and the performance of a wind turbine. Two-dimensional velocity fields were measured using particle-image velocimetry (PIV). Specifically, several escarpment models were used, which vary in the windward side shape from forward facing steps (FFS) with different curvatures at the leading-edge to sinusoidal ramp shapes with varying slopes. The difference in the baseflow (flow without the turbine) resulting from the change in the geometry of the escarpment leads to significant differences in the average and dynamic characteristics of the turbine wake. As a result, traditional analytical models, which assume homogeneous incoming atmospheric flow (over flat, homogeneous terrain) yield large errors in the prediction of mean wake. This research was published in the journals *Renewable Energy* (Dar and Porté-Agel, 2022a), *Energies* (Dar and Porté-Agel, 2022b) and *Physics of Fluids* (Dar and Porté-Agel, 2024) and *Physical Review Fluids* (Dar and Porté-Agel, 2024).

To further understand and generalize the aforementioned effects of the non-uniform baseflow induced by topography, a set of wind-tunnel experiments was designed and carried out to systematically study the effect of flow acceleration and deceleration on wind turbine performance and wakes. Based on these results, a new analytical wake model is proposed that is capable to account for the pressure gradient effects. The new model substantially improves the accuracy of analytical models for the prediction of the flow and turbine performance over complex terrain and other situations where the baseflow is non-uniform. This research has been published in the journals *Physics of Fluids* (Dar et al., 2023; Dar and Porté-Agel, 2024).

Wind tunnel experiments for validation of numerical models of wind farm flows

Wind-tunnel experiments were designed and performed to study the wake flow and power performance of a row of three wind turbines using at different inter-turbine distances, lateral displacements (to study full wake and partial wake conditions) and yawing strategies. The laser-based particle-image velocimetry (PIV) technique was used for the measurements. Sample measurements are presented in Figure 10 for some selected active yaw control strategies.

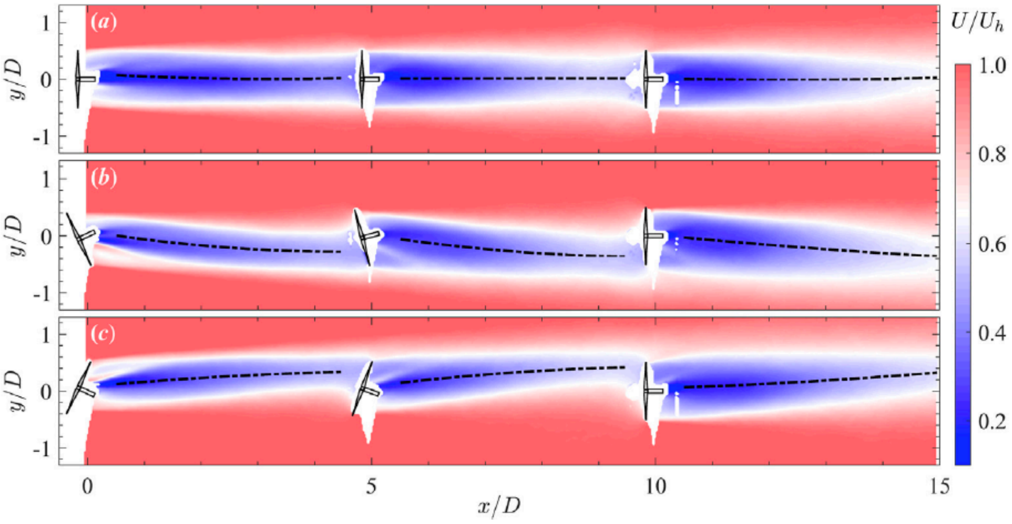
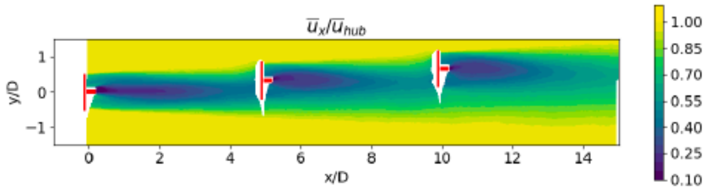


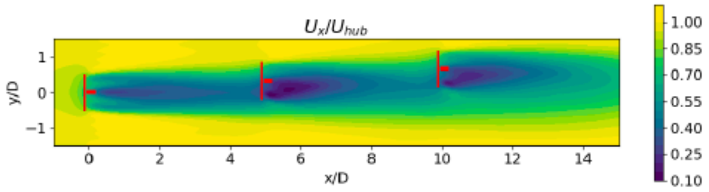
Figure 10: Time-averaged wake velocity contours obtained from PIV measurements for full wake condition (*Sy=0* in Fig. 2). (a) Baseline non-yawed case; (b) case A: yaw angles: γ_1=+25° and γ_2=+15°; (c) case B: yaw angles: γ_1= -25° and γ_2=-20°. The trajectories of wind turbine wakes extracted by fitting the spanwise velocity profile with a Gaussian function are superimposed as dash-dot black lines.

The flow and power measurements collected during the aforementioned experiment were used to validate both analytical models as well as LES. For the analytical model validation, the reader is referred to the previous section. The LES validation focused on one of the key parameterizations used in LES of wind turbine and wind farm flows (see Figure 11). In particular, we conclude that **LES using the ADM-BE (previously developed in our Laboratory) provides an optimum balance of accuracy and computational cost for turbulence-resolving simulations of the flow through wind farms**.

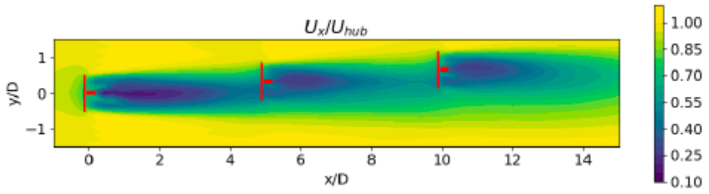
Results from this research have resulted in two papers published in the journals *Energies* (Revaz and Porté-Agel, 2021) and *Wind Energy Science* (Lin and Porté-Agel, 2022).



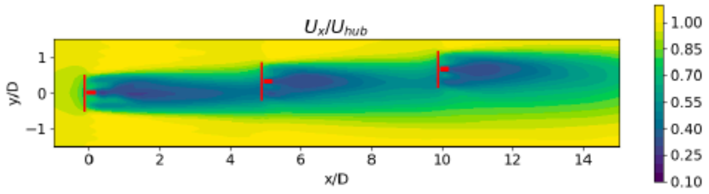
(a) Experiment, Case 3 (0°,0°,0°)



(c) ADM-std, Case 3 (0°,0°,0°)



(e) ADM-BE, Case 3 (0°,0°,0°)



(g) ALM, Case 3 (0°,0°,0°)

Figure 11: Top-view contours of the normalised streamwise mean velocity u/u_{hub} in the x-y plane at hub height obtained from the wind-tunnel experiments, LES using the ADM-std, ADM-BE and ALM. The wind turbines are offset in the spanwise direction with a distance of D=3 (Cases 3 and 4).

LiDAR field measurements for characterization of turbine wake flow meandering and model validation

Two EPFL scanning wind lidars were installed on the nacelle of an operational wind turbine in Iowa (USA). One of the lidars was used to measure the lateral component of the incoming wind velocity, which is responsible for most of the lateral wake meandering. The other scanning wind lidar was used to simultaneously scan the wake of the wind turbine (see Figure 12 for a picture of the setup and a sample flow measurement). The dynamic wake meandering model (DWMM), based on the analogy to passive scalar transport, and two statistical wake meandering models have been compared to the field measurements of the wake. Based on our results, we have proposed an improvement of the DWMM that accounts for the fact that momentum transport is less efficient than scalar transport in the turbine wake. Figure 13 shows representative results of the model performance. Results from this research have recently been published in the journal *Wind Energy Science* (Brugger and Porté-Agel, 2022, 2024).

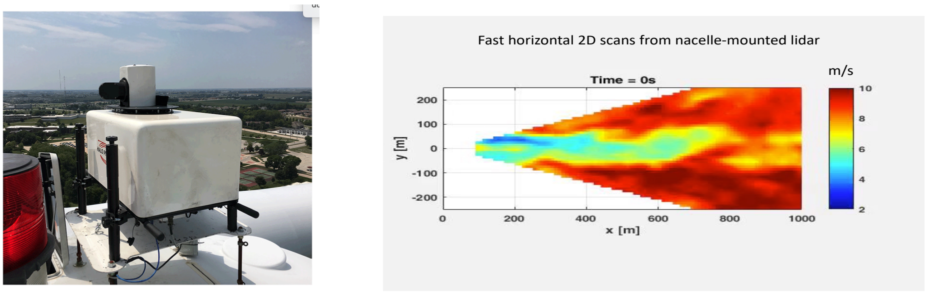


Figure 12. Left: Picture of EPFL scanning wind lidar mounted on the wind turbine nacelle. Right: Sample of instantaneous wind speed measurement obtained from a fast horizontal scan, where spanwise wake meandering is evident.

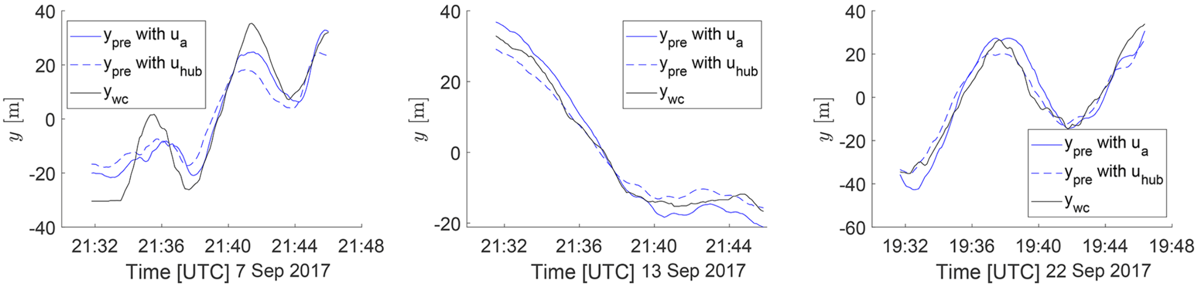


Figure 13. The time series of observed and predicted wake center positions for four example cases, which were selected for their high correlation. The predictions are shown for mean wind speed (dashed blue) and average of wake center velocity and mean wind speed (solid blue) as downstream advection velocity. The reference from the observations is shown in black.

LIDAR field measurements in the AWAKEN International Collaborative Experiment

The WiRE Laboratory has participated (as the main European partner) in the AWAKEN (American WAKE experimeNt) experiment, which is an unprecedented effort involving several research groups to measure wind turbine and wind farm flows in an operational wind farm in Oklahoma, USA. It should be noted that the experiment was delayed due to the complex coordination of the multiple research groups and instrumentation. For that reason, the measurements were just made during 2024. Specifically, within the AWAKEN Experiment, the WiRE Laboratory deployed three nacelle-mounted lidars. Together with the three lidars provided by the National Renewable Energy Laboratory (NREL) of the USA, we were able to gather unique measurements of wind flow within the wind farm at high spatial and temporal resolutions. The data is currently being analysed, while we are waiting for the wind-turbine SCADA data (including turbine power and operational parameters) to be released by the wind farm operator, after all legal agreements relative to data sharing are finalized. We expect that the rich dataset collected during this experiment will provide unique insights and opportunities for testing scientific hypothesis and validate/improve numerical models in the coming years.

A first manuscript on the description of the AWAKEN experiment is currently under review in the *Journal of Renewable and Sustainable Energy* (Moriarty et al., 2024).

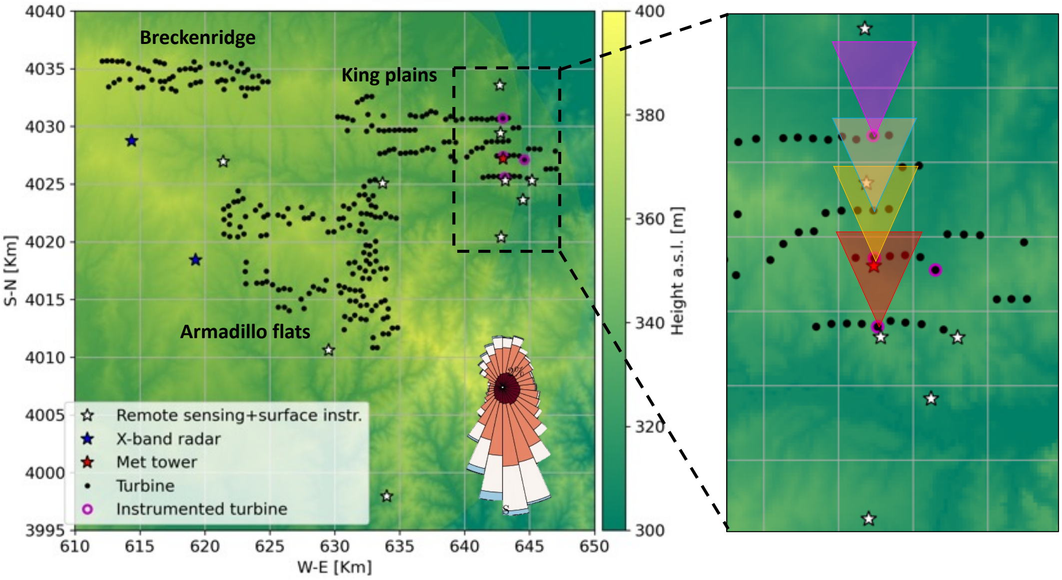


Figure 6. Left: Map of the overall study area in Oklahoma (USA) with several wind farms. The dots represent wind turbine locations. Right: Zoom into the area of intensive measurements with the nacelle-mounted lidars (from EPFL and NREL) locations and sample scanning areas to capture the interaction of multiple wakes within the wind farm..

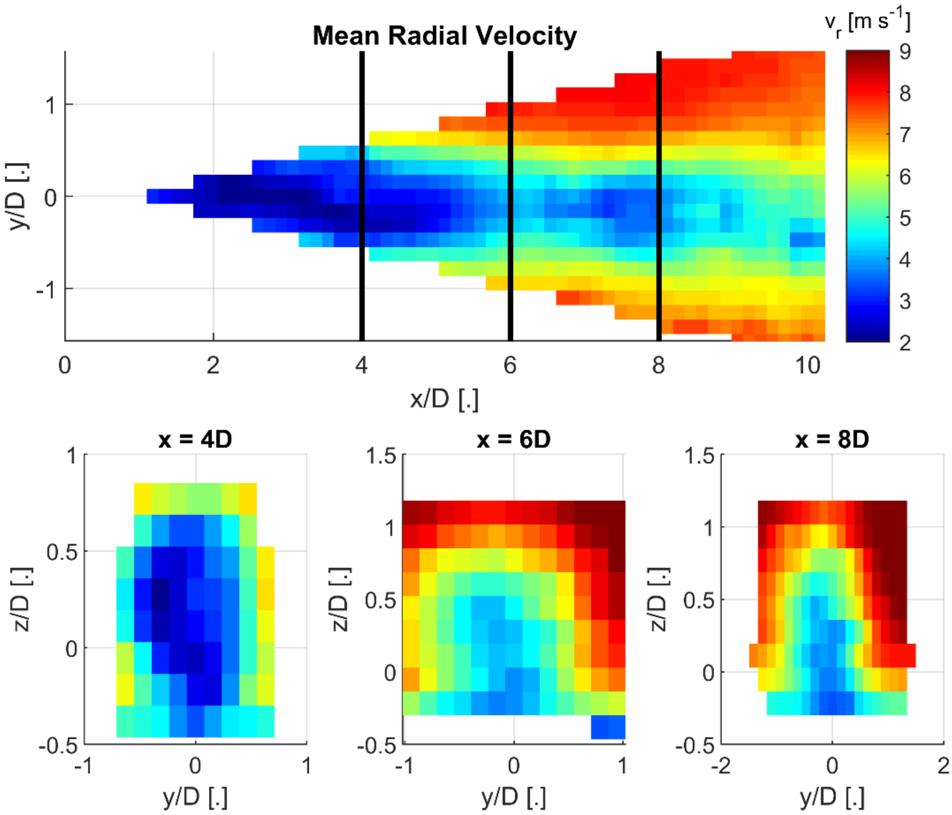


Figure 6. Top: Sample of a volumetric scan of the wake flow from one of the EPFL scanning Doppler LiDARs. The black lines are selected locations where cross-flow contours of wind speed are plotted in the bottom panels. The wake recovery and deformation are evident in the results.

Work Package 3: Artificial intelligence

Wind farm layout optimization

A new wind farm layout optimization framework has been developed, which is based on a novel self-adaptive genetic algorithm (GA) that uses the fast predictions from our newly developed fast analytical models (see WP 1). The new optimization framework is applied to the optimization of the power density in wind farms, with emphasis on its relationship with the considered wind farm area size. With the levelized cost of energy (LCOE) as cost function, it is able to self-adapt to the specific PD (i.e., to the specific number of turbines T) at each stage, and to self-balance the trade-off between exploration and exploitation. The new optimization framework is applied to the original wind farm size (Horns Rev 1) and provides a 2.25% improvement in LCOE with respect to the original layout. This research has been published in the journal *Renewable Energy* (Kirchner-Bossi and Porté-Agel, 2024).

The newly-developed framework has also been used to optimize the wind farm layout using variable wind turbine heights. Overall, it is found that using different wind turbine heights leads to additional increases in the LCOE of about 3% with respect to the optimized single turbine height case. Results from this research have been published in the Journal of Physics: Conference Series (Kirchner-Bossi and Porté-Agel, 2022).

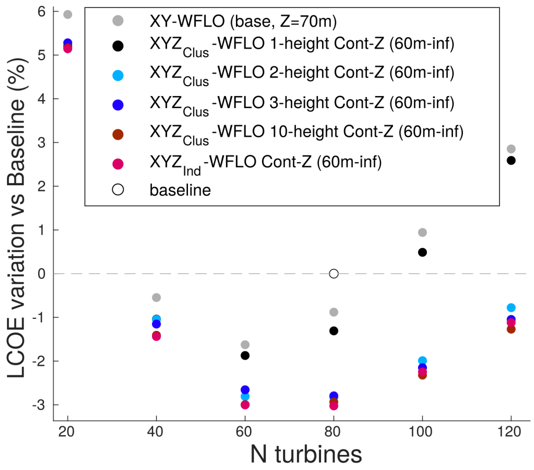


Figure 8. LCOE variation (%) with respect to the baseline case (HR1 operational layout), for different amounts of turbines, for results obtained in the XY-WFLO (baseline height, 70 m) and XYZ-WFLO problems.

Development of new short-term forecasting methods using machine learning models fed by stochastic-optimized weather predictors

The fluctuating and intermittent nature of wind (alongside to that of other increasing energy sources as solar) makes the short-term management of wind energy production (typically <48h) especially hard, and foresees the grid energy balance tasks to become more and more challenging in next years. This is the context where the improvement of the forecasts of the fluctuating energy sources becomes crucial. In addition to ease this problem, short-term wind power forecasting (STWPF) has multiple potentially beneficial applications for the energy industry, as e.g., energy market traders bidding and trading tasks, operational planning by energy producers, etc.

STWPF contributions can be divided into physics-based models (e.g., numerical weather prediction models, NWP), statistics-based, which includes models relying on big data by means of machine-learning (ML) models, or hybrid, which consist of the combination of the former two. In recent years, multiple hybrid strategies have risen in the field of STWPF, which have mostly focused in the development of new improvements in the ML tool. However, they tend to consider very few meteorological variables from just the closest grid points to the studied location. Our contribution to the improvement of STWPF relies on harnessing the relationship between wind and the rest of the Earth-system as a whole, through the drastic expansion of the predictor space provided by the weather model (in this case a 1.1 km horizontal resolution COSMO-1 provided by MeteoSwiss). This is done by remarkably increasing the degrees of freedom of both the potential meteorological predictor candidates, and the number and positions of the considered grid-points spread through both the horizontal and the vertical exploration space. The selected variables and positions progressively evolve by means of the implementation of genetic algorithms (GA). Throughout a series of generations (figure 1a), the GA selects and evaluates the performance of the predictors after submitting them as inputs for a multi-layer perceptron (MLP, a quite common type of artificial neural network, ANN), until a maximum performance is reached in terms of prediction accuracy.

The new forecasting framework is applied to the **Juvent wind farm** through our **collaboration with BKW**. Preliminary results using our proposed approach were compared against considering only a basic set of meteorological variables (wind components u and v, temperature, pressure and relative humidity) from the four grid-points closest to the wind farm, used as inputs for the same type of MLP network (Figure 9). They showed significant improvement, with for instance 12.9% overall decrease in the power prediction (12h horizon, figure 1b) root-mean squared error (RMSE), this decrease ranging between 10.6% and 14.4% throughout the 16 turbines of the wind farm.

Results from this research have recently been published in the journal *Applied Energy* (Kirchner-Bossi et al., 2024).

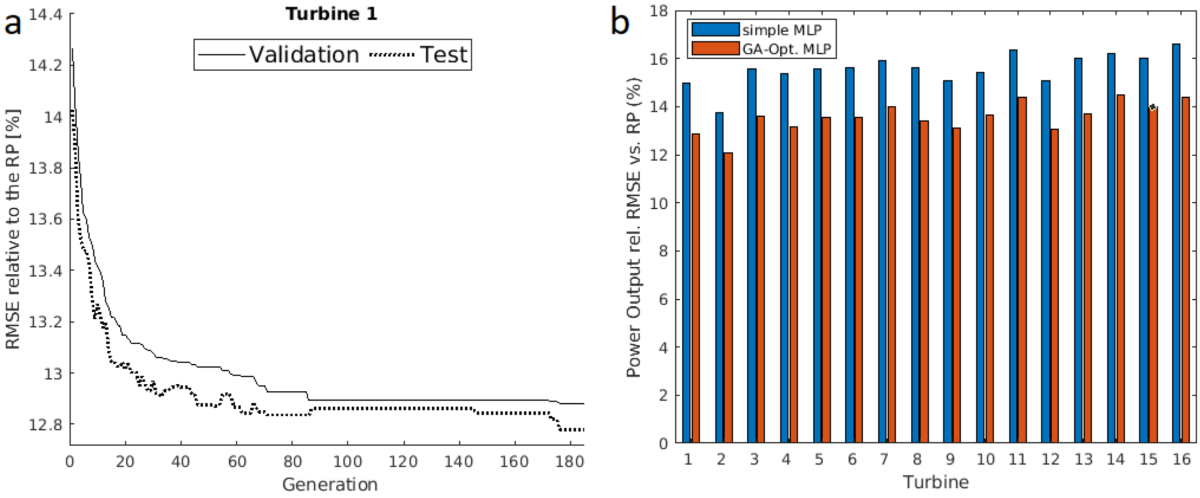


Figure 9. RMSE (relative to the turbine rated power), in %, (a) throughout the evolution of the GA generations (Turbine 1), and (b) as the final result for each of the 16 turbines at the Juvent wind farm (Switzerland), for both the simple ANN (simple predictors) and the proposed method (GA-Opt. MLP).

National cooperation

During the course of the project, active collaboration has been carried out with the following national partners:

- **BKW:** We have established a fruitful collaboration with BKW, the company operating the Juvent wind farm located in the Swiss Jura Mountains. Specifically, BKW has provided operational SCADA data from the Juvent wind turbines, which has been essential to develop and test flow models as well as the newly developed short-term power forecasting tools.

- **Our partners of the SCCER-FURIES Project ('The Future Swiss Electrical Infrastructure'):** Our Laboratory (WiRE) has led a Subtask on 'Energy Power Forecasting Tools', which has focused on the development of prediction tools for renewable energies and their integration to the grid in the context of the Swiss Energy Strategy 2050. Our partners in that Subtask included other Laboratories at EPFL, ETHZ (LEC Laboratory) and the Institute of Computational Science of the USI.

- **Our partners of the ongoing Urban Twin Project as part of the ETH Board Joint Initiative:** Within that project, we participate in the Work Package and our task is focused on short-term wind farm and solar plant power forecasting, which is complementary to the Work Package 3 of the current project. Our partners in that project include other Laboratories at EPFL (DESL, ESL, IPESE,), **ETHZ** (FEN Laboratory) and **EMPA**'s Dynamical Processes Laboratory. Two industrial partners provide operational power data from power plants in Switzerland: **BKW** and **Romande Energie**.

- **Axpo Group:** During the project, we have had discussions with the Axpo Group, which has shown interest in collaborating in the area of wind power forecasting. Axpo is Switzerland's largest producer of renewable energy and an international leader in energy trading and the marketing of solar and wind power.

International cooperation

The following international collaborations have been carried out during the duration of the project:

- Our Laboratory has been the Swiss representative at the **WAKEBENCH Task 31 (Benchmarking Wind Farm Flow Models) of the IAE (International Energy Agency) Wind**. Particularly, the datasets being collected in our wind tunnel and in the field (Work Package 2) are proposed as cases to be used within WAKEBENCH for validation of numerical models used for the prediction of wind turbine wake flows and power losses in wind farms.

- International collaboration has been carried out with the French company **Engie** for the application of the analytical models recently developed at WiRE for the prediction of wake effects in wind farms managed by Engie. A Master thesis has been co-supervised and the results were presented during the 2023 Wake Conference.

- International collaboration has been carried out with international colleagues from several European universities (Danish Technical University, University of Copenhagen, University of Bergen and University of Tubingen) as part of the **H2020 project Train2Wind**. The project is focused on the study of large wind farms and the interaction with the atmospheric boundary layer.

- Collaboration was carried out with **Prof. Corey Markfort** (University of Iowa) for the analysis of the measurements collected using the EPFL lidars mounted on the nacelle of a wind turbine in Iowa City (USA), as part of Work Package 2.

- International collaboration has also continued with the partners in the **AWAKEN Experiment**, a large-scale international experiment aiming to study wind farm performance under different atmospheric conditions. The experiment was carried during 2024 in Oklahoma (USA). The EPFL WiRE Laboratory was an active participant deploying three scanning wind lidars.

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