Recent advances in flow diagnostics and (predictive) control at UC3M

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With contributions from: Junwei Chen, Luca Franceschelli, Luigi Marra, Alicia Rodriguez, Marco Raiola, Andrea Meilán Vila, Andrea Ianiro,…

ERCOFTAC
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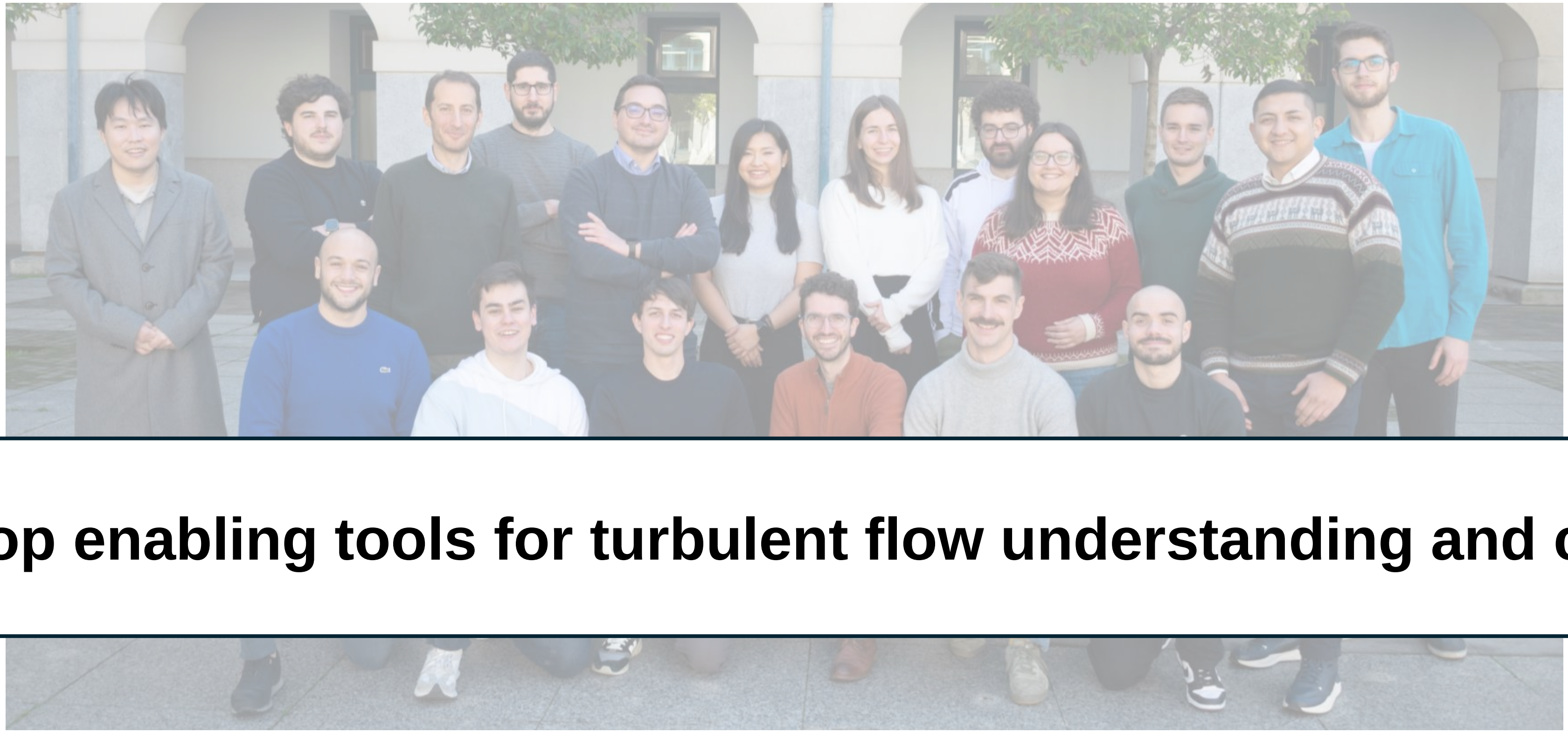
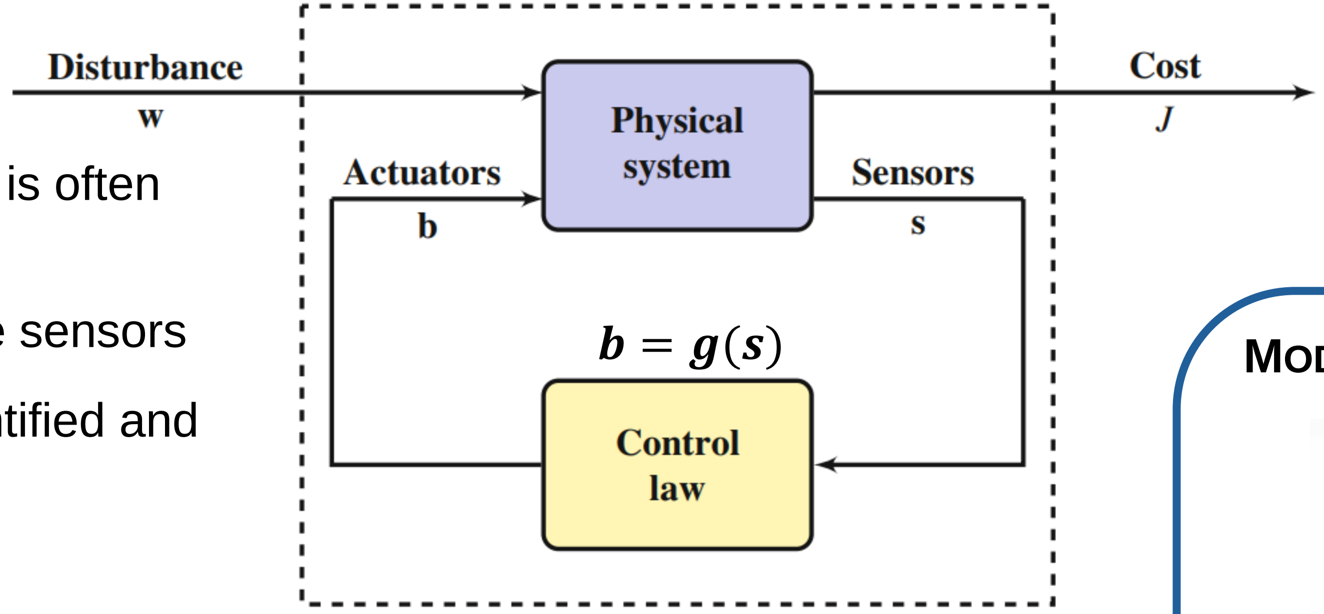


Develop enabling tools for turbulent flow understanding and control

Challenges in turbulent flow control

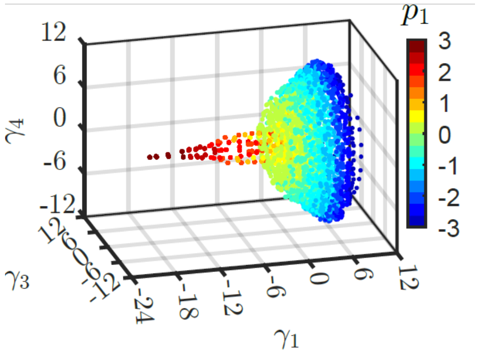
- High dimensionality
- $\boldsymbol{f}(\boldsymbol{x}, \boldsymbol{b}, \boldsymbol{w})$, if available, is often not of practical use
- Time resolution → use sensors
- $\boldsymbol{b} = \boldsymbol{g}(\boldsymbol{s})$ must be identified and must fulfil constraints
- … and many more!

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{b}, \boldsymbol{w})$$

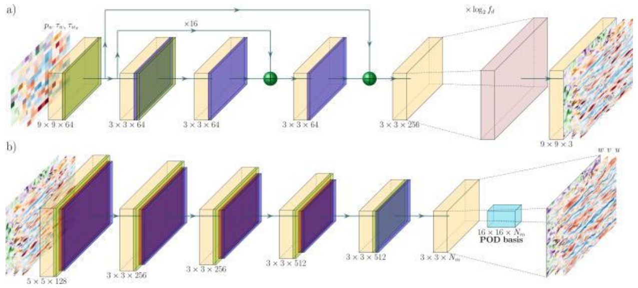


*Duriez, Brunton, Noack (2017)

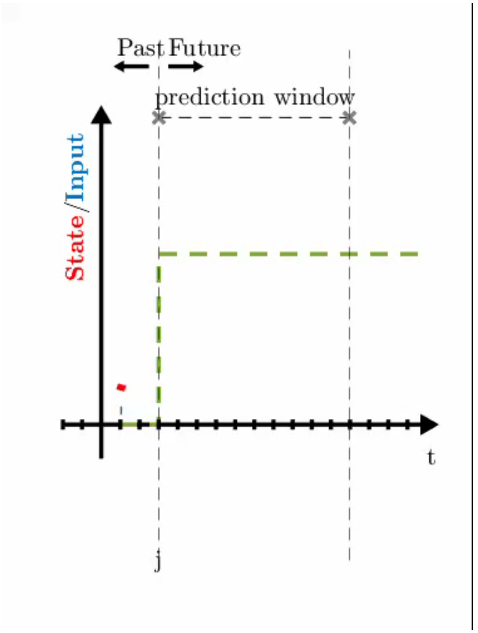
Dimensionality reduction



Estimation from sensors



Model Predictive Control



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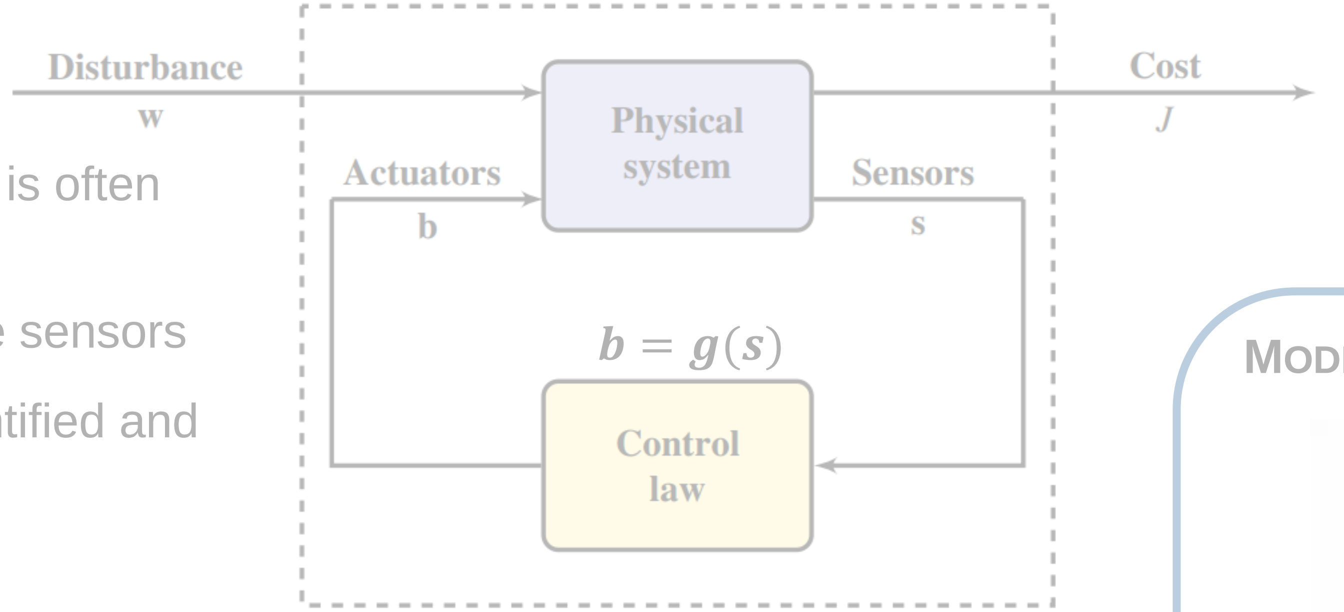

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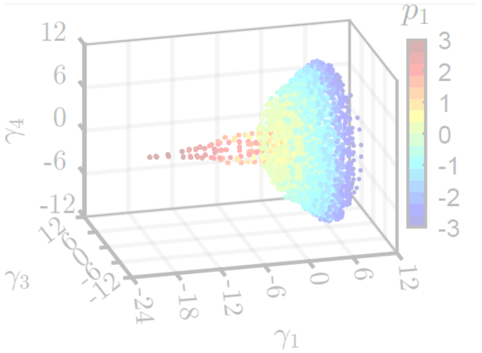

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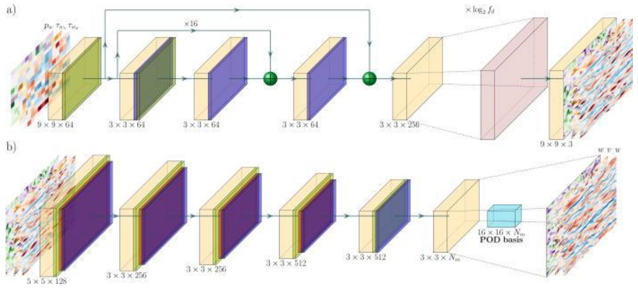

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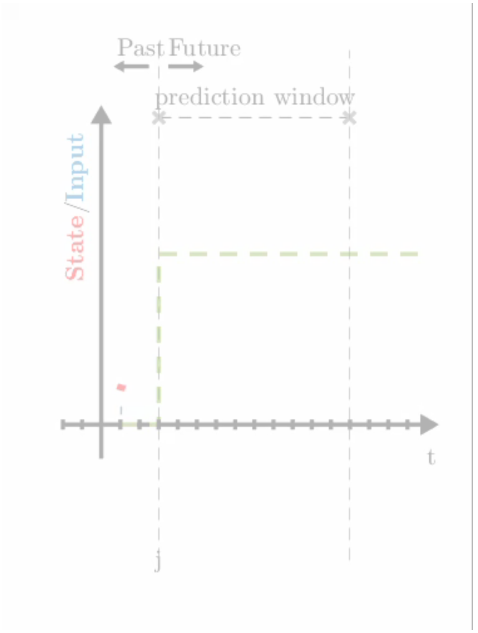
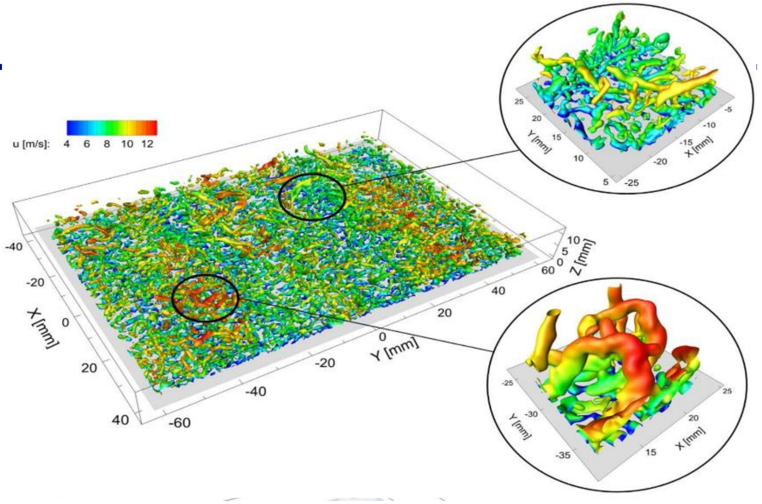


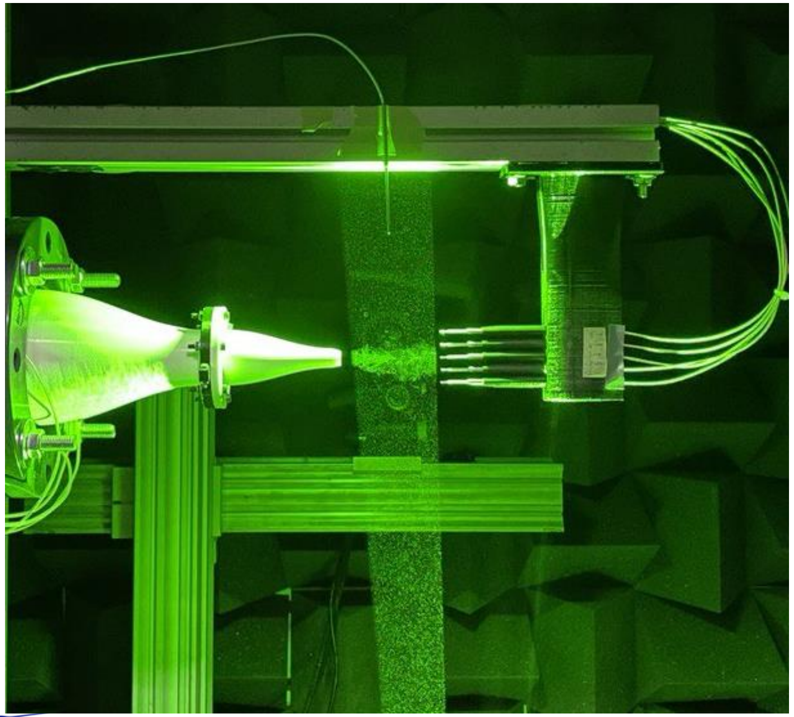
Full-field estimation from sensors

- Key for interpretability
  - PIV “sees” the flow but time-resolution is often unaccessible

TRPIV → expensive and not always feasible



Novara et al EiF 2019



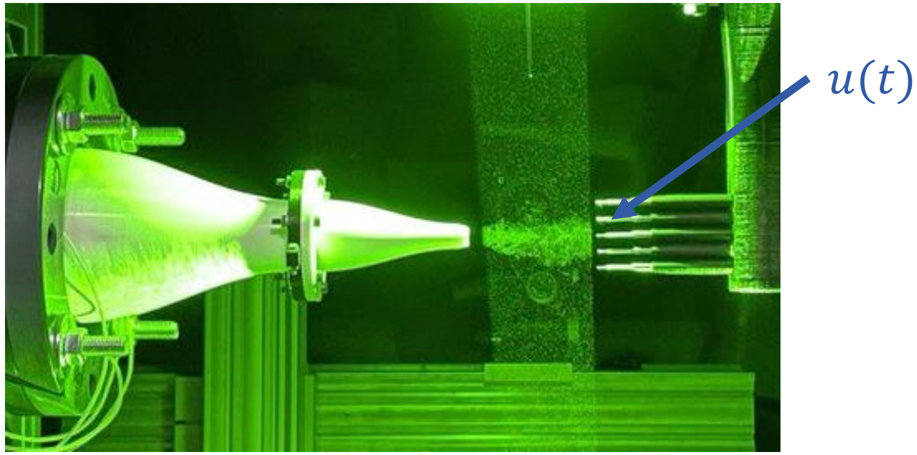
Sensors are going to be there anyway for the control…

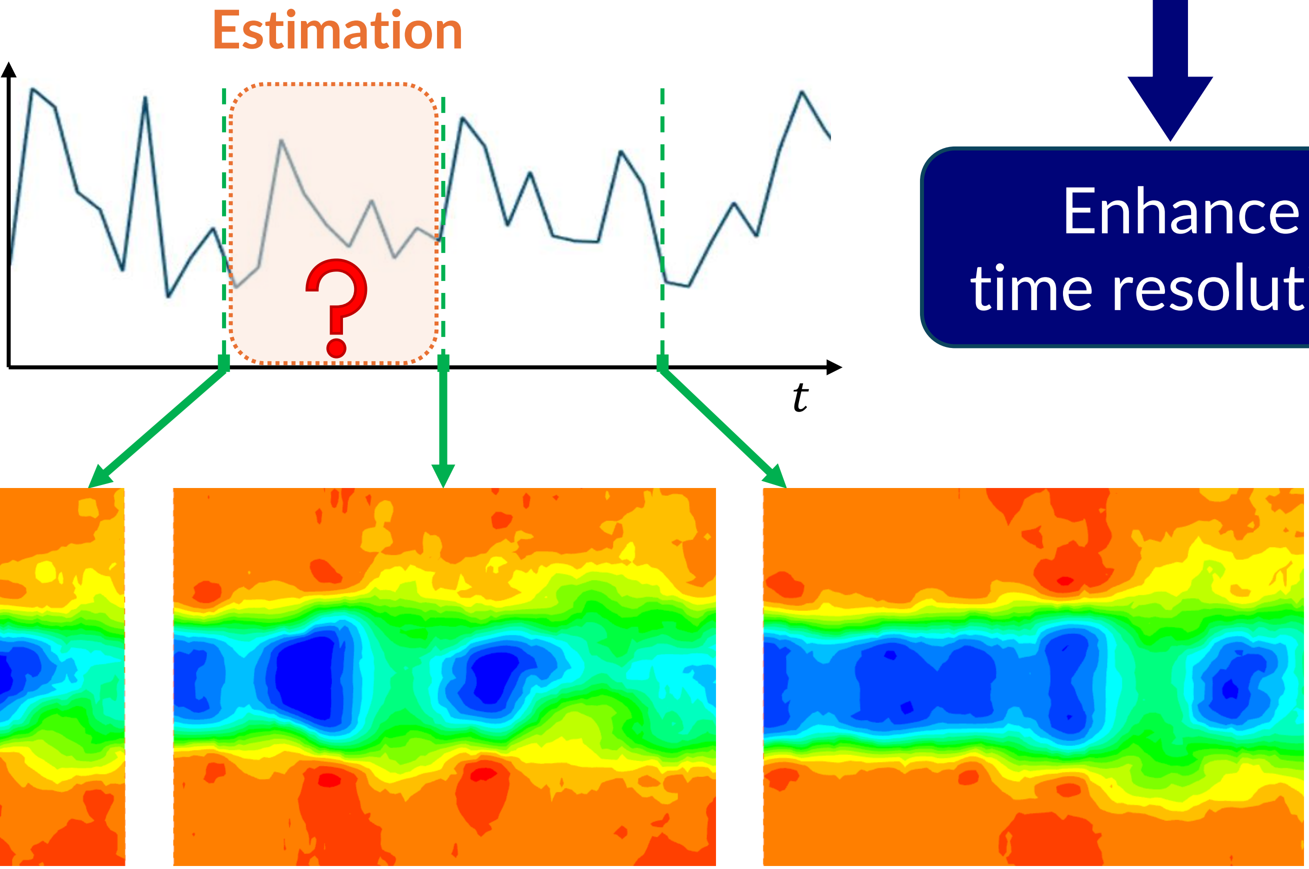
Can we get the picture of the flow fields from them?

Full-field estimation from sensors

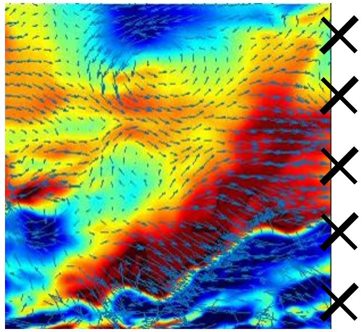
- ✓ Fast response probes → ~~Point-wise measurement~~, high temporal resolution
- ✓ Snapshot PIV → Instantaneous Flow-field, ~~no temporal resolution~~

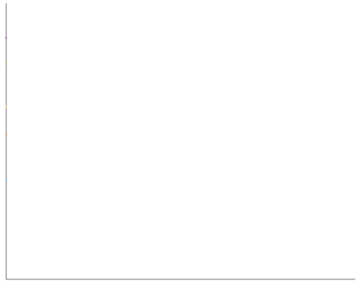
Enhance time resolution





Full flow description from probes





HOT-WIRE,
PRESSURE
TRANSDUCERS…

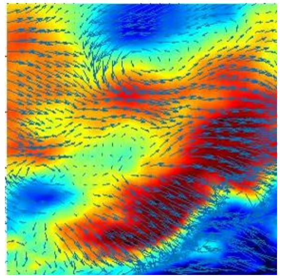
NON-TR-PIV

FAST PROBES

TIME- RESOLVED
VELOCITY

$$\nabla \cdot \boldsymbol{u} = 0$$

$$\rho \frac{D\boldsymbol{u}}{Dt} = -\nabla p + \mu \nabla^2 \boldsymbol{u}$$



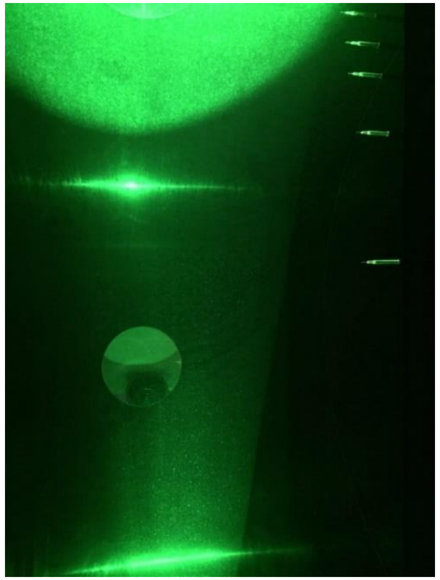
FULL FLOW
DESCRIPTION

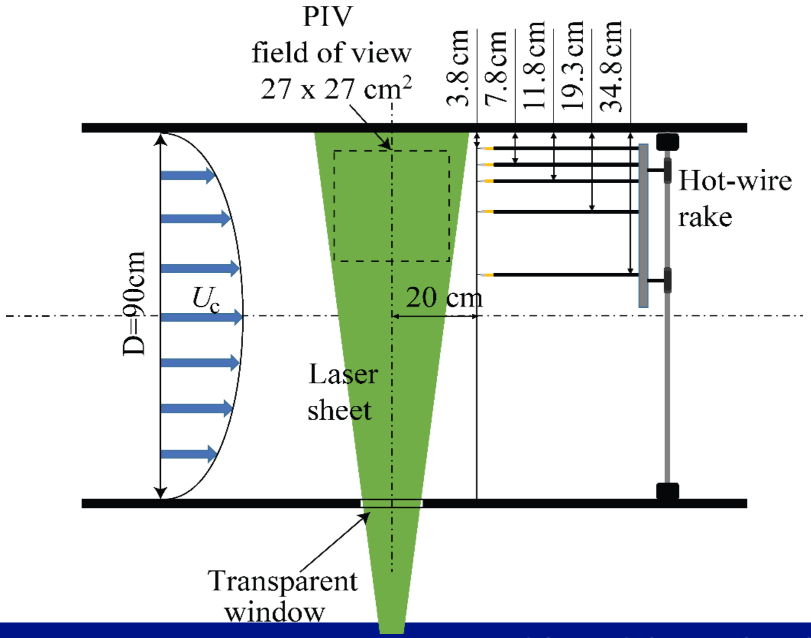
STANDARD EQUIPMENT

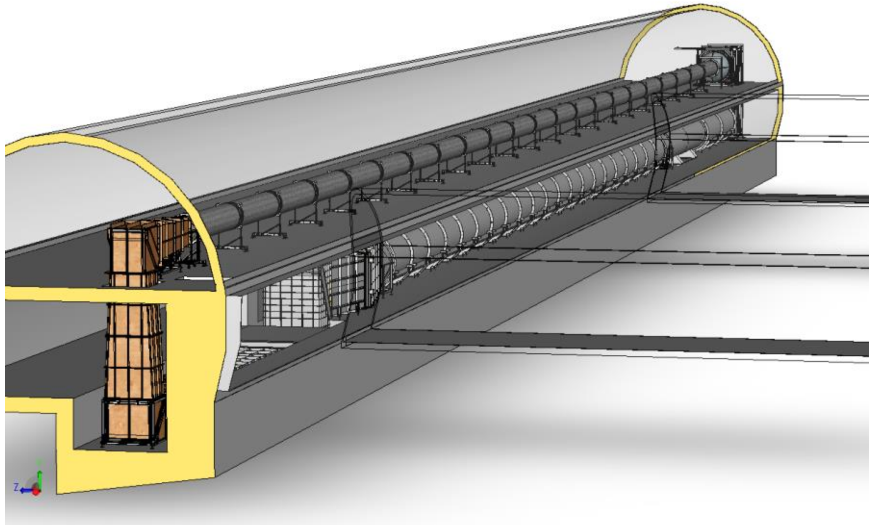
REQUIRES ROBUST
METHODS FOR FIELD
ESTIMATE

DIMENSIONALITY
REDUCTION IS THE KEY

LargeView project

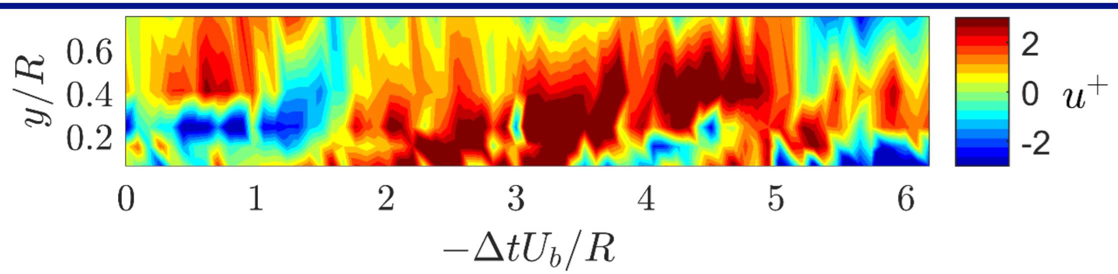




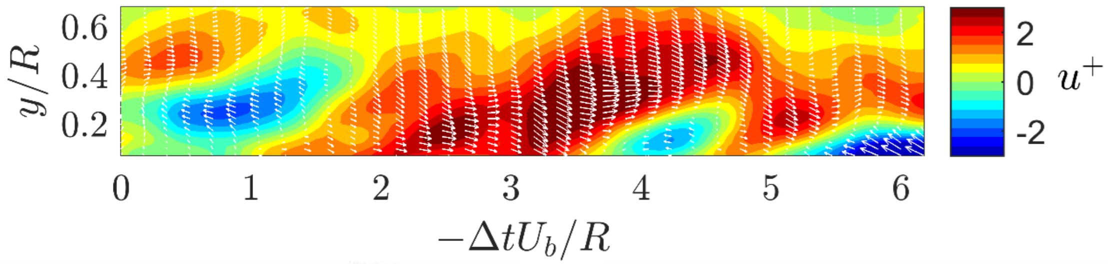


Discetti et al (2019) Exp Therm Flu Sci

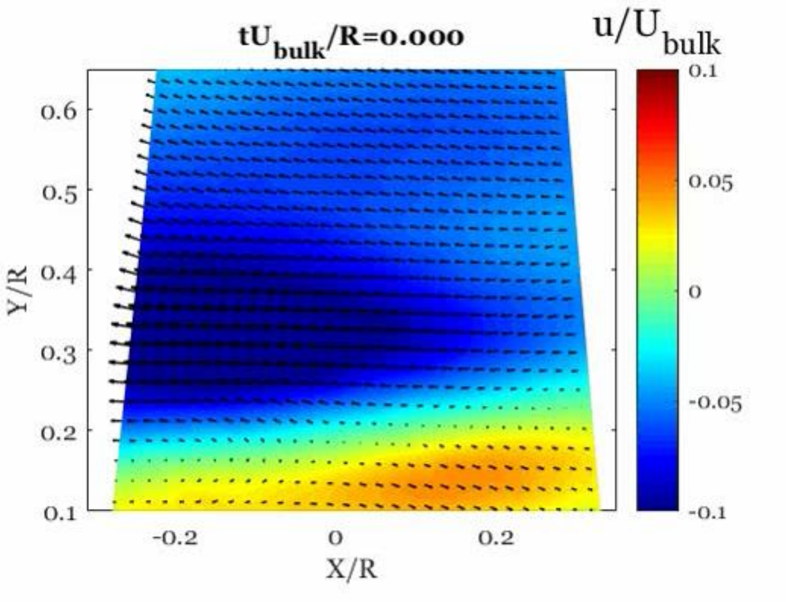
Flow fields estimation



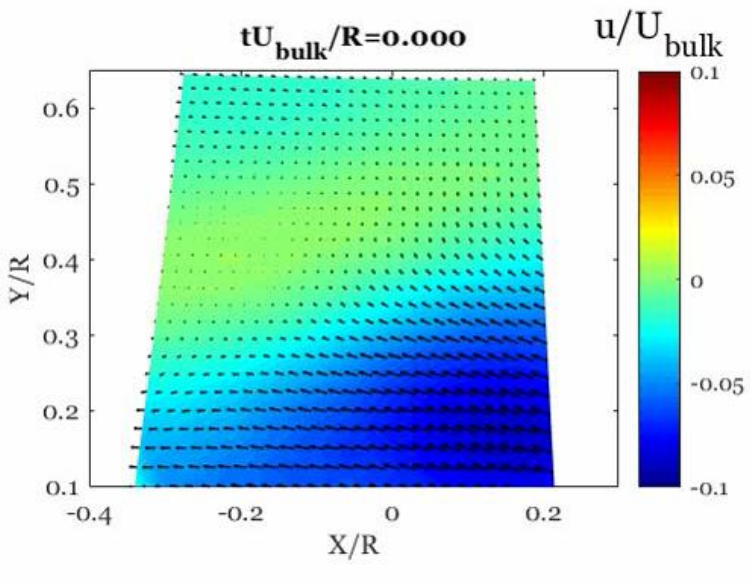
HWA



EPOD-PIV

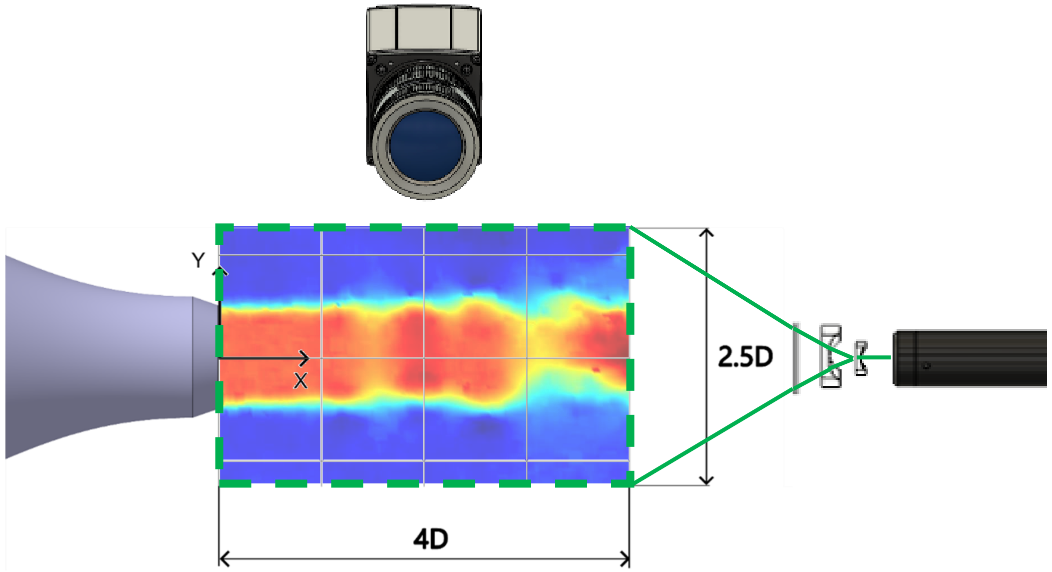


$Re_\tau = 9500$



$Re_\tau = 19900$

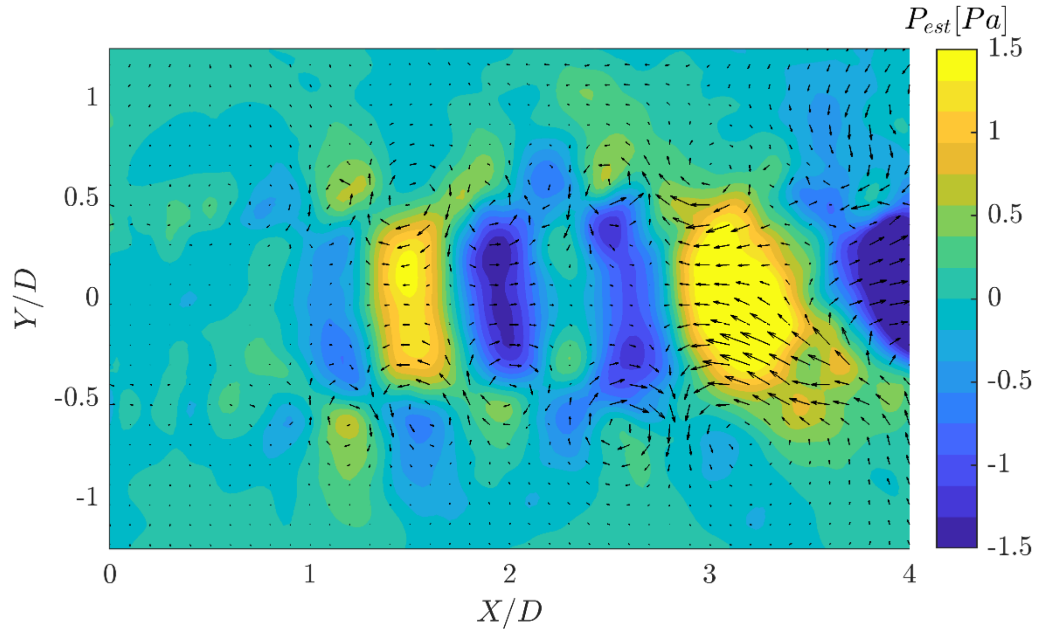
Experimental setup – wáter jet flow



Parameter	Value
D	30 mm
U_j	0.08 m/s - 0.16 m/s
Re	2400 - 4800
f	100 Hz
Resolved Area	120x75 mm
Acquired Snapshots	10^4

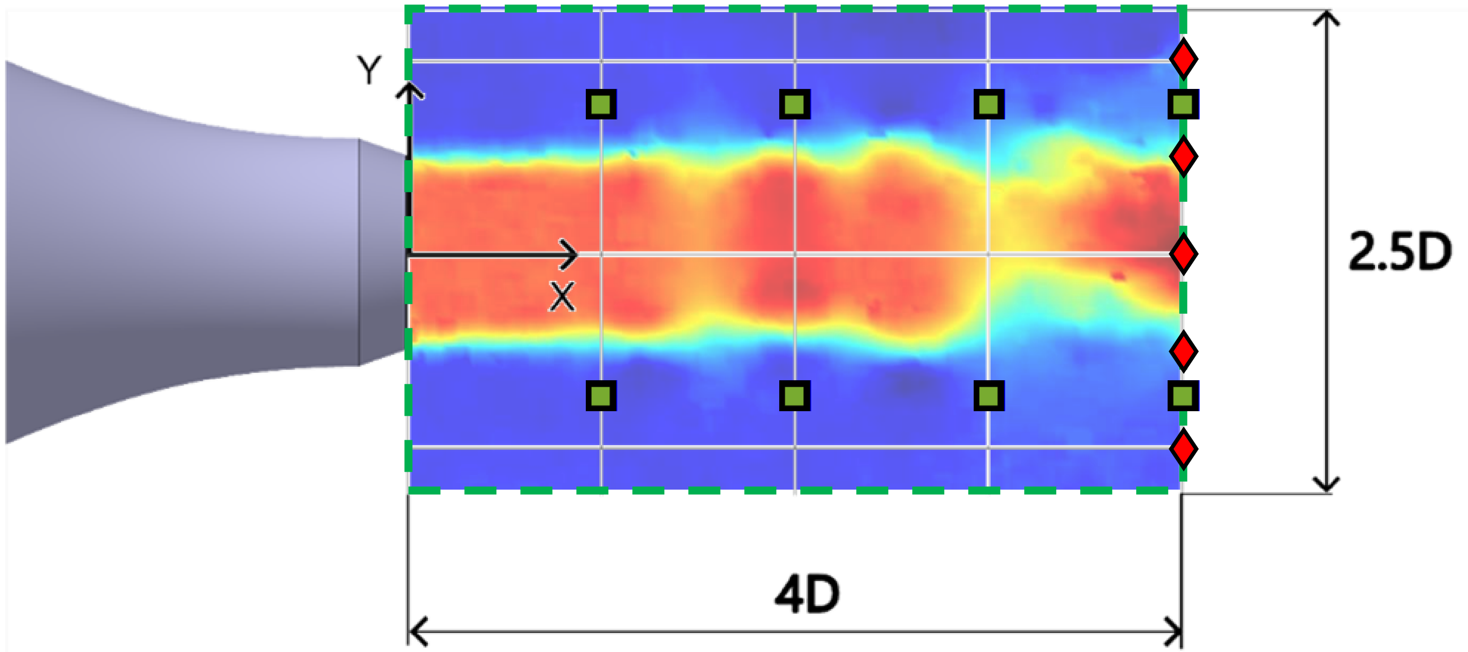
Time-resolved 2D PIV

Pressure field estimation
Chen et al. (2022)



Synthetic Dataset Generation

Simulate **non-TR PIV** experiment with point-wise probes



Down-sampled PIV data

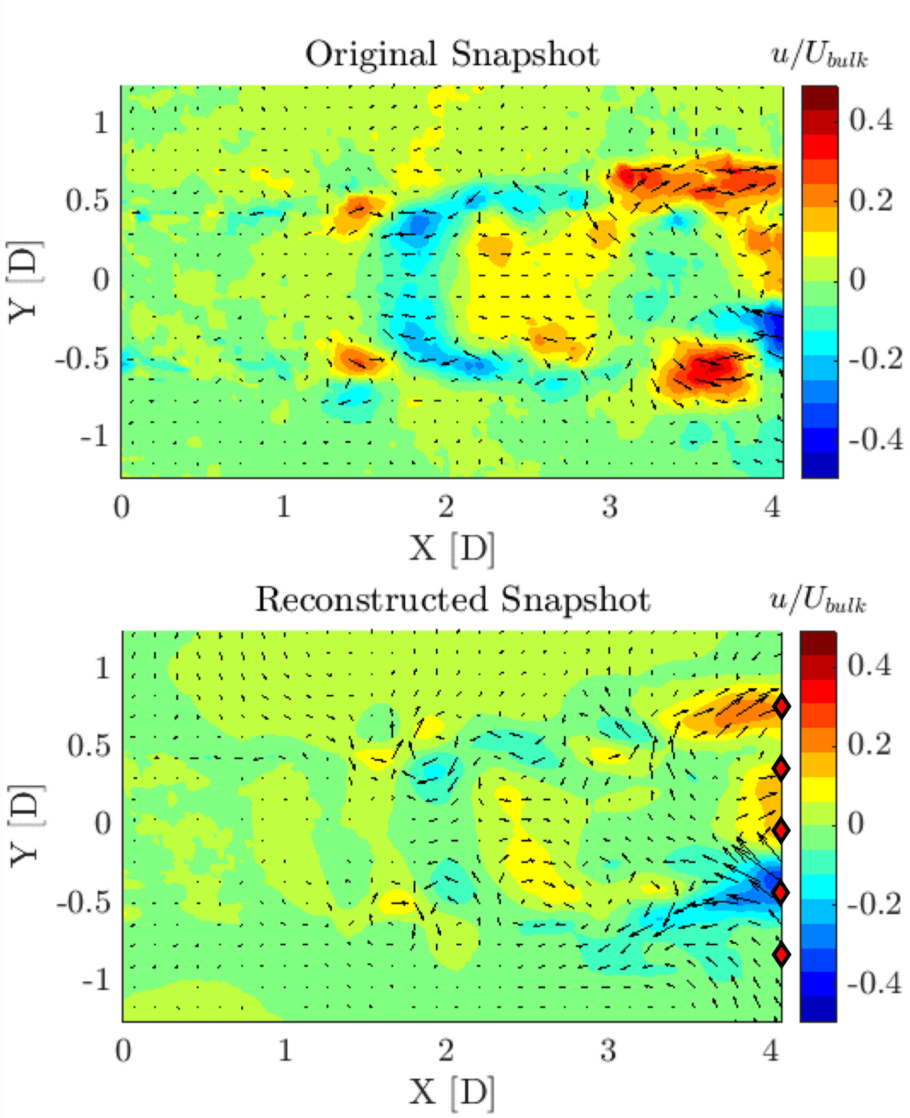
TR-PIV fields

Point-wise fully-resolved synthetic probes

Hot-wires → $\vec{u}(\boldsymbol{x}, t)$

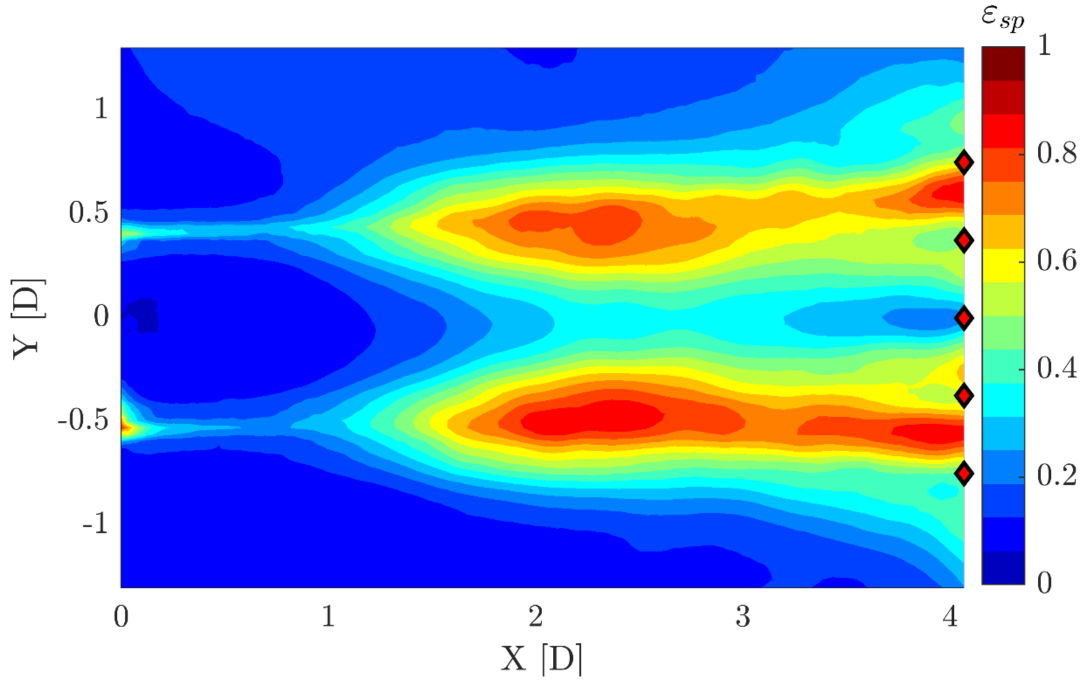
Microphones → $p(\boldsymbol{x},$

Extended POD – 5 Virtual Hot-Wires

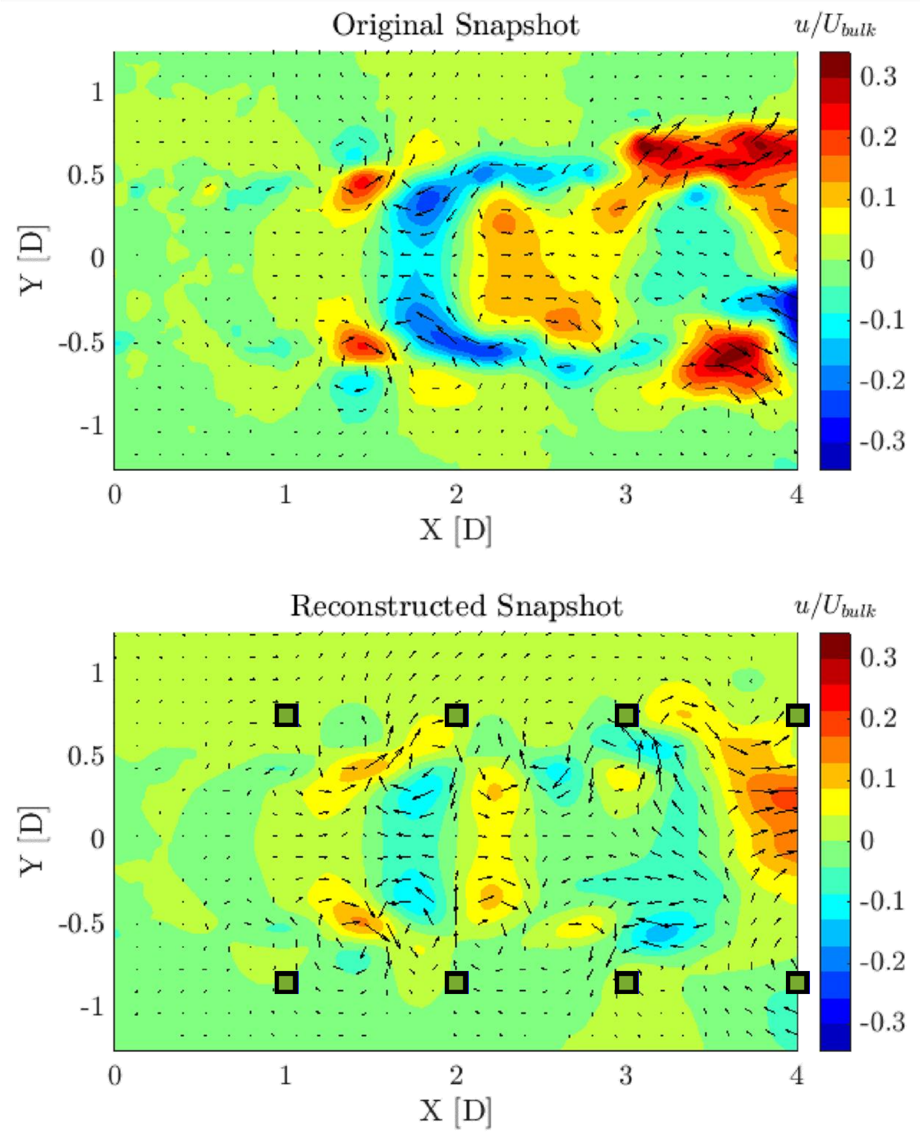


$$\left\{\begin{array}{ll} u_i & = i^{th} \text{ exact velocity fluctuation component} \\ \tilde{u}_i & = i^{th} \text{ estimated velocity fluctuation component} \\ N_t & = \text{Number of reconstructed snapshots} \end{array}\right.$$

$$\boxed{\varepsilon_{sp}(\boldsymbol{x}) = \frac{RMSE(\boldsymbol{x})}{2 \cdot TKE_{\max}} = \frac{1}{2 \cdot TKE_{\max}} \sqrt{\frac{\sum_{i=1}^{2} \sum_{j=1}^{N_t} (\tilde{u}_{i,j} - u_{i,j})^2}{N_t}}}$$



Extended POD – 8 Virtual Microphones



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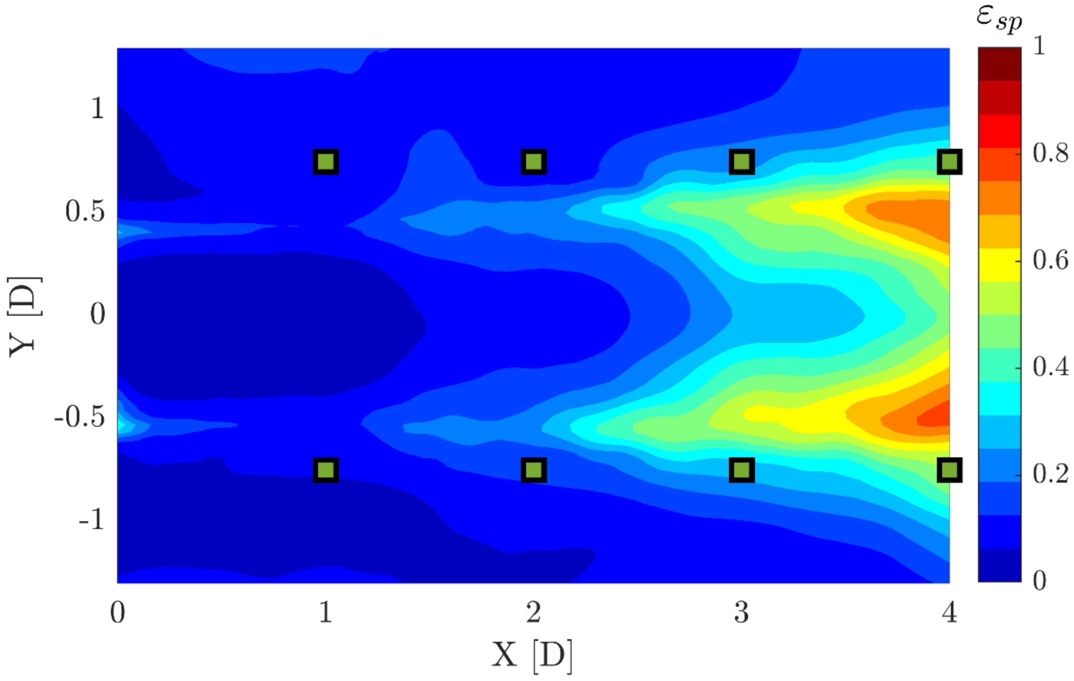
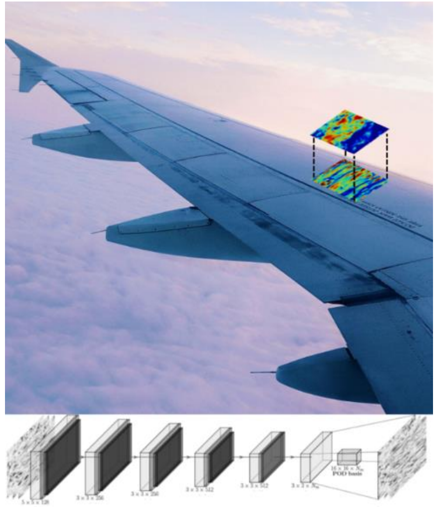
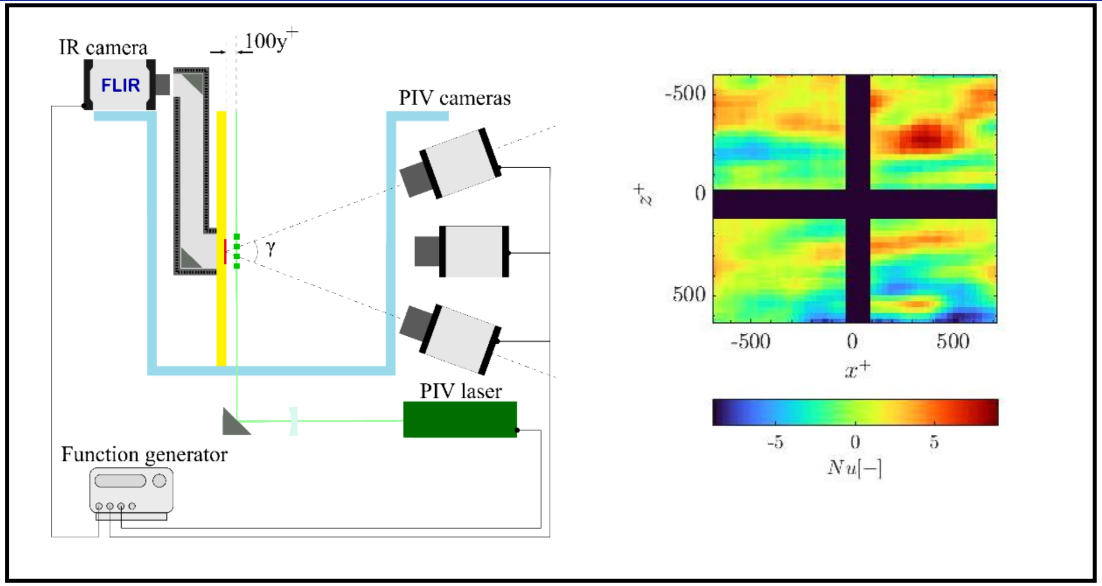
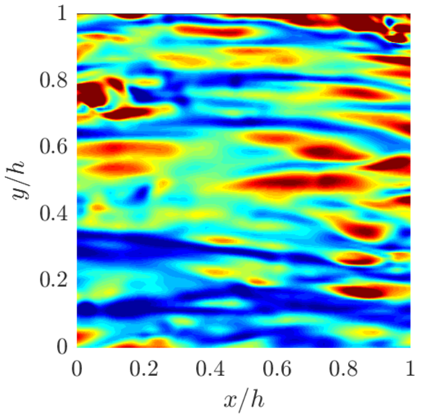


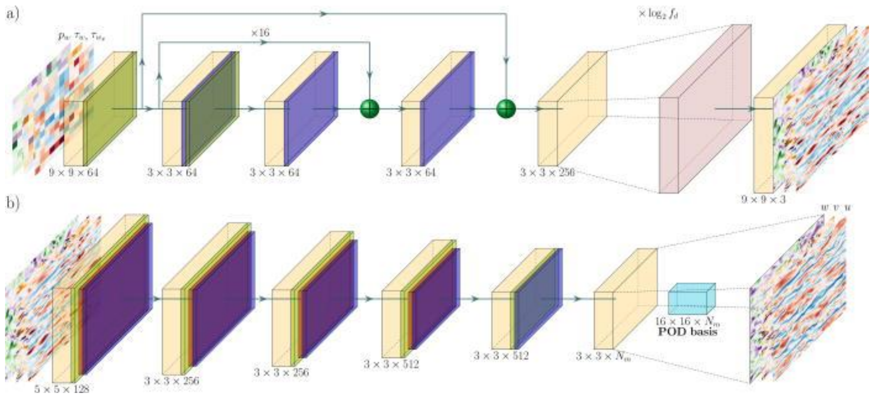
Sensing from the wall



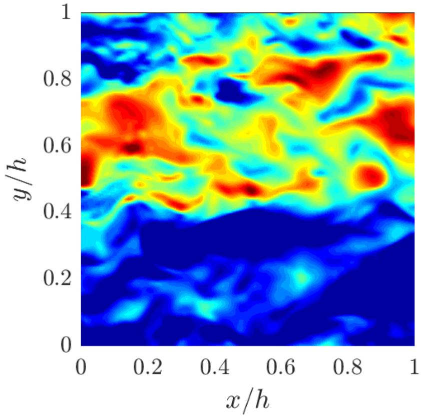




Wall-measured quantity (τ_w, p)



Güemes et al. "From coarse wall measurements to turbulent velocity fields through deep learning." *Physics of fluids* 33.7 (2021): 075121.



Wall-parallel velocity field

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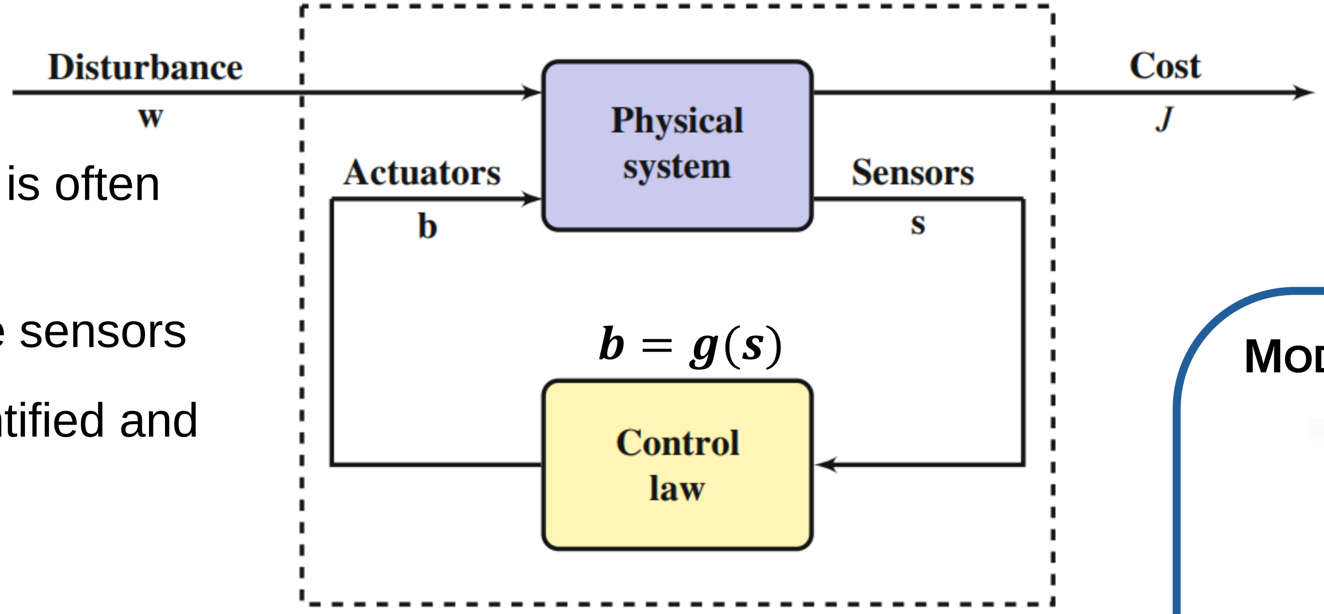

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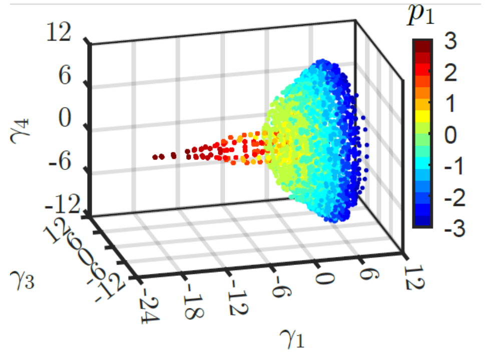
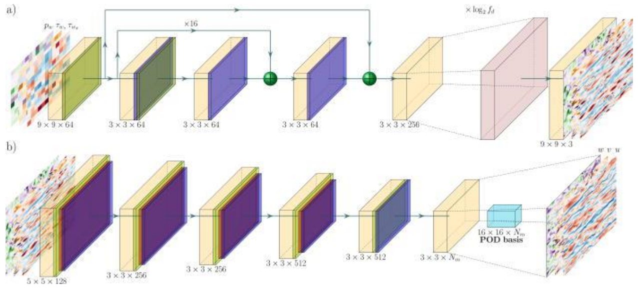
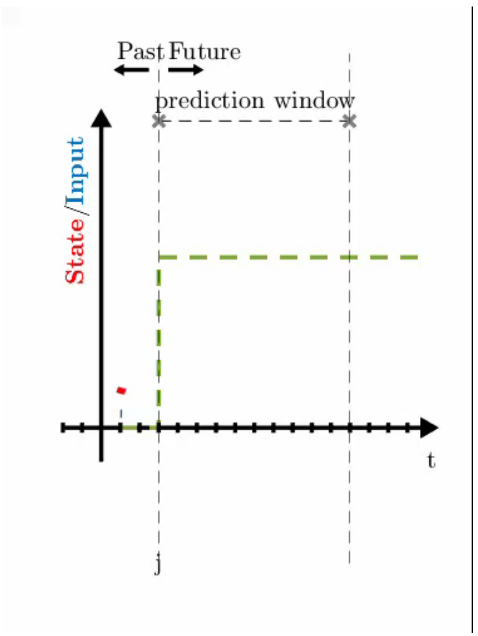
Dimensionality reduction



Estimation from sensors



Model Predictive Control



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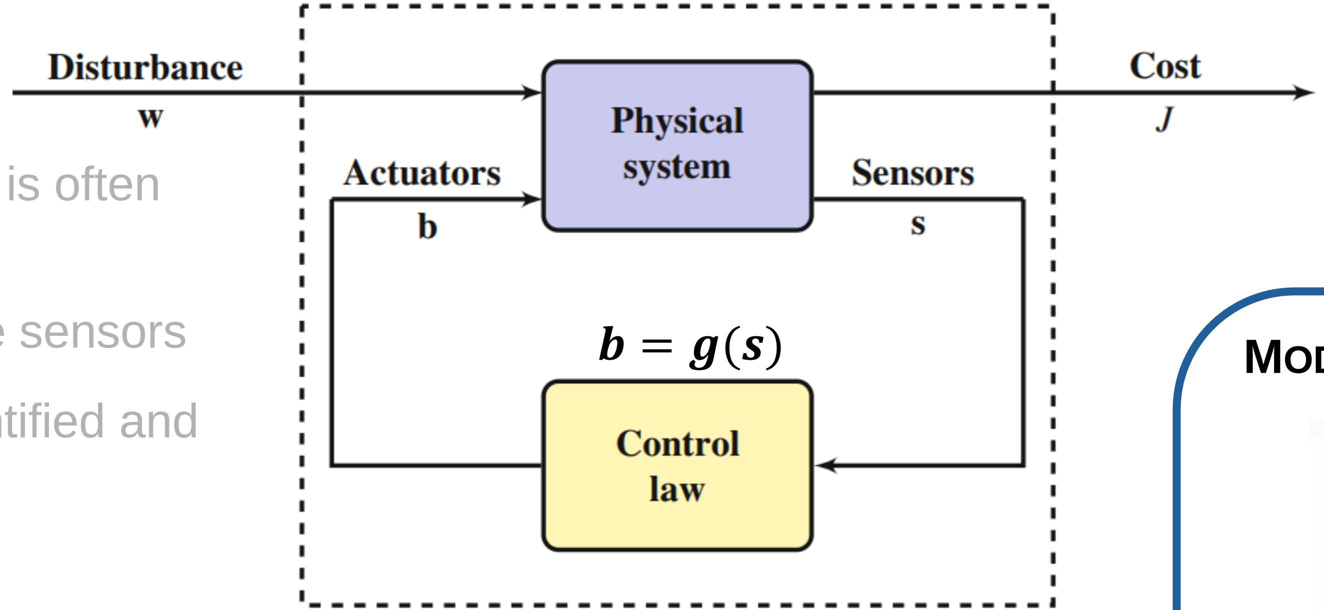

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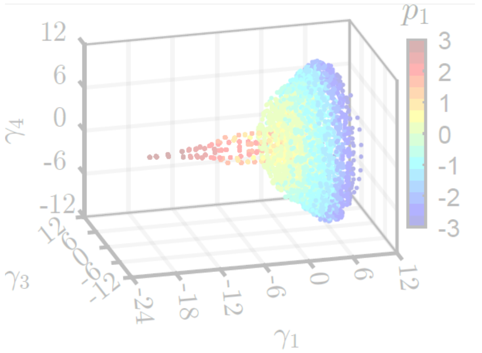

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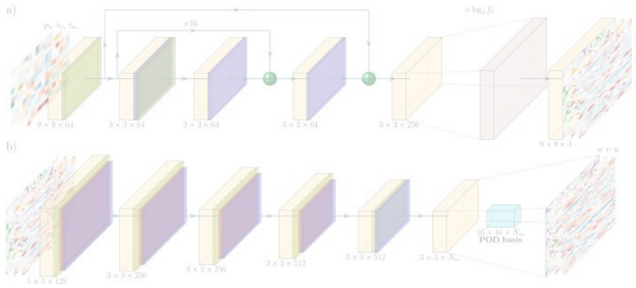

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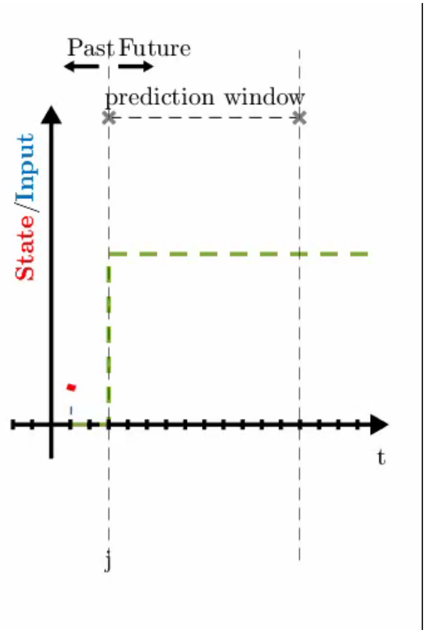


Model Predictive Control

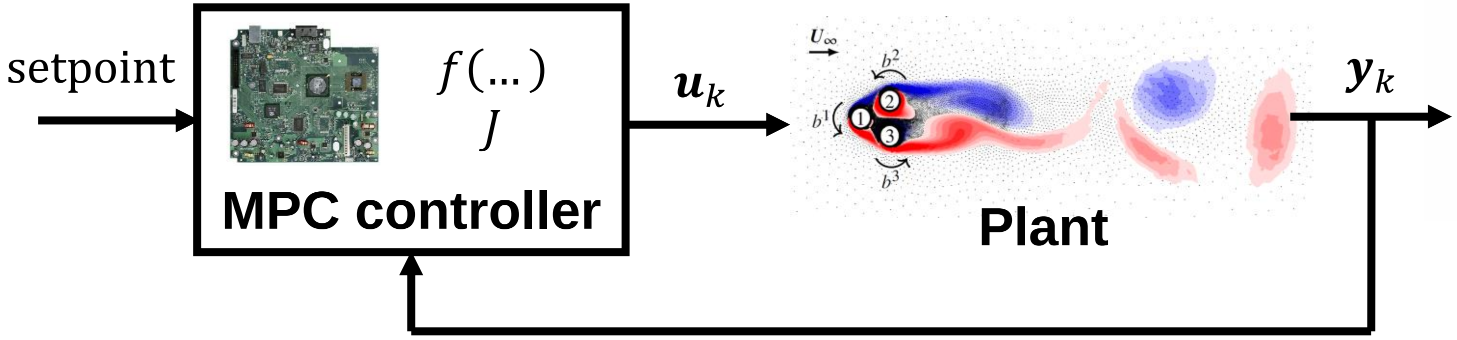
Optimization of **control** actions in receding horizon with **model**-based state **predictions**.

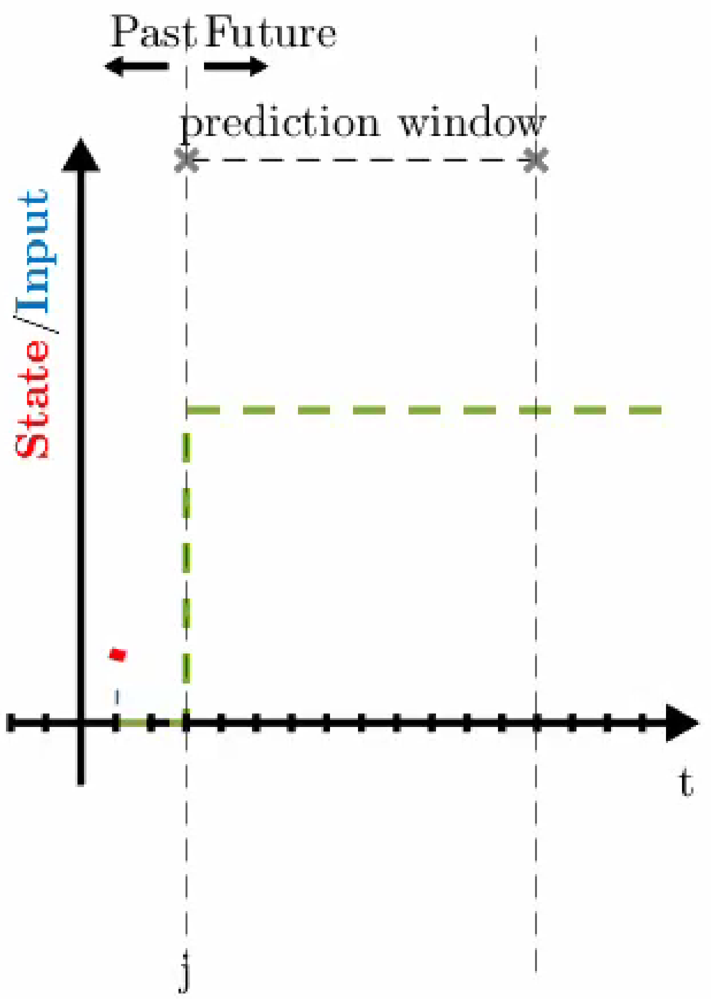
$$\min_{[u_0,u_1,\ldots,u_N]} J(\boldsymbol{x}_0, \boldsymbol{u}_{0,\ldots,N}, \ldots)$$

$$subj.to \quad \boldsymbol{x}_{\boldsymbol{k}+\mathbf{1}} = f(\boldsymbol{x}_{\boldsymbol{k}}, \boldsymbol{u}_{\boldsymbol{k}})$$

+ constraints

given $\boldsymbol{x}_0$

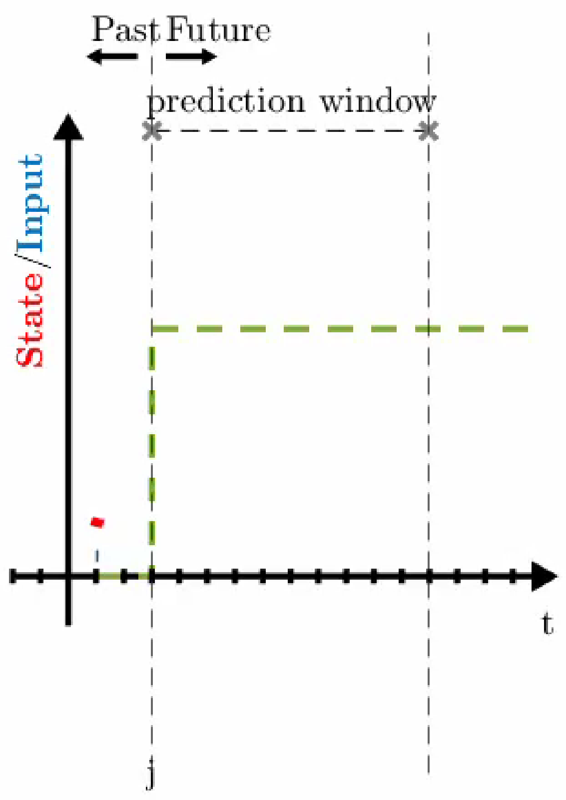




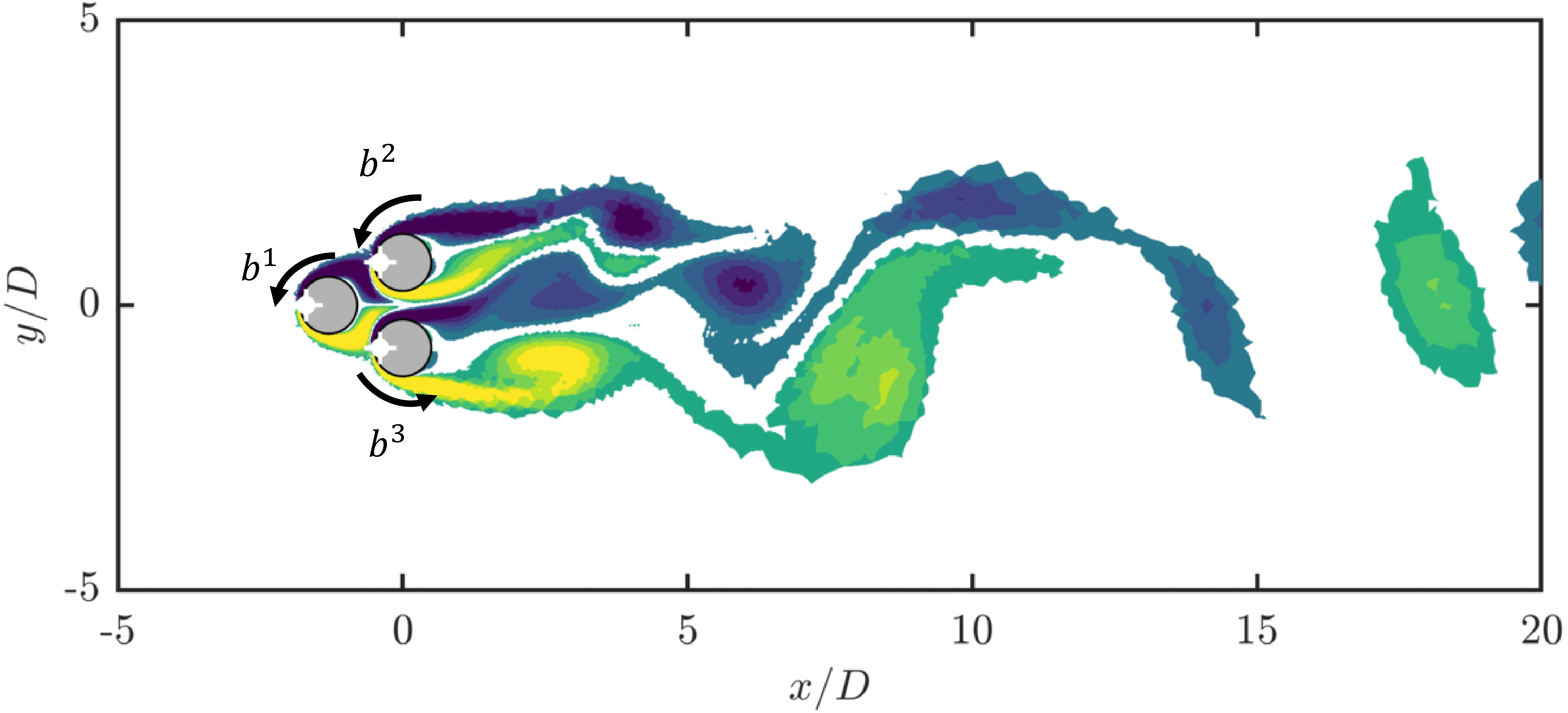
Why Model Predictive Control

- ✓ Linear control, nonlinear control,…
- ✓ Handling easily hard and soft contraints
- ✓ Anticipative actions, not simply reactions
- ✓ Handles well multiple inputs → coordinated “strategies”
- ✓ It uses explicitly a model of the system

- ✗ Computational cost
- ✗ You need good models!
- ✗ Assessing stability and feasibility guarantees



A test case: self-tuning control of a fluidic pinball wake

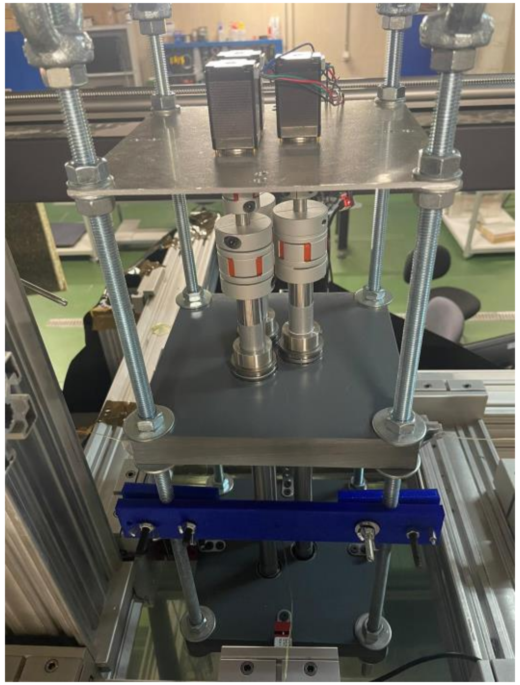


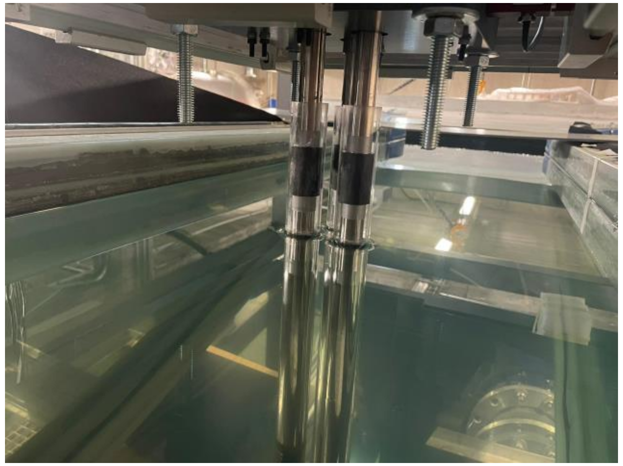
MPC goal: Drag reduction and lift oscillation minimization

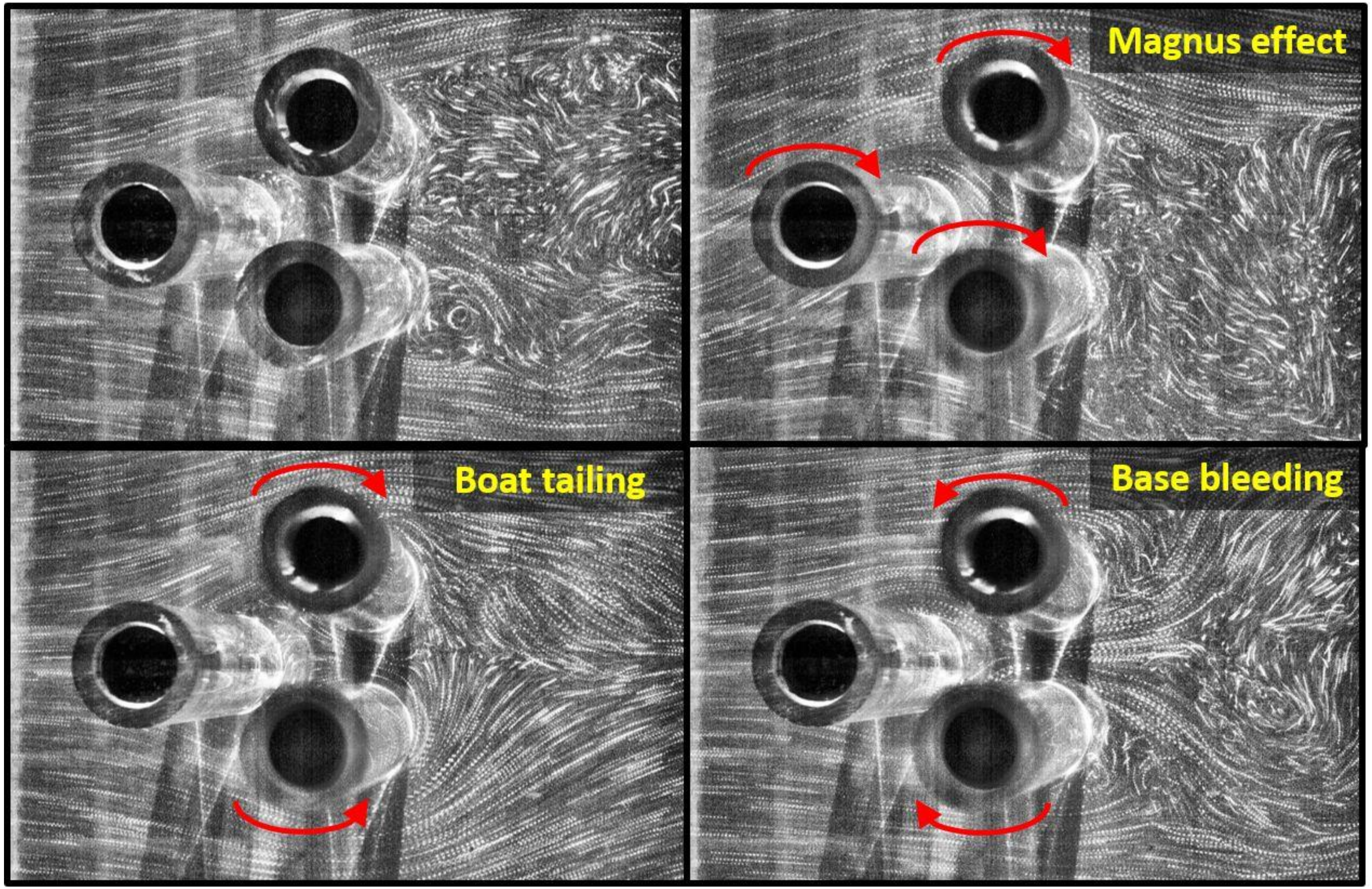
Control actuation: Rotation of the three cylinders

Is it feasible with minimal input from the user?

A test case: self-tuning control of a fluidic pinball wake







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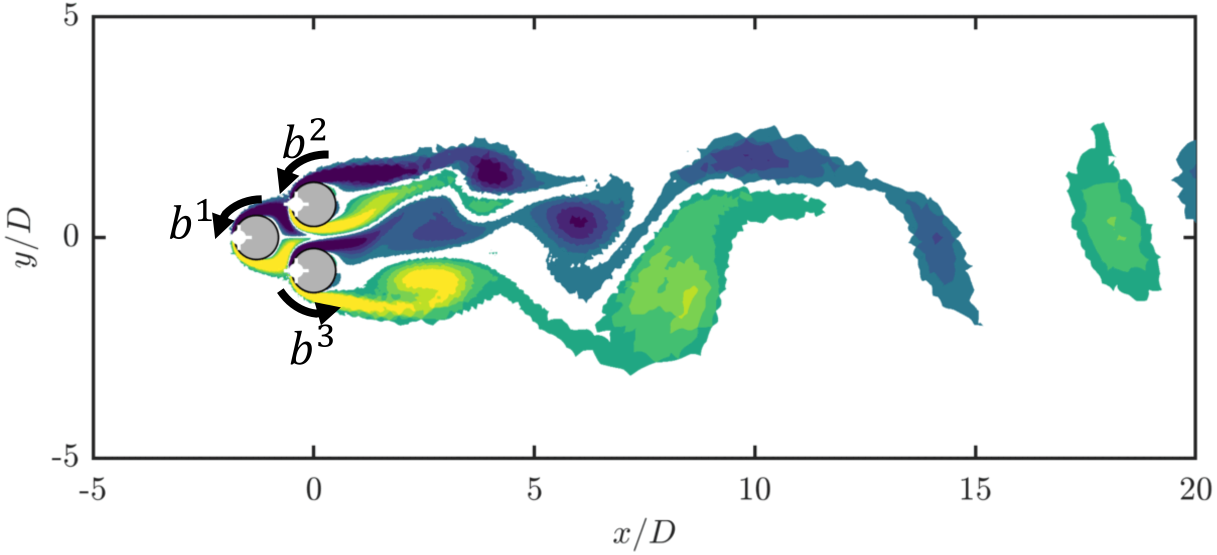

- **Identify the system**
  - Coordinates? Model?
- **Select automatically the best control actions**
  - Account also for constraints
- **Automatically balance the hyperparameters**

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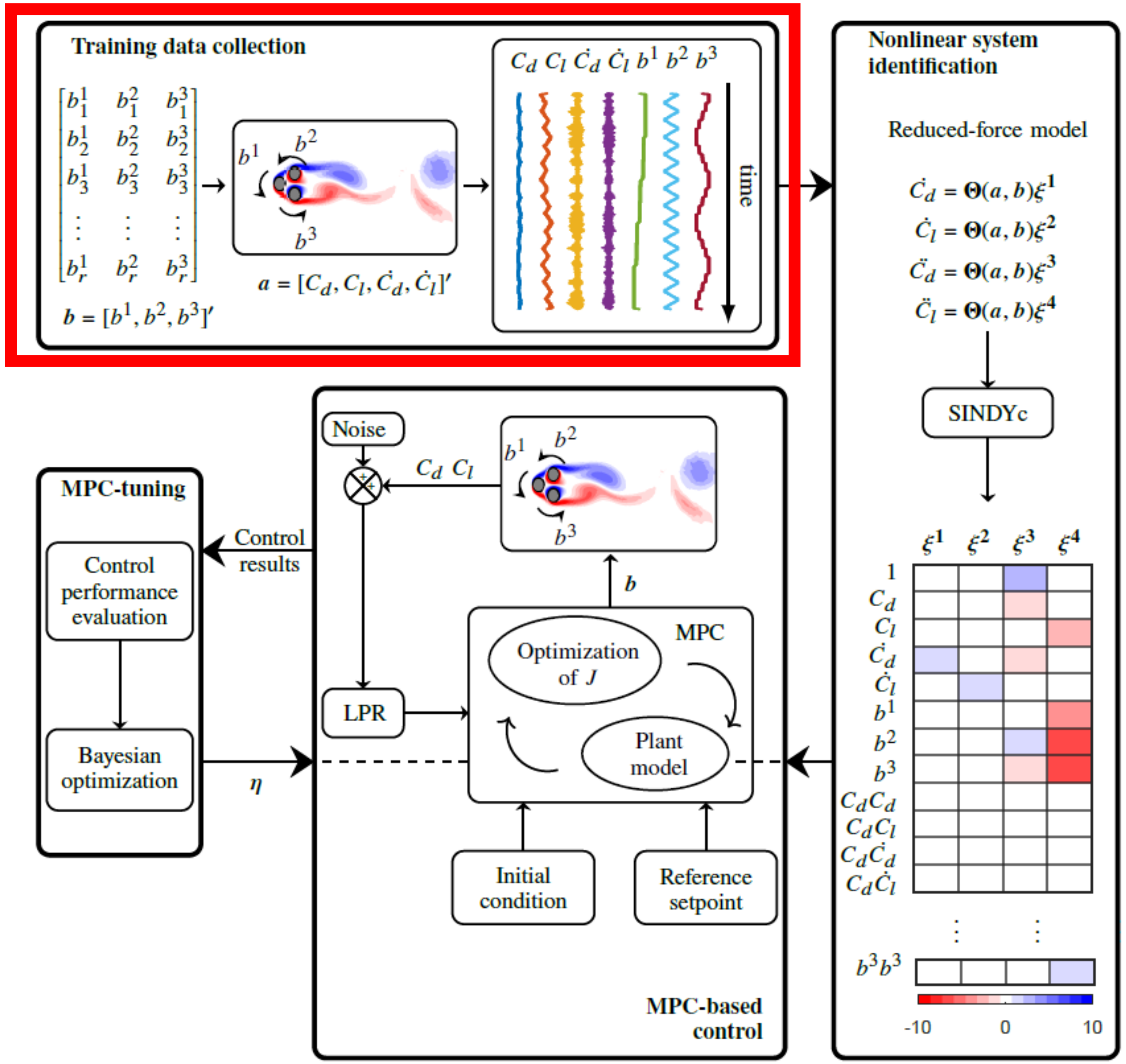

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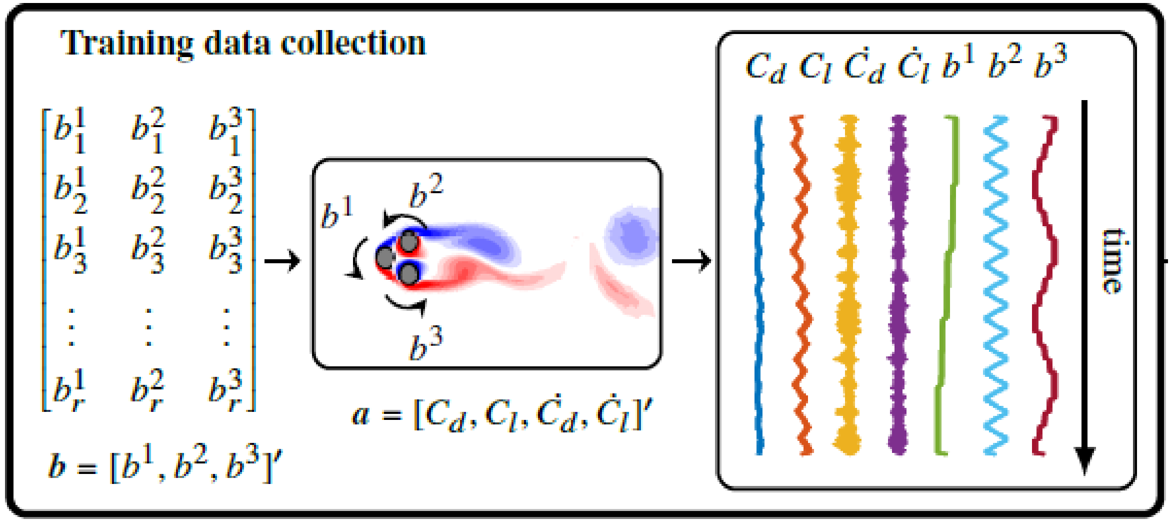
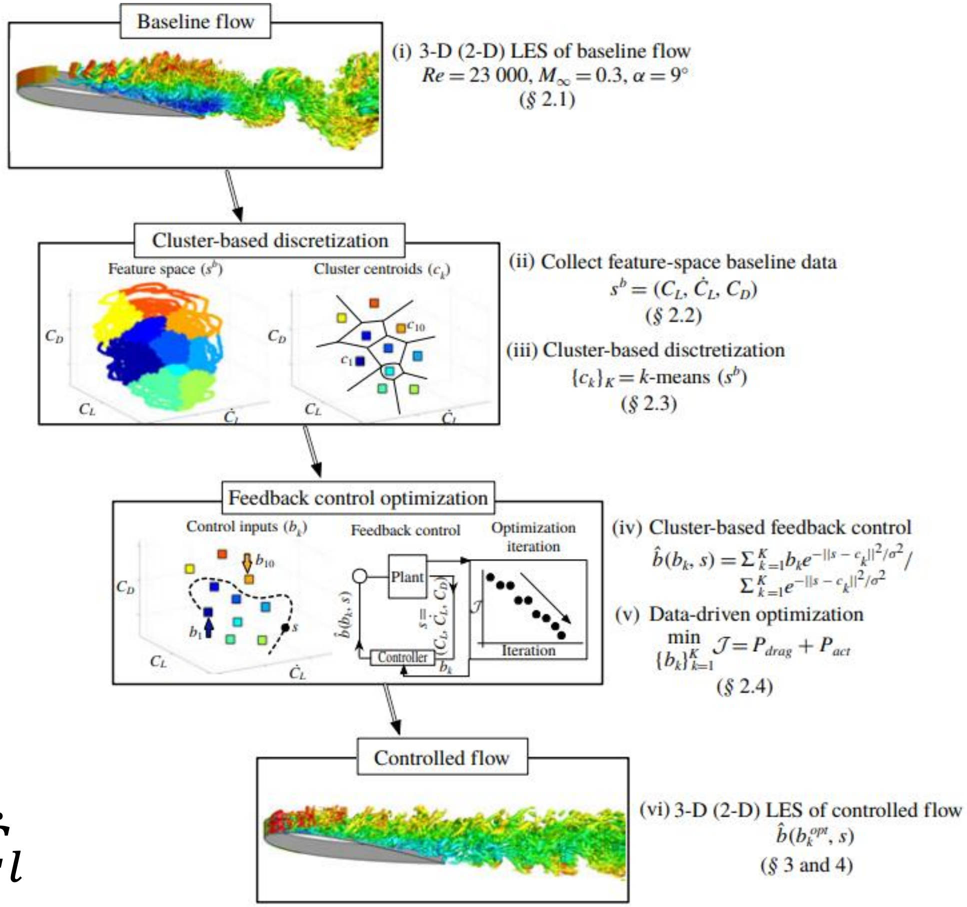
Marra, L., Meilán-Vila, A., & Discetti, S. (2024). Self-tuning model predictive control for wake flows. *J. Fluid Mech*, 2024;983:A26

Selection of the coordinates



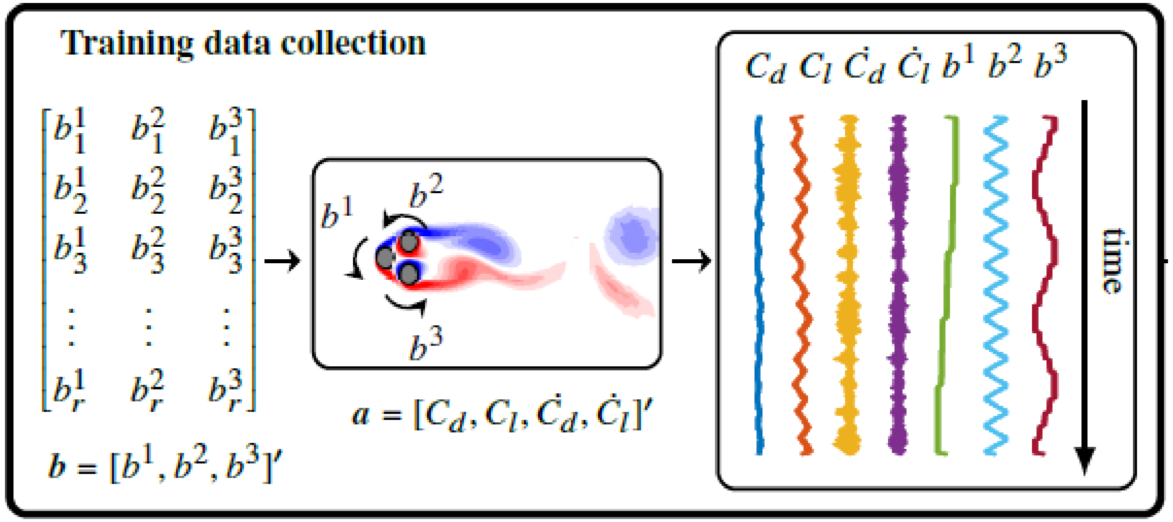


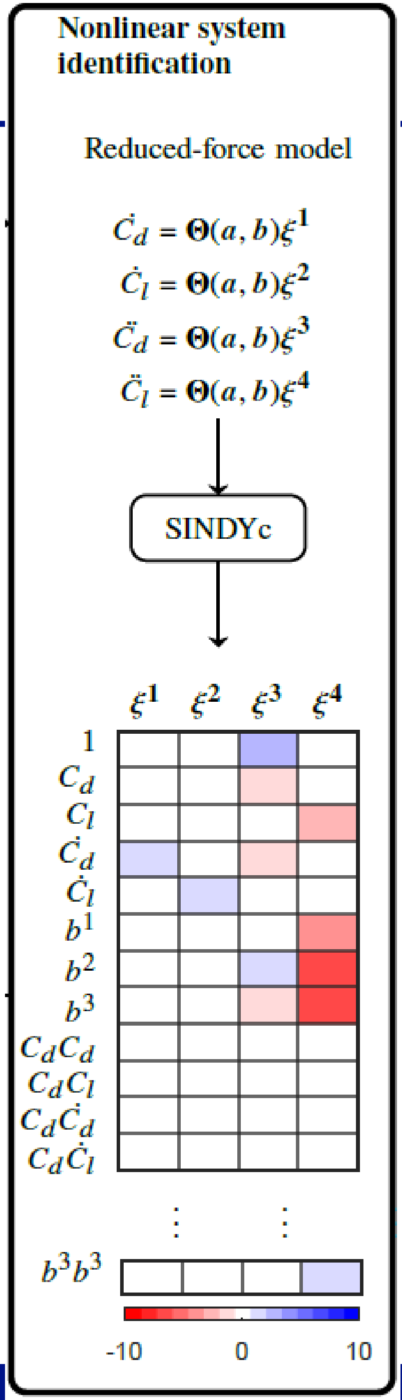
Several automatic options but…

- Mean flow shift → C_d
- Limit cycle of unsteady oscillations → C_l, $\dot{C}_l$

Nair et al (2019) J. Fluid Mech.

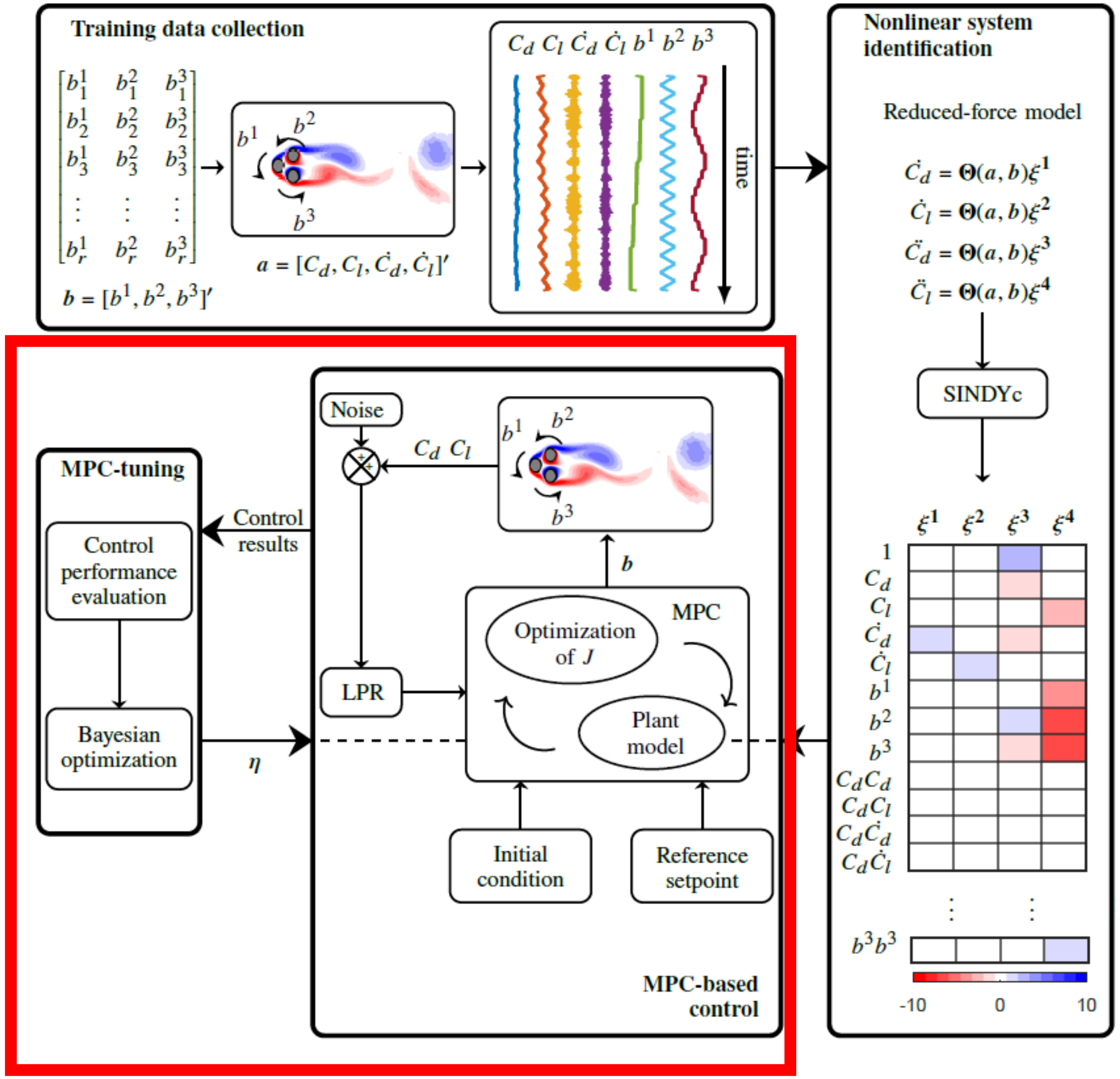
System identification





SINDy (Brunton et al 2016) based on polynomials up to 2nd order

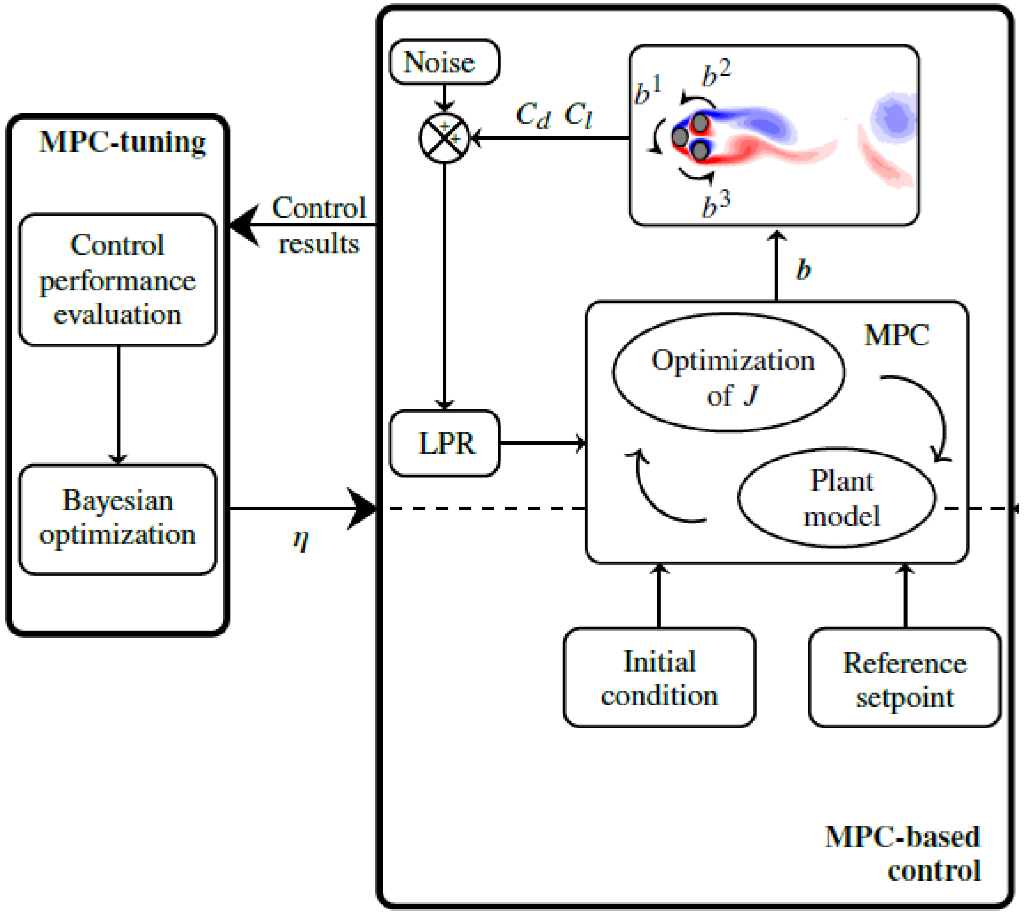
A test case: self-tuning control of a fluidic pinball wake



- **Identify the system**
  - Coordinates? Model?
- **Select automatically the best control actions**
  - Account also for constraints
- **Automatically balance the hyperparameters**

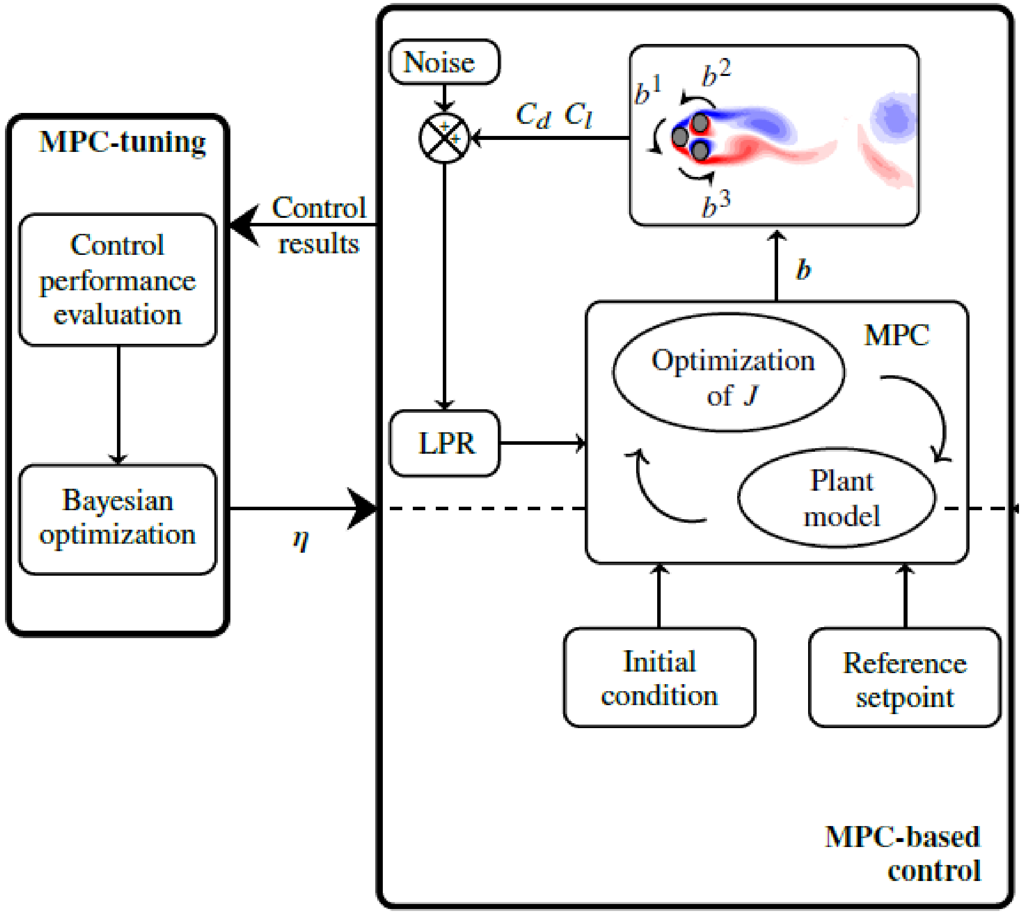
Marra, L., Meilán-Vila, A., & Discetti, S. (2024). Self-tuning model predictive control for wake flows. *J. Fluid Mech*, 2024;983:A26

Selection of the hyperparameters



$$J=\sum_{k=0}^{w_p}\left\|\hat{c}_{j+k|j}-c_*\right\|_Q^2+\sum_{k=0}^{w_c}\left(\left\|b_{j+k|j}\right\|_{R_b}^2+\left\|\Delta b_{j+k|j}\right\|_{R\Delta_b}^2\right)$$

Selection of the hyperparameters

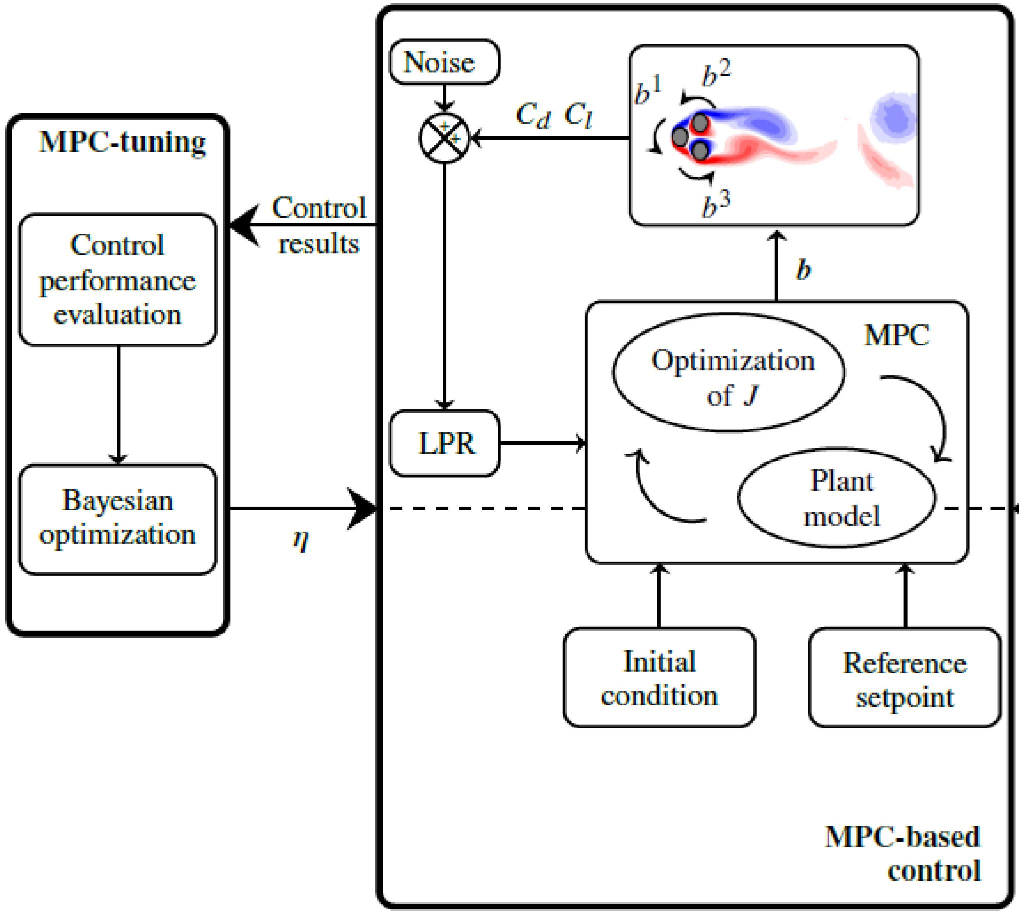


$$J = \sum_{k=0}^{w_p} \left\| \hat{c}_{j+k|j} - c_* \right\|_Q^2 + \sum_{k=0}^{w_c} \left(\left\| b_{j+k|j} \right\|_{R_b}^2 + \left\| \Delta b_{j+k|j} \right\|_{R\Delta_b}^2 \right)$$

State penalty

$$\left\| \hat{c}_{j+k|j} - c_* \right\|_Q^2 = \left(\hat{c}_{j+k|j} - c_* \right)^T \begin{bmatrix} Q_{C_d} & 0 \\ 0 & Q_{C_l} \end{bmatrix} \left(\hat{c}_{j+k|j} - c_* \right)$$

Selection of the hyperparameters



$$J = \sum_{k=0}^{w_p} \left\| \hat{c}_{j+k|j} - c_* \right\|_Q^2 + \sum_{k=0}^{w_c} \left(\left\| b_{j+k|j} \right\|_{R_b}^2 + \left\| \Delta b_{j+k|j} \right\|_{R\Delta_b}^2 \right)$$

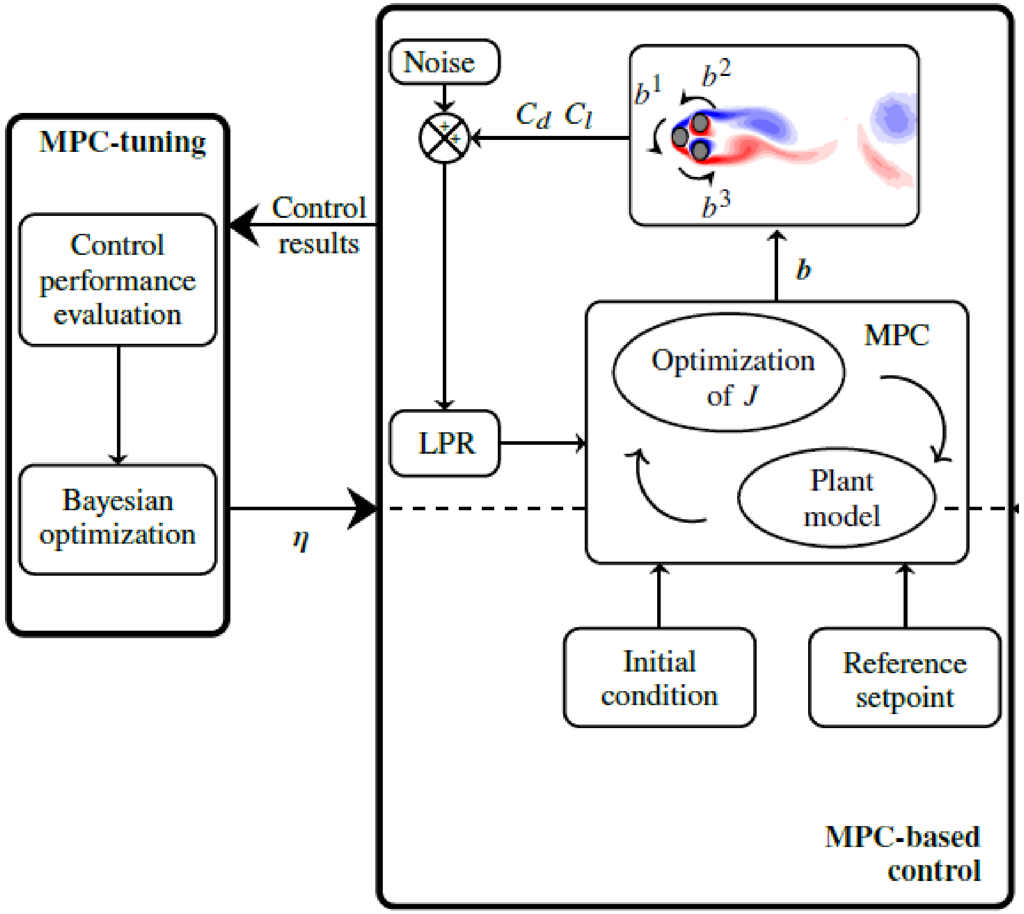
State penalty

$$\left\| \hat{c}_{j+k|j} - c_* \right\|_Q^2 = \left(\hat{c}_{j+k|j} - c_* \right)^T \begin{bmatrix} Q_{C_d} & 0 \\ 0 & Q_{C_l} \end{bmatrix} \left(\hat{c}_{j+k|j} - c_* \right)$$

Actuation cost

$$\left\| b_{j+k|j} \right\|_{R_b}^2 = \left(b_{j+k|j} \right)^T \begin{bmatrix} R_{b^1} & & \\ & R_{b^2} & \\ & & R_{b^3} \end{bmatrix} \left(b_{j+k|j} \right)$$

Selection of the hyperparameters



$$J = \sum_{k=0}^{w_p} \left\| \hat{c}_{j+k|j} - c_* \right\|_Q^2 + \sum_{k=0}^{w_c} \left(\left\| b_{j+k|j} \right\|_{R_b}^2 + \left\| \Delta b_{j+k|j} \right\|_{R\Delta_b}^2 \right)$$

State penalty

$$\left\| \hat{c}_{j+k|j} - c_* \right\|_Q^2 = \left(\hat{c}_{j+k|j} - c_* \right)^T \begin{bmatrix} Q_{C_d} & 0 \\ 0 & Q_{C_l} \end{bmatrix} \left(\hat{c}_{j+k|j} - c_* \right)$$

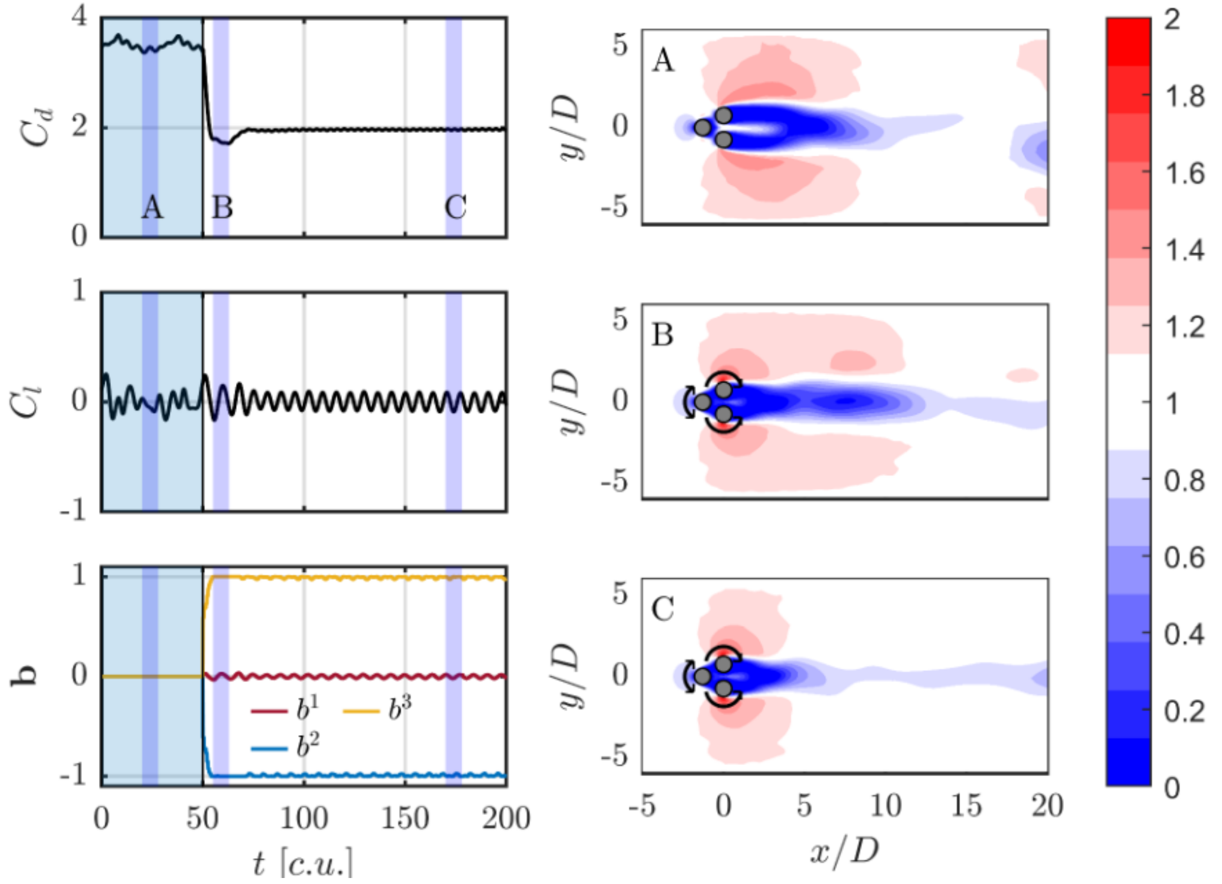
Actuation cost

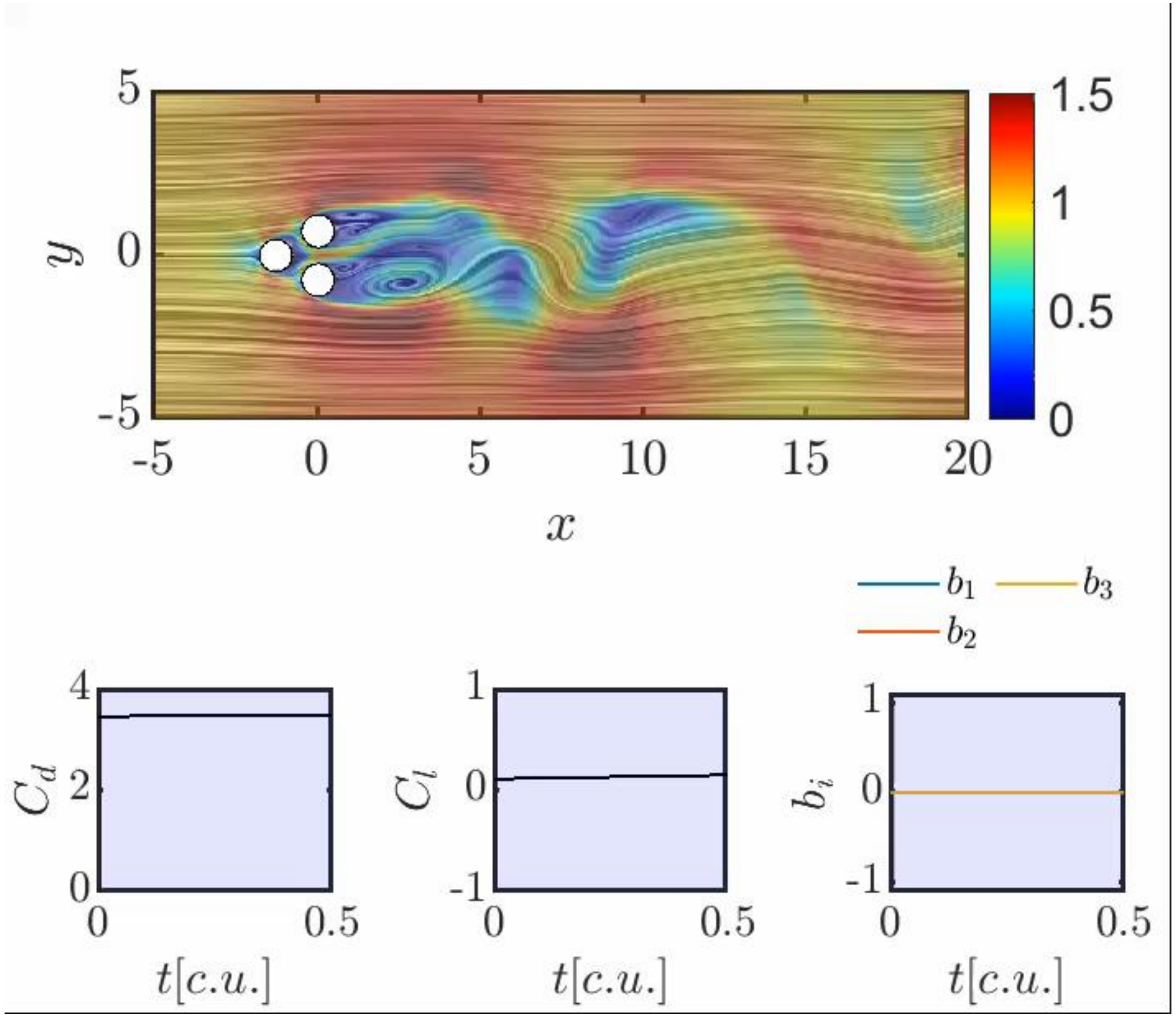
$$\left\| b_{j+k|j} \right\|_{R_b}^2 = \left(b_{j+k|j} \right)^T \begin{bmatrix} R_{b^1} & & \\ & R_{b^2} & \\ & & R_{b^3} \end{bmatrix} \left(b_{j+k|j} \right)$$

Input variability

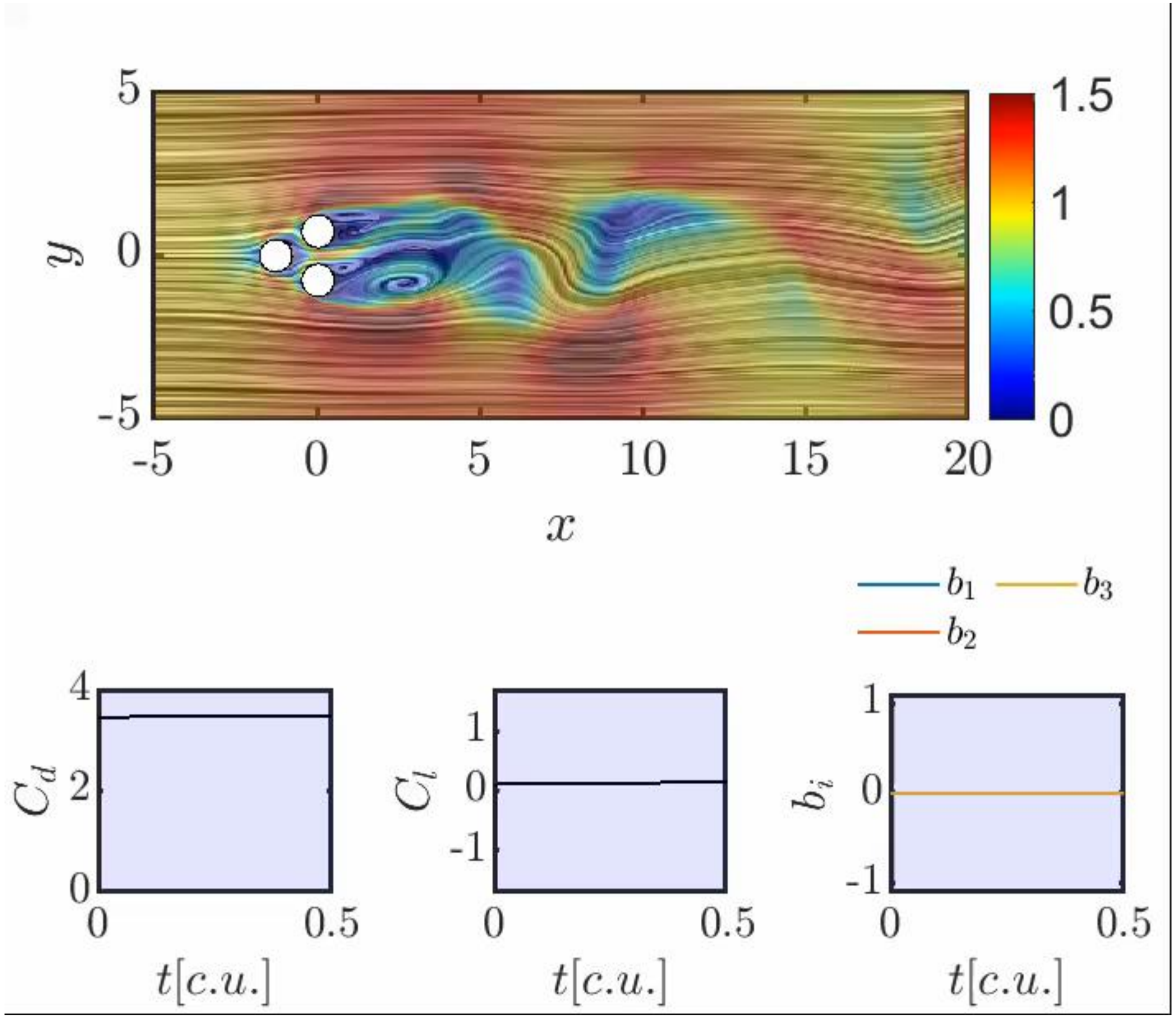
$$\left\| \Delta b_{j+k|j} \right\|_{R_b}^2 = \left(\Delta b_{j+k|j} \right)^T \begin{bmatrix} R_{\Delta b^1} & & \\ & R_{\Delta b^2} & \\ & & R_{\Delta b^3} \end{bmatrix} \left(\Delta b_{j+k|j} \right)$$

Control strategy





Setpoint tracking



References and funding

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MPC

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DIMENSIONALITY REDUCTION

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nextflow

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