Vortex shedding control by non-linear identification of low order model

EFMC9 — Rome

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Office Nationale d'Etudes et de Recherches Aérospatiales

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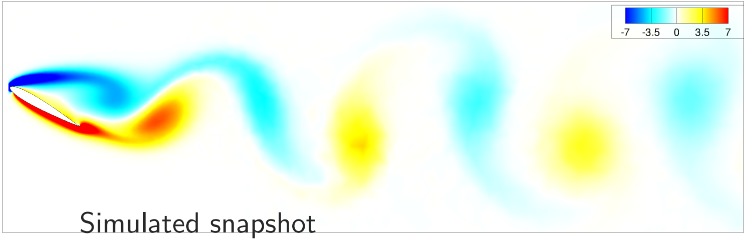
Plan

Configuration



NACA012, $Re = 200$, 30°AoA

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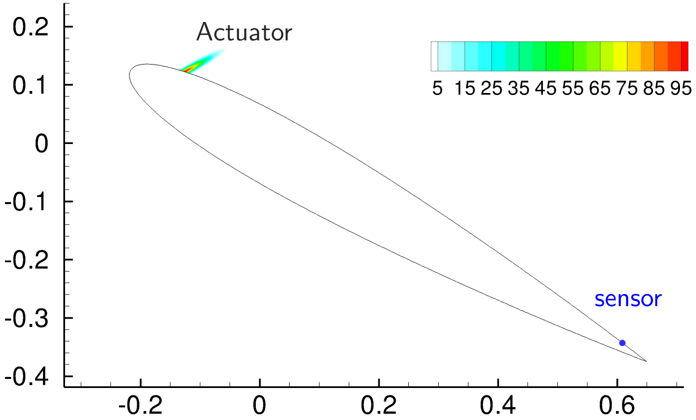

Model identification : framework

Method

1. Identification of unforced dynamics, using POD trajectories
2. Temporal ARX model to include the external forcing effects

Benchmarking

1. Required
   - linearly unstable model, showing oscillations of right amplitude and frequencies
   - Existence of an equilibrium point, that fits the projection of the baseflow onto the reduced order basis
2. Required
   - Good prediction of a forced simulation

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Model structure

1. **POD computation, around Reynolds = 50** :
   $U = \bar{U}_{|Re=50} + \sum_i x_i \Phi_i \quad \varepsilon = \frac{1}{Re_0} - \frac{1}{Re}$

2. General structure of the model (dependency in Reynolds is kept) :

$$\begin{aligned} x_i^{t+1} &= \varepsilon A_i + \sum_j (B_{ij} + \varepsilon \beta_{ij}) x_j + \sum_{j,k} C_{ijk} x_j x_k \\ &= f_i(X(t)) \end{aligned}$$

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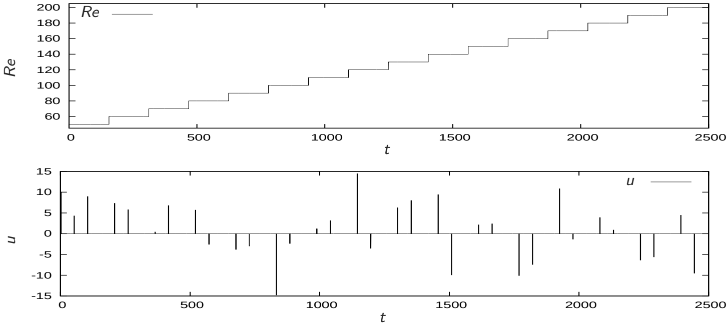
\end{aligned}
$$

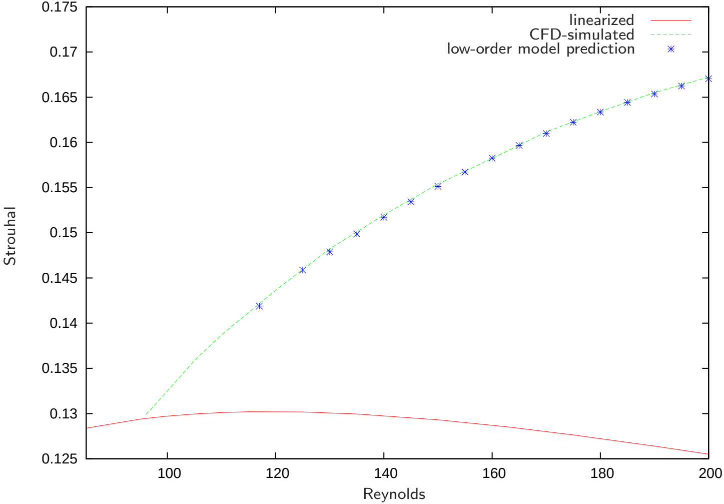
Model equation :

$$x_i^{t+1}(X,\varepsilon) = \varepsilon A_i + \sum_j B_{ij}x_j + \sum_j \varepsilon\beta_{ij}x_j + \sum_{j,k} C_{ijk}x_jx_k$$

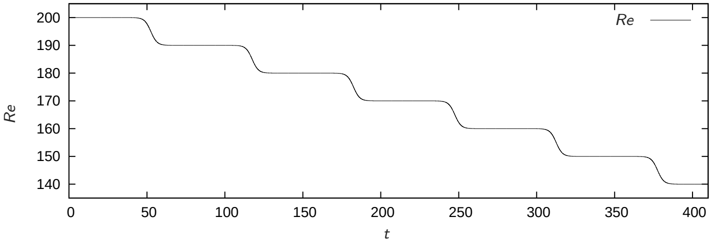


Training dataset. Seldom forcing peaks are used to trigger richer dynamics

Variations of Strouhal numbers

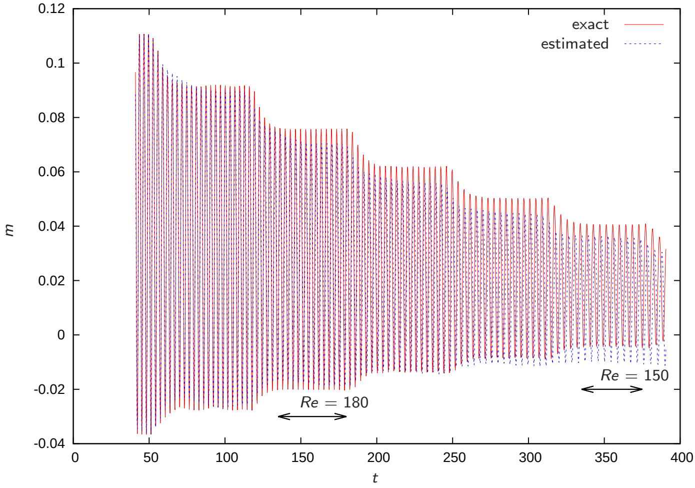


Testing Dataset



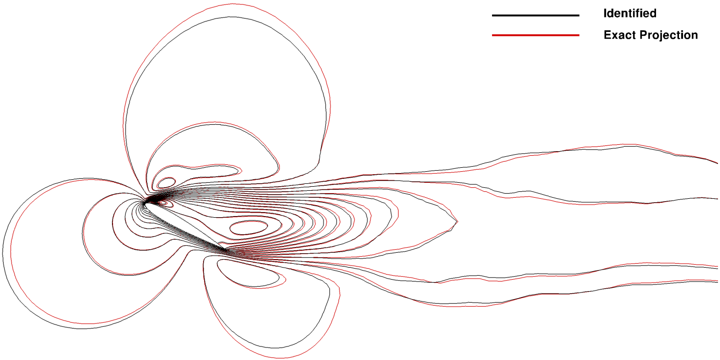
Training dataset

Training dataset simulation



Training dataset simulation

Prediction of the projected baseflow from the model dynamics



Comparison at $Re = 200$ between the exact projected base-flow and the model-identified base-flow. The iso-contours represent horizontal velocity.

Identification of the external forcing effects onto the reduced order basis

- CFD computation of a random forced flow
- $\Delta(t) = X(t+1) - f(X(t), \varepsilon(t))$
- *ARX model :* $\Delta(t) = \sum_k \alpha_k u(t-k)$

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Modeling the external forcing effects

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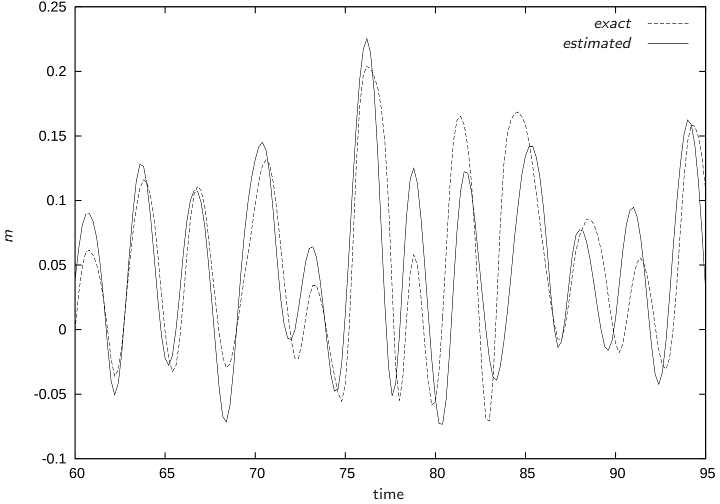
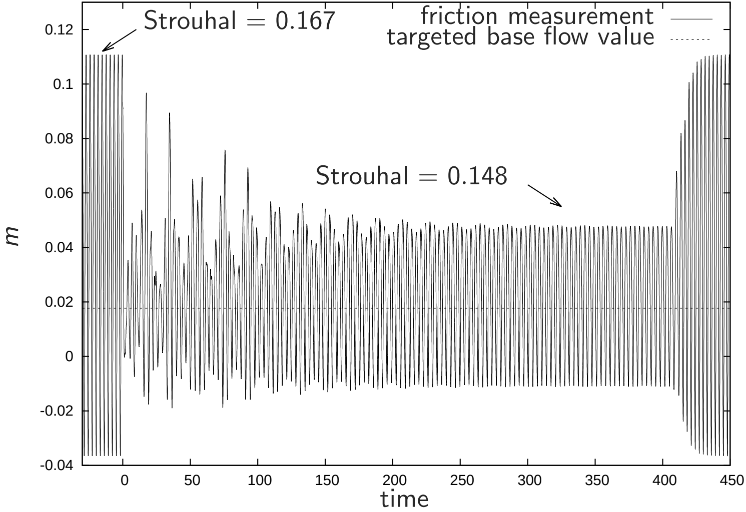
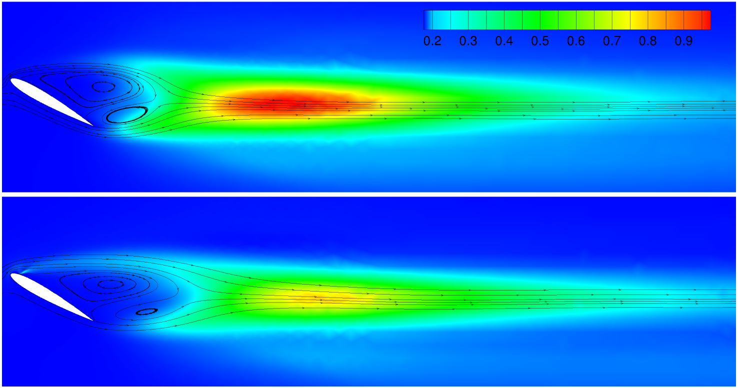
Full forced dynamics prediction



Non linear control



Turbulent kinetic energy reduction



Control results. Contours of mean kinetic energy of the fluctuations around the baseflow $\left(v'^2_x + v'^2_y\right)$ *are plotted, as well as some streamlines of the averaged flows. The peak of fluctuation energy is reduced by 20%.*

Conclusions

Low order model

- Accurate modeling of the unforced dynamics using 5 pod modes, and over a large range of Reynolds numbers
- Deduction of the projected baseflow from the model dynamics
- Temporal ARX model to include the external forcing effects
- Efficient control to reduce the given objective

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