# Master 2 Internship in Control Theory applied to Wind farms

# Resilient control of a wind farm despite climatic disturbances

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## Context

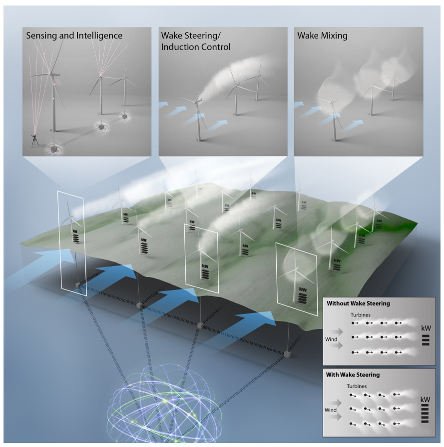


Figure 1: Wind farm and different control strategies for maximizing its electric production (figure from [1]).

Most systems are affected by disturbances and potential extreme disruptions that can affect their optimal behaviour and performances, and lead to system faults or anomalies. To reduce these negative impacts, resilience aims at adaptation to maintain good performances. Replacing the fossil fuels by renewable energies requires to develop efficient and resilient green power plants, and in particular wind farms. However, the control of a cluster of different turbines in a wind farm is a challenging task because of the interactions between the wakes and the turbines: modifying the control on one wind turbine affects its wake, which in turn modifies the wind characteristics (velocities, turbulence, energy) feeding the other downstream turbines, see Figure 1.

In short, the different wind turbines are coupled by the flow and their control modifies it. The control objective is either (or both) to maximize the total electric power generated by the farm, but also to prevent potential damages and fatigue on the wind turbines. Besides, any change in the incoming wind speed and orientation results in new boundaries conditions on the incoming flow and also in a different coupling between the wind turbines, see Figure 2.

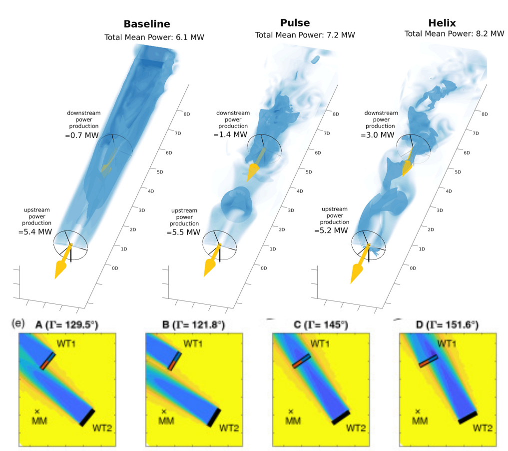


Figure 2: (a) Two wind turbines with constant (left) to time-varying (right) control inputs. (b) Two wind turbines with different incident wind flow: the resulting wake induces a different coupling depending on the incoming wind orientation. Figures from [1], [2].

The flow and the fluid structure interaction are classically modeled using the Navier Stokes equations, whose computational load is not compatible with real-time resilient control objectives. On the other hand, too simplistic industrial models [3]–low fidelity models– are well-fitted for feedbacks yet may fail to capture the flow behaviour and its nonlinearities, such as advection. Consequently, different compromises have been proposed between high and low-fidelity models, such as Large Eddy Simulations [4], reduced Partial Differential Equations (PDE) models [5], [6], and data-driven Reduced Order Models (ROM) models [7], [8] in order to propose less or more adaptive and efficient control strategies. Controlling a wind farm thus requires skills from both fluid mechanics and control theory.

PRISME is a pluridisciplinary laboratory and this work requires interactions between its two departments. Another concomitant internship, with a fluid mechanics major, is proposed to develop a reduced model of a wind turbine wake, using a porous disk representation of the wind turbine. The resulting model and collected data will feed the present internship reflexion about the modeling to develop control solutions.

## Planned work

The coupling between the wind turbines will be investigated through both PDEs models (transport, Burgers or Ginzburg-Landau equations [5], [6]) and CFD low-dimensional surrogate models using data-driven ROM resulting from the other internship. As explained hereinbefore, the interest of data-driven models is to provide reduced models, often linear ODEs, whose control is an easy task; however such approaches often capture the flow dynamics only at a given configuration of the incoming flow: they need to be trained on sufficiently rich data to provide a representative model over a wide range of incoming winds and wind farms configurations. On the contrary the precited PDEs models are obtained from the Navier Stokes equations after some simplifying assumptions so they can capture the nonlinearities of the flow dynamics whatever the climatic circumstances. Anyway, the proposed modelings are required to be simple enough to be analyzed and compatible with real-time control objectives. Their validity will be compared with high/medium-fidelity simulations such as NREL FAST and the fluid mechanics internship results. An internal model based Model Predictive Control (MPC) will then be developed to investigate tracking and maximization of the total electric power produced by the farm despite external disturbances, and compared to results obtained using existing results such as [9], [7], [10].

After a solid bibliographic work, modeling will first be studied in 1D using both PDE and ROM models, and the accuracy of the resulting models will be compared to CFD results; 2D will be investigated afterwards. In the meantime, the control efficiency, robustness and computational cost will be evaluated with respect to higher fidelity simulation results and data obtained by the other internship student.

**Profile and required skills**: Master 2 student in control theory or applied mathematics; with good programming skills (Scilab & Scicos or Matlab & Simulink). Advanced proficiency in English is also expected, as well as scientific curiosity since this work requires regular exchanges with the other internship student from another scientific community.

**How to apply?** Please send us cover letter, CV, grades and ranking for the last two years including a transcript of the current academic records –even if incomplete– as well as any recommendation letter to:


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Candidate recruitment is subject to ZRR approval (at least one month delay so ).

Duration: February/March-June/July 2024 (5 months)

Location: Laboratoire Prisme, Orléans or Bourges, France.

**Supervisors**:

- Matthieu Fruchard, Nacim Ramdani, Automatique Team (Control Theory), IRAUS Department
- Cédric Raibaudo, Nicolas Mazellier, Ecoulements et Systèmes Aérodynamiques Team (Fluid Mech.), FECP Department.

## References


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