Real-time unsteady air flow prediction to reduces mechanic load variations and wind turbine maintenance costs

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ABSTRACT

For actively controlling aerodynamic systems – like Wind Turbine (WT) blades -- it can be necessary to estimate in real-time and predict the air flow around those systems. We propose here a new method which combines machine learning, physical models and measurements for this purpose. Very good numerical results have been obtained on wake flows.

Physics-driven simulations | Machine Learning | In-situ measurements

Reduced order models | Data assimilation | Data assimilation

Our approach

APPLICATIONS

- **Lower WT maintenance costs**
- **Longer WT life cycle**
- Higher wind farm power

How ? Active control loops with robust and fast aerodynamic short-time prediction to reduces :

- blade lift variations
- wake effects within wind farms

Estimation and prediction:
- Air flow
- Lift, drag, AoA

Controller (Simple model)

- Blade pitch
- Fluidic actuators
- WT yaws (for wind farms)

Observer (Simple model) ← WT sensors (• e-telltale • lidar) ← Wind Turbine (or wind farm) ← Wind fluctuations

Which simple model? How to combine model & measurements?

METHODOLOGY

1. Ultra-fast CFD simulations with intrusive reduced order models (ROM)

- Principal Component Analysis (PCA) on a *dataset* to reduce the degrees of freedom (dof) :

Off-line simulation → Snapshots $(v(x,t_i))_i$ → PCA → PCA residual

Spatial modes $(\phi_i(x))_i$ — Learned and set up once for all

- Approximation (at small dof n):

$$v(x,t) \approx \sum_{i=o}^{n} \boxed{b_i(t)}\, \phi_i(x)$$

- Projection of the "physics" onto the spatial modes : (POD-Galerkin)

$\int_\Omega dx\, \phi_i(x) \cdot$ (*Physical equation* (e.g. Navier-Stokes))

We get a n coupled ordinary differential equations for very fast simulation of temporal modes $b_i(t)$

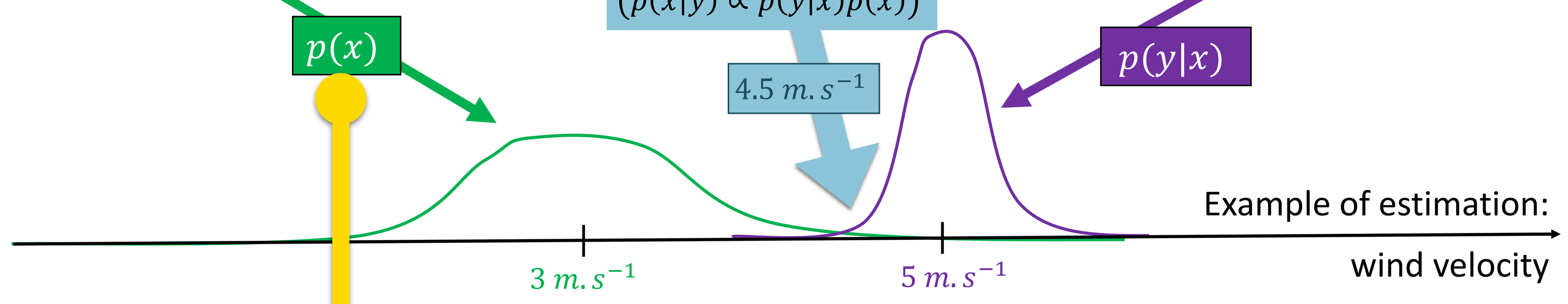
2. Measurement-simulation coupling (data assimilation)

Numerical simulations (ROM)
- Globally in space
- Erroneous

Data assimilation (particle filter + tempering)
More accurate estimation globally in space

On-line measurements
- Sparse
- Possibly noisy

$(p(x|y) \propto p(y|x)p(x))$



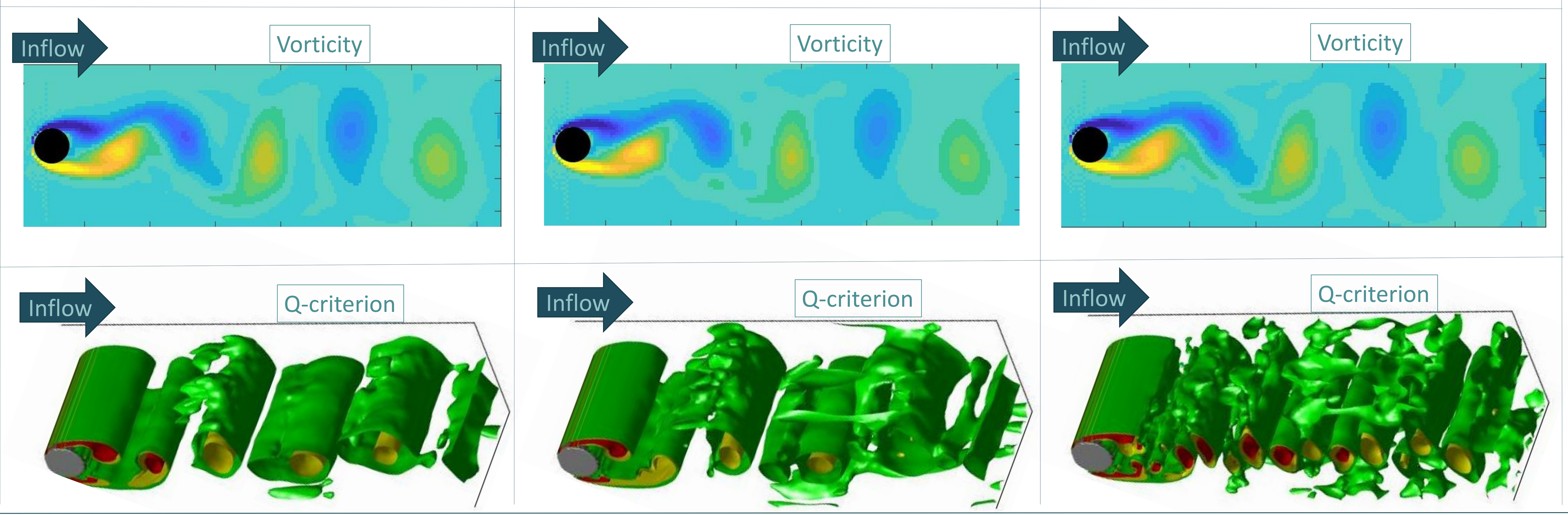
Need for accurate uncertainty / errors quantification : **Novelty is here !**

3. Randomized physics $p(x_{t+1}|x_t)$ → Location uncertainty models (LUM)

Rigorous CFD stochastic closure, with physically-based multiplicative noise

RESULTS FOR 8-DEGREE-OF-FREEDOM (DOF) SIMULATIONS COUPLED WITH A SINGLE MEASUREMENT POINT

	Reference : PCA-projection of the DNS (Optimal from 8-dof linear decomposition)	**Our method :** POD-Galerkin with Navier-Stokes under location uncertainty (LUM)	**State-of-the-art :** POD-Galerkin with Navier-Stokes + optimally tuned eddy viscosity & additive noise
Re 100, 2D 10 vortex shedding cycles after the learning period (DNS has 10^4 dof)			
Re 300, 3D 14 vortex shedding cycles after the learning period (DNS has 10^7 dof)			



METHODOLOGY SUMMARY

Off-line : Building ROM

Physics (Navier-Stokes) → DNS code → Data → Stochastic ROM ← Randomized Physics (LU)

On-line : Simulation & data assimilation

Measurements → Data assimilation → Stochastic ROM → Temporal modes b_i → Flow $v = \sum_{i=0}^{n} b_i \phi_i$

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CONCLUSION

- Reduced order model (ROM) : for very fast and robust CFD
  Combine data & physics (built off-line)
- Data assimilation : to correct the fast simulation on-line
  by incomplete/noisy measurements
- Robust flow prediction far outside the learning period
  Optimal unsteady flow estimation/prediction
  in the whole spatial domain

NEXT STEPS

- Real measurements
- Increasing complexity
- Control loop

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