Turbulence Control — Better, Faster and Easier with Machine Learning

→

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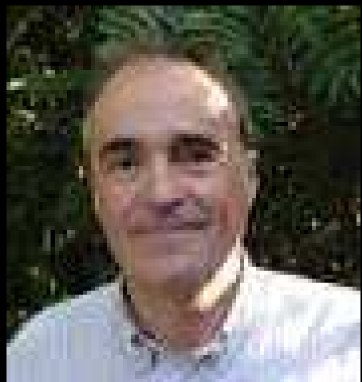

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Overview

1. An eldorado of engineering applications
. . . . *The need for closed-loop turbulence control*

2. Machine learning control
. . . . *Complex MIMO laws in ∼1h wind-tunnel test*

3. Cluster-based control
. . . . *Simple feedback laws in few dozen simulations*

4. Tool development with fluidic pinball
. . . . *A new benchmark for modeling + control*

5. Summary and outlook of turbulence control
. . . . *Paradigm change by machine learning*

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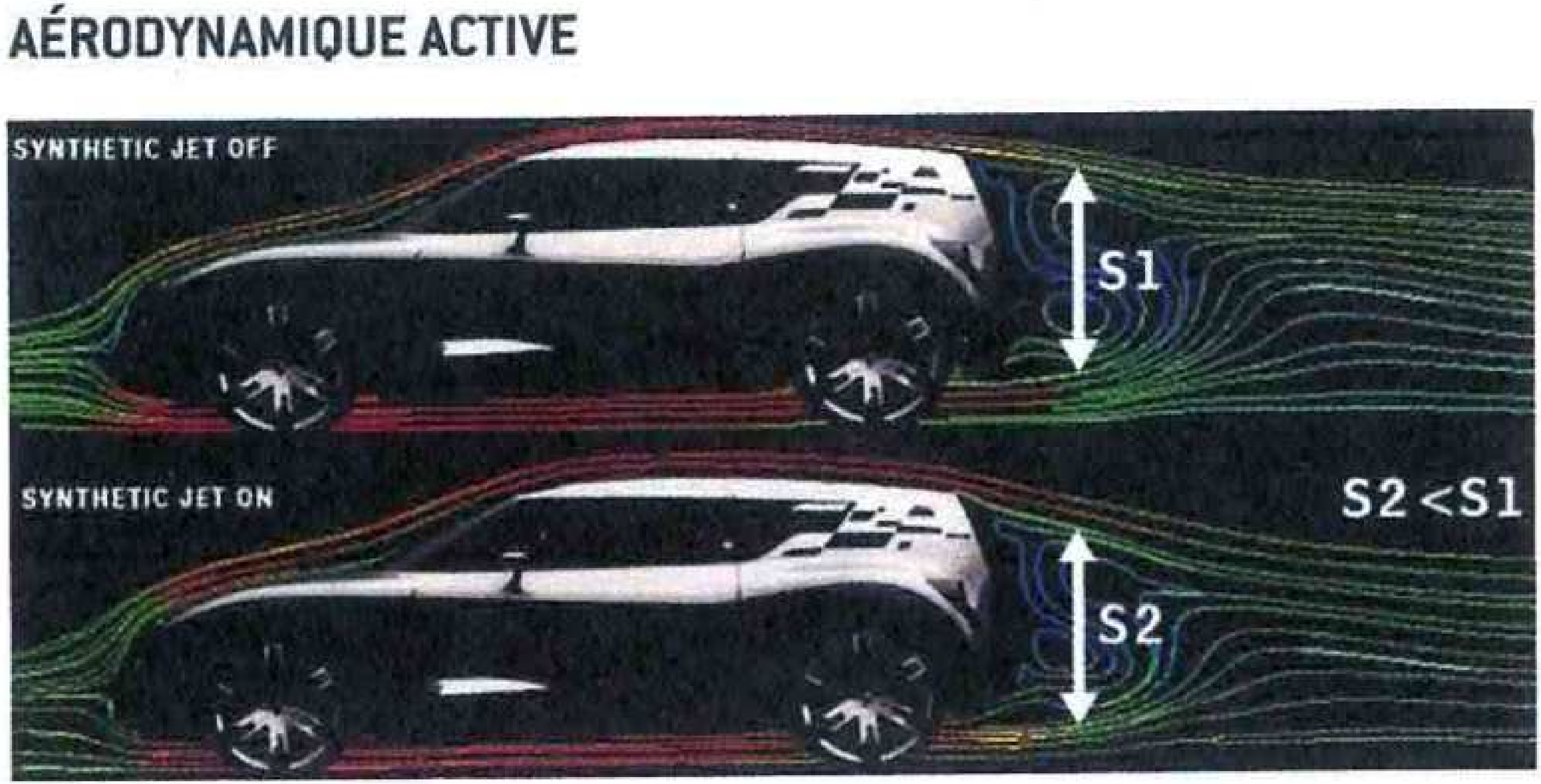
Turbulence control ↦ car drag reduction

Control strategies

- aerodynamic design
- passive (e.g. spoilers)
- active, open-loop
  (e.g. periodic blowing)
- active, closed-loop
  (largest opportunities!)

Renault Altica 2006 ↦

Renault Altica – Article in R & D 06/2004

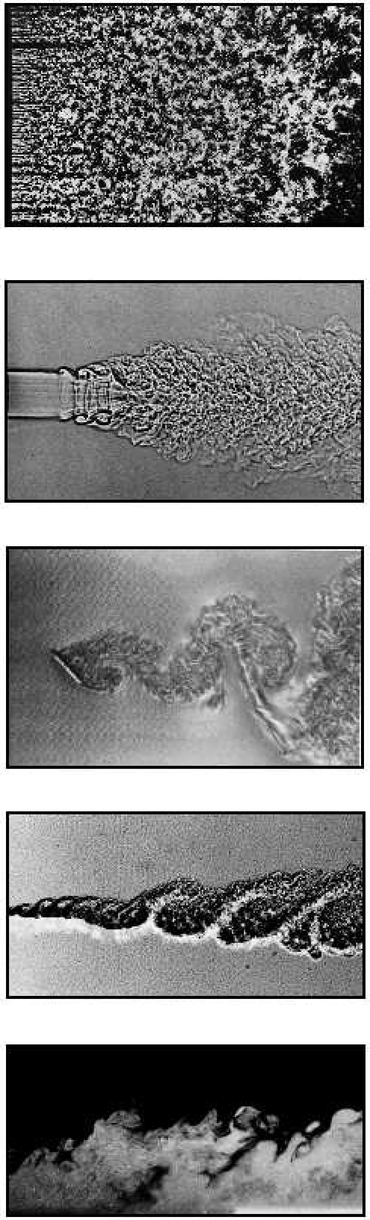


Active flow control with synthetic jets:

- 20% drag reduction at 90km/h;
- 1l fuel saving per 100 km;
- only 10 Watt actuation energy.

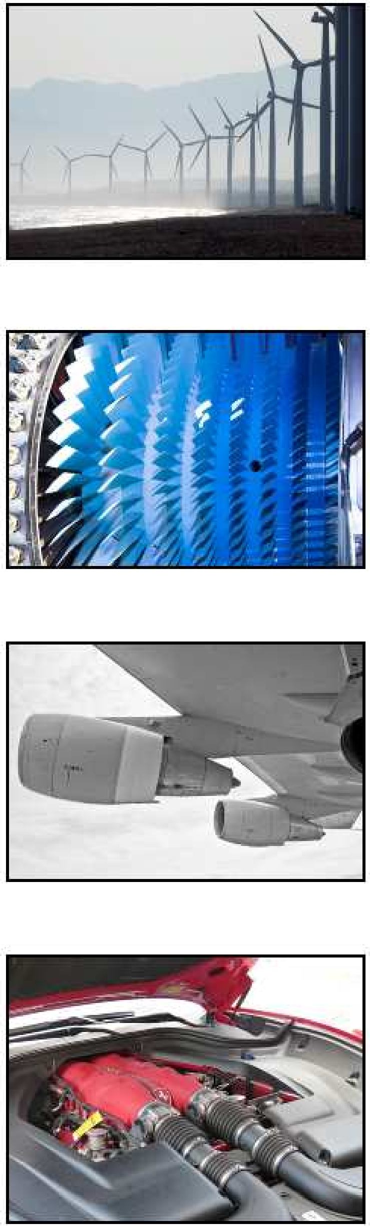
Turbulence control $\mapsto$ myriad applications

Simple prototype flows

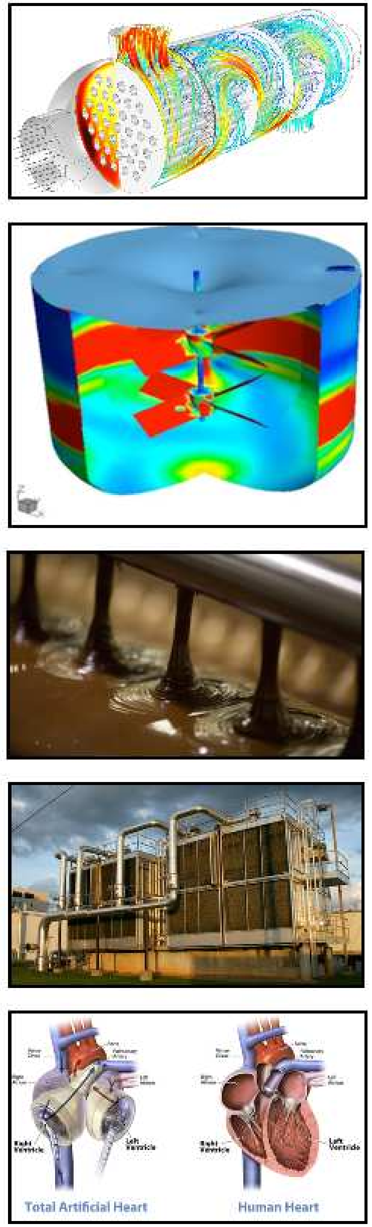


Transport vehicles

Energy systems



Production etc.



Paradigms for turbulence control laws

Machine learning makes turbulence control student-proof

Feedback law: $b = K(s)$, b: actuation, s: sensing

Classical paradigm	**Machine learning**
(1) Understand ↓	(4) Understand ↑
(2) Modeling ↓	(3) Modeling ↑
(3) Control design ↓	(2) Control law ↑
(4) Test+tune control in plant	(1) Control optimization in plant
Lots of human modeling	**(1)-(3) Fully automated**
Simple control laws	**Complex control laws**
for 1+2 frequencies	**$\sim$ 1h wind-tunnel test**

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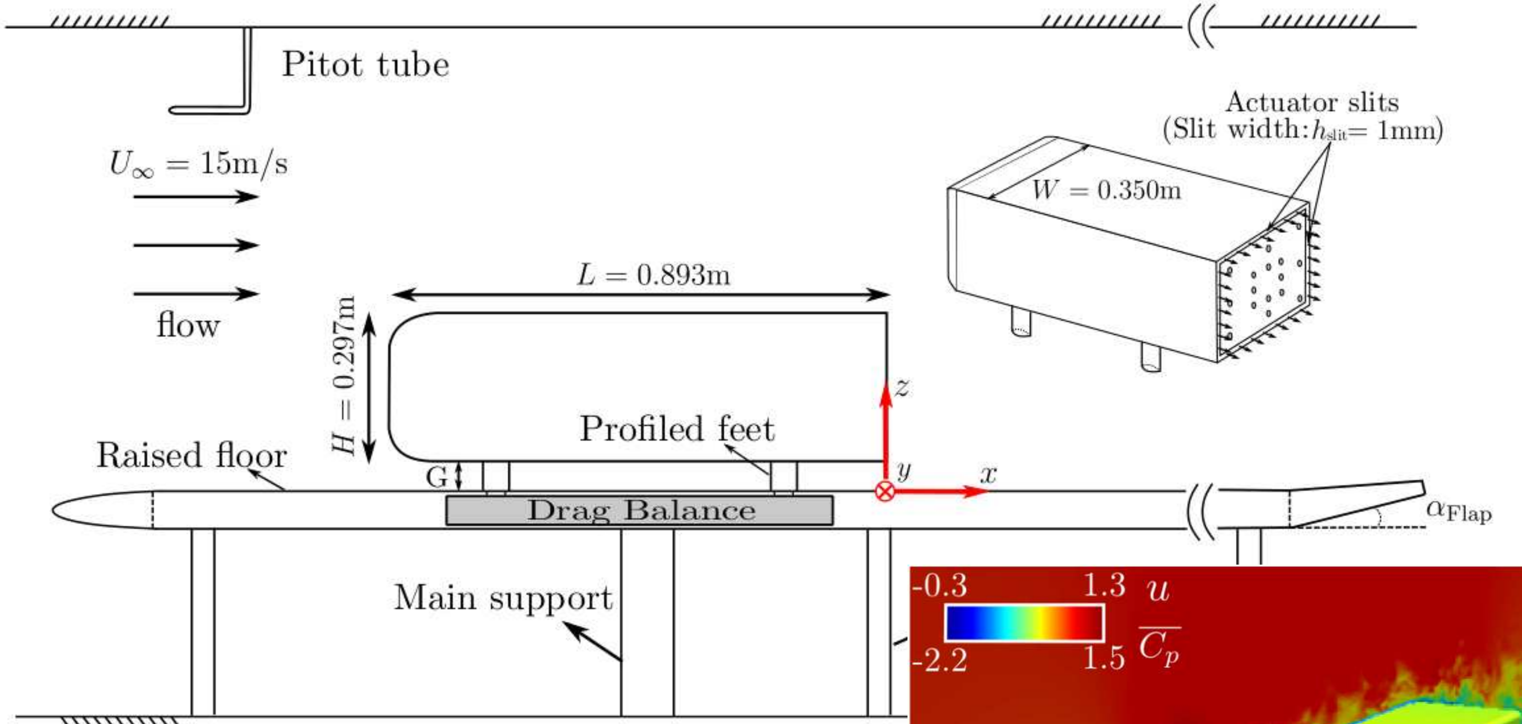
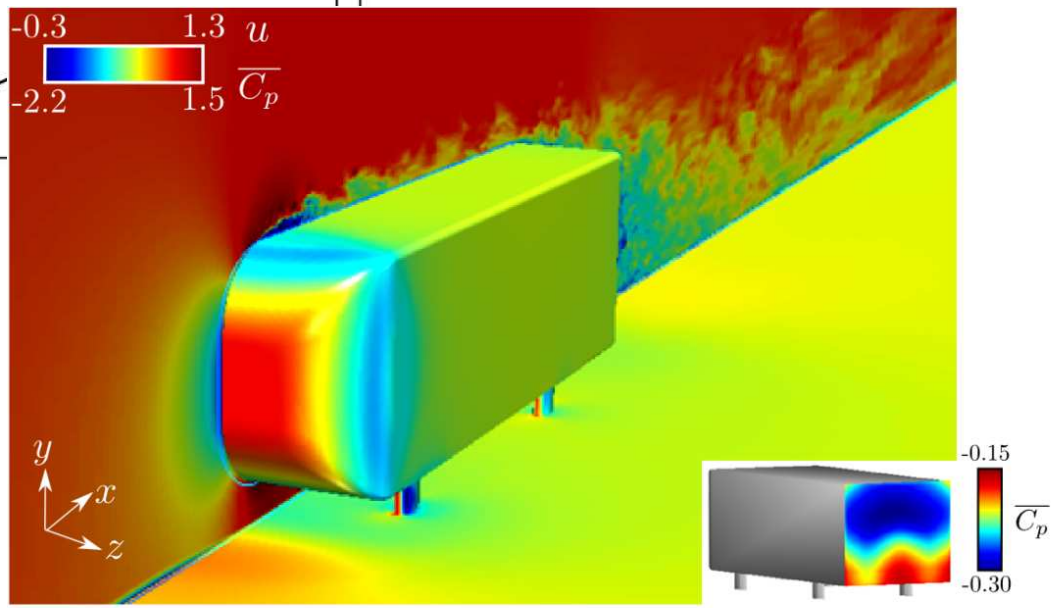
Drag reduction of simplied car model

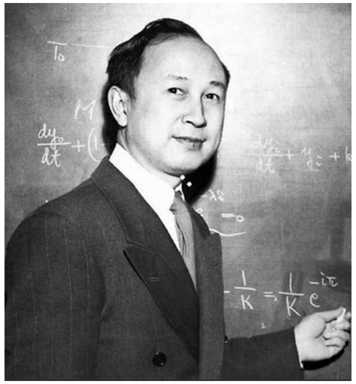
≡ *Barros, et al. 2016 JFM* & ≡ *Östh et al. 2014 JFM*

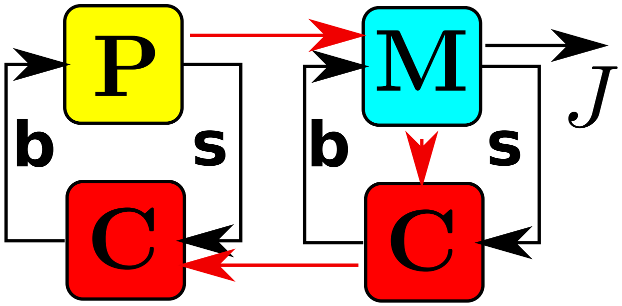




LES simulation
of same configuration →
≡ Jan Östh et al. 2014 JFM

Model-based control





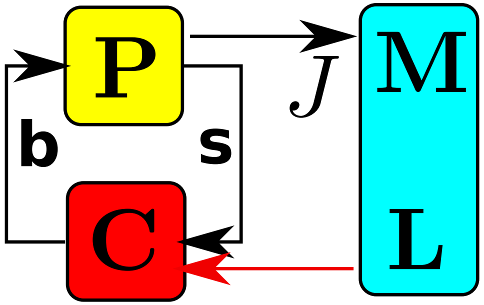
Build model:

$$\frac{da}{dt} = F(a,b)$$
$$s = G(a,b)$$

Derive control:

$$b = K(s)$$

Machine learning control



Define cost function:

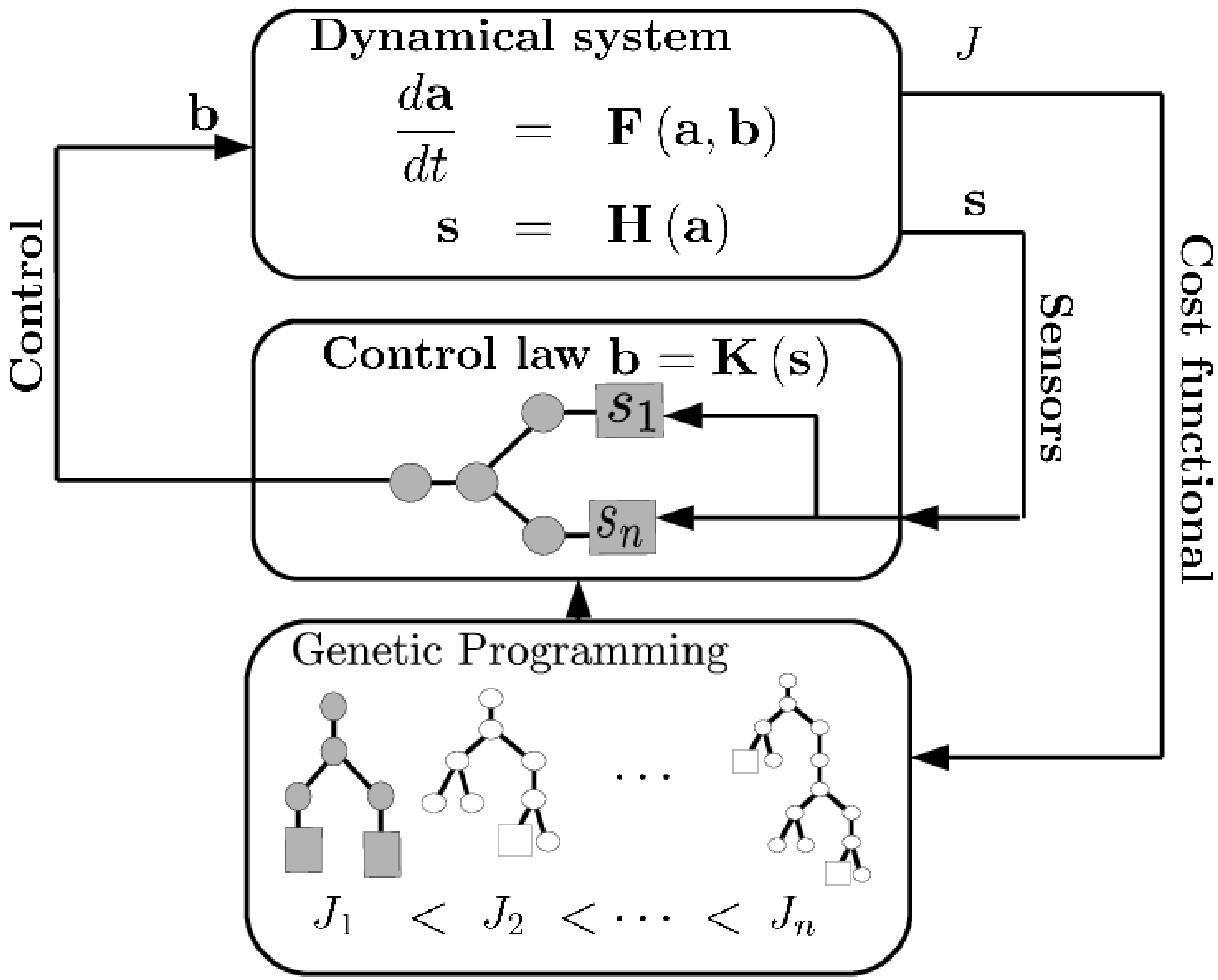
$$J = J_a + J_b = min$$

Solve regression problem:

$$K_{opt}(s) = \arg\min J\,[K(s)]$$

Machine learning control

Duriez, Brunton & Noack 2016 Springer, Wahde 2008



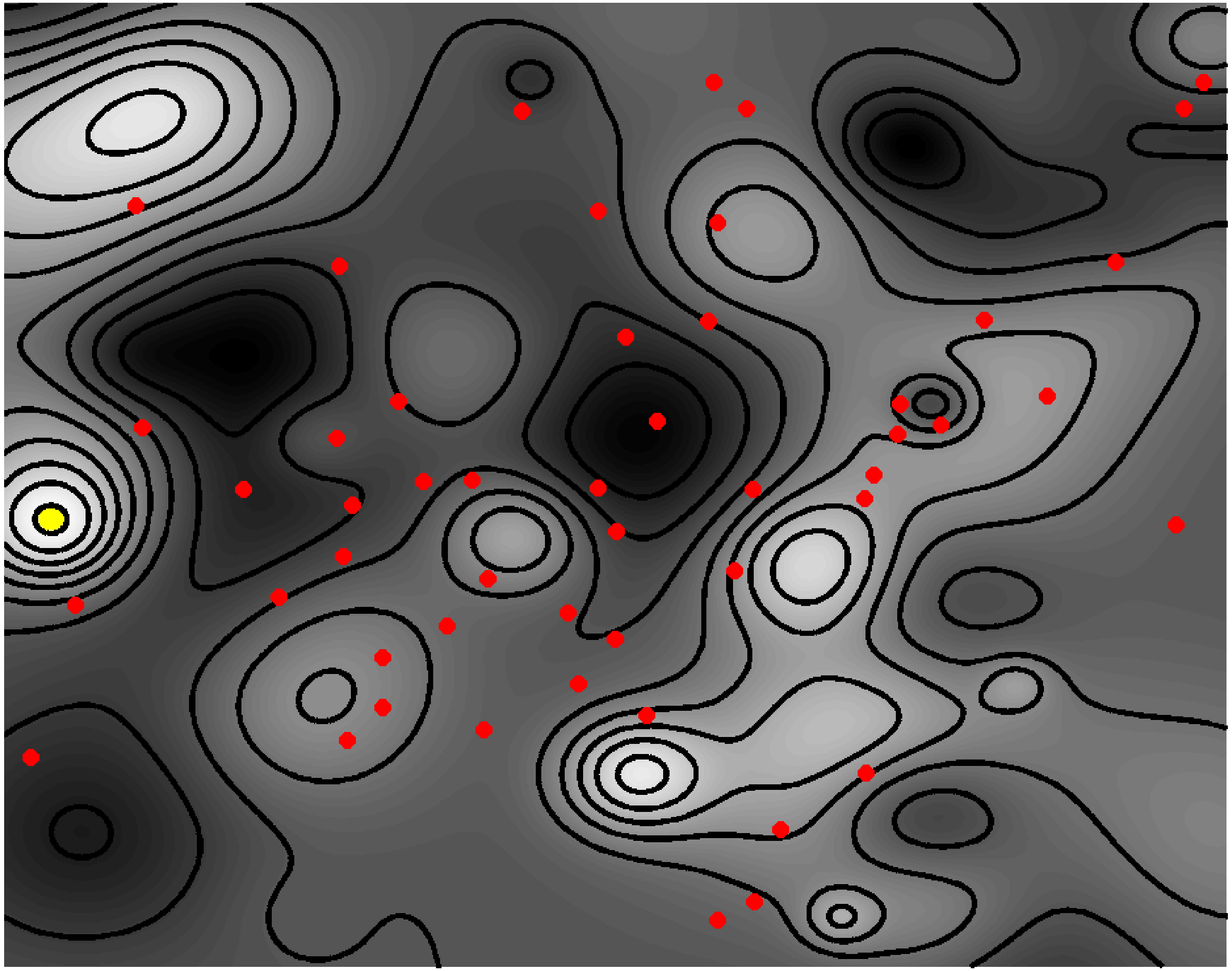
Regression problem: Find $b = K(s)$ so that $J = min$

Regression method = Genetic programming

Machine learning control

≡ *Duriez, Brunton & Noack 2017 Springer,* ≡ *Gautier et al. 2015 JFM*

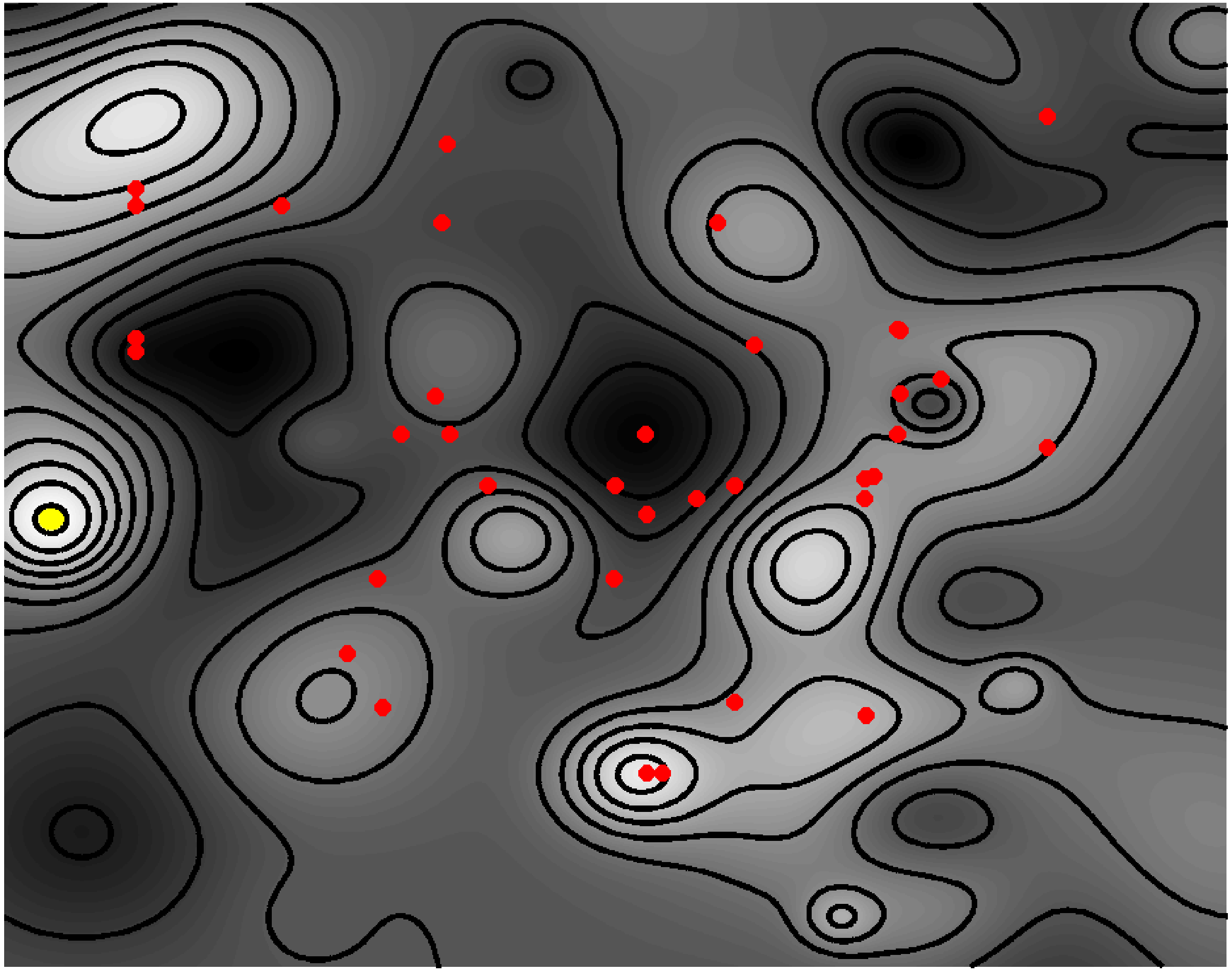
$n = 1$



Machine learning control

≡ *Duriez, Brunton & Noack 2017 Springer,* ≡ *Gautier et al. 2015 JFM*

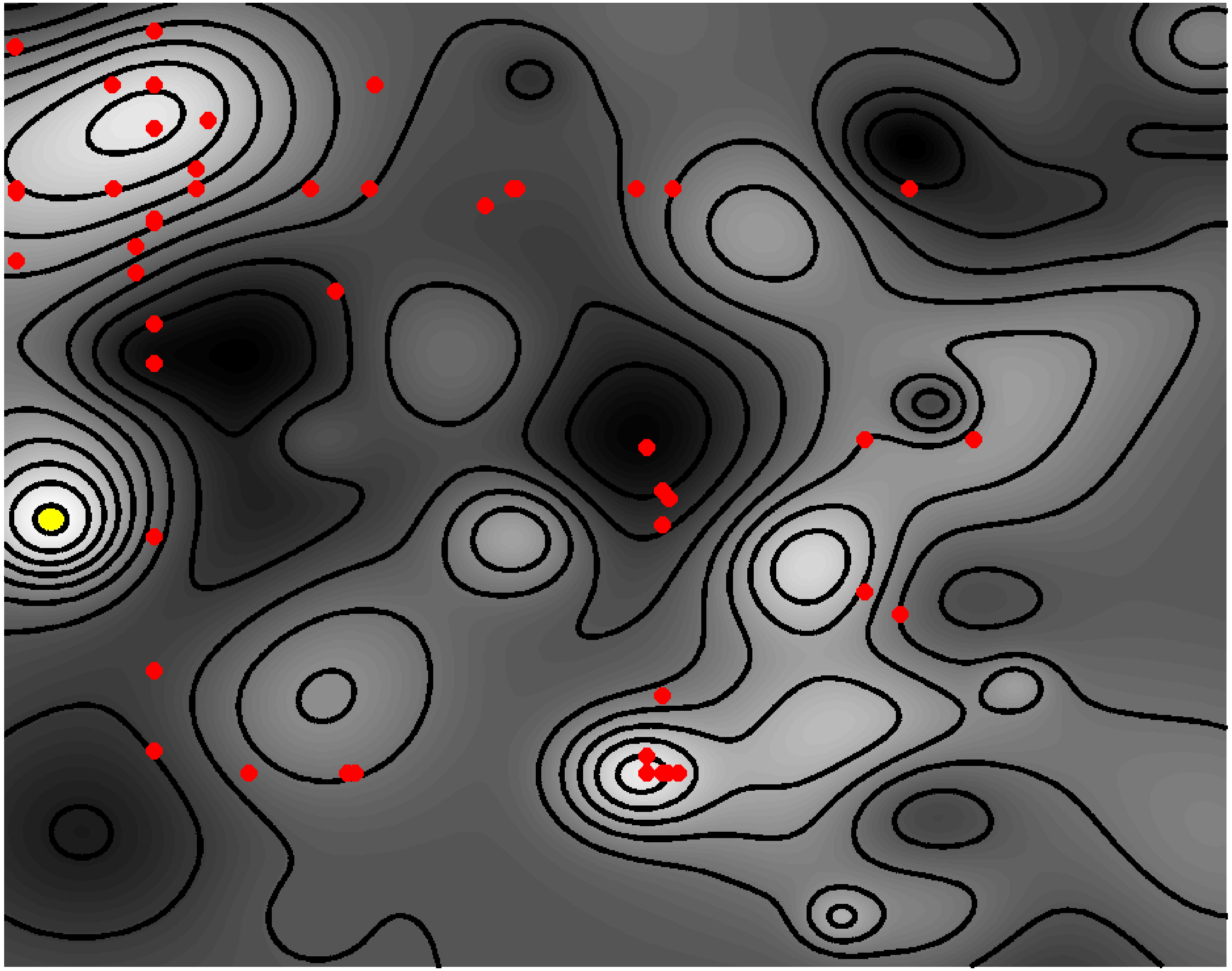
$n = 2$



Machine learning control

≡ *Duriez, Brunton & Noack 2017 Springer,* ≡ *Gautier et al. 2015 JFM*

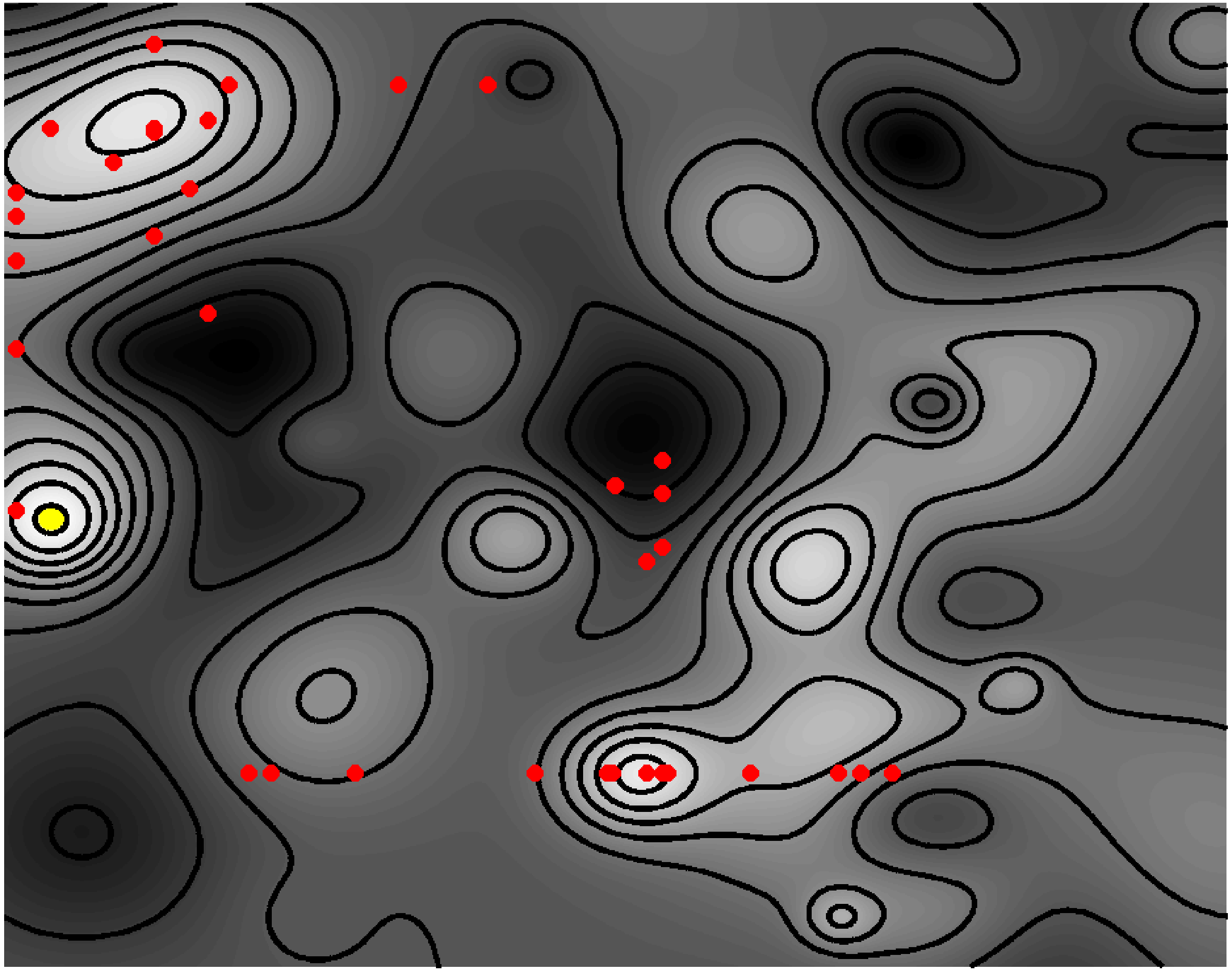
$n = 3$



Machine learning control

≡ Duriez, Brunton & Noack 2017 Springer, ≡ Gautier et al. 2015 JFM

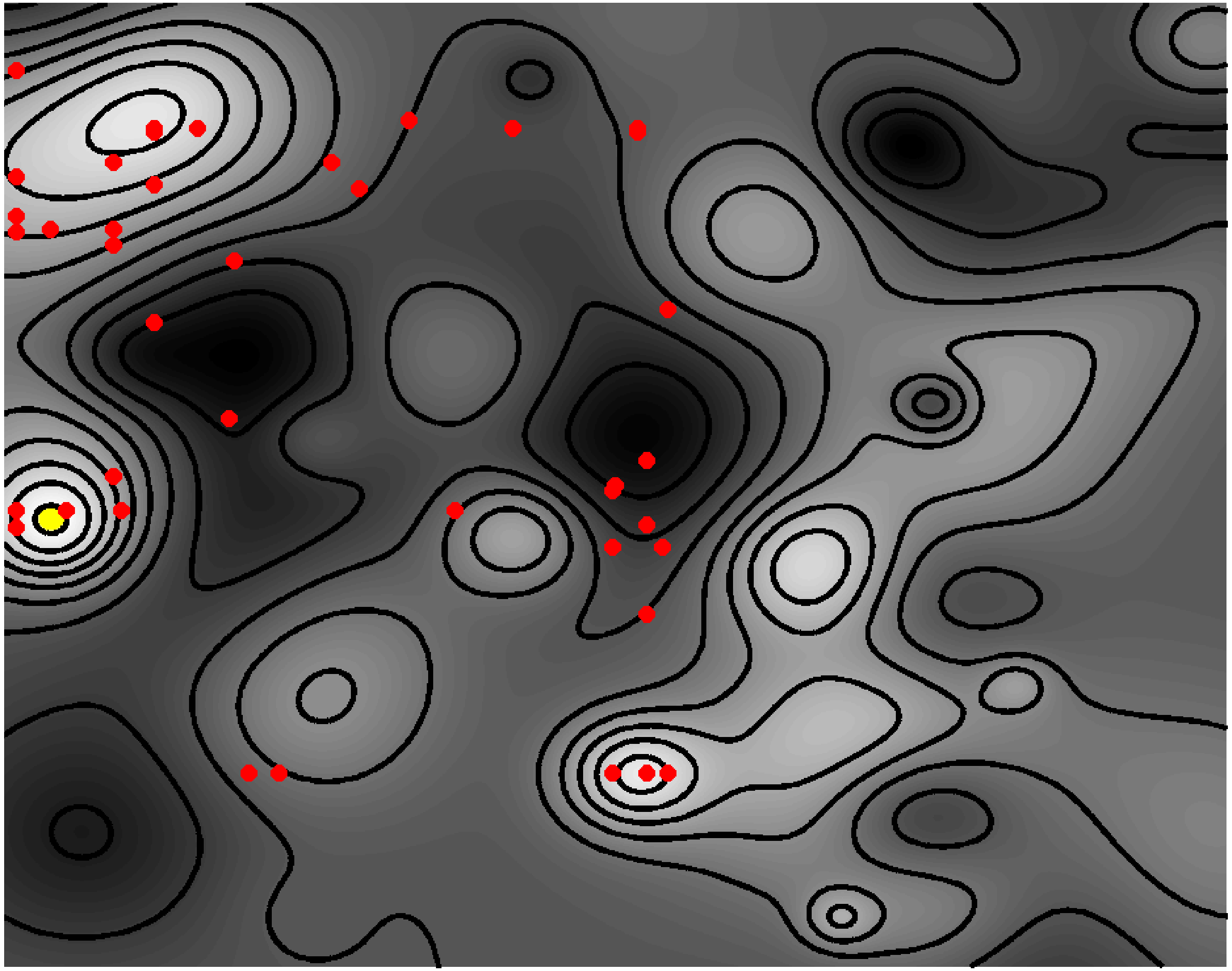
$n = 4$



Machine learning control

≡ Duriez, Brunton & Noack 2017 Springer, ≡ Gautier et al. 2015 JFM

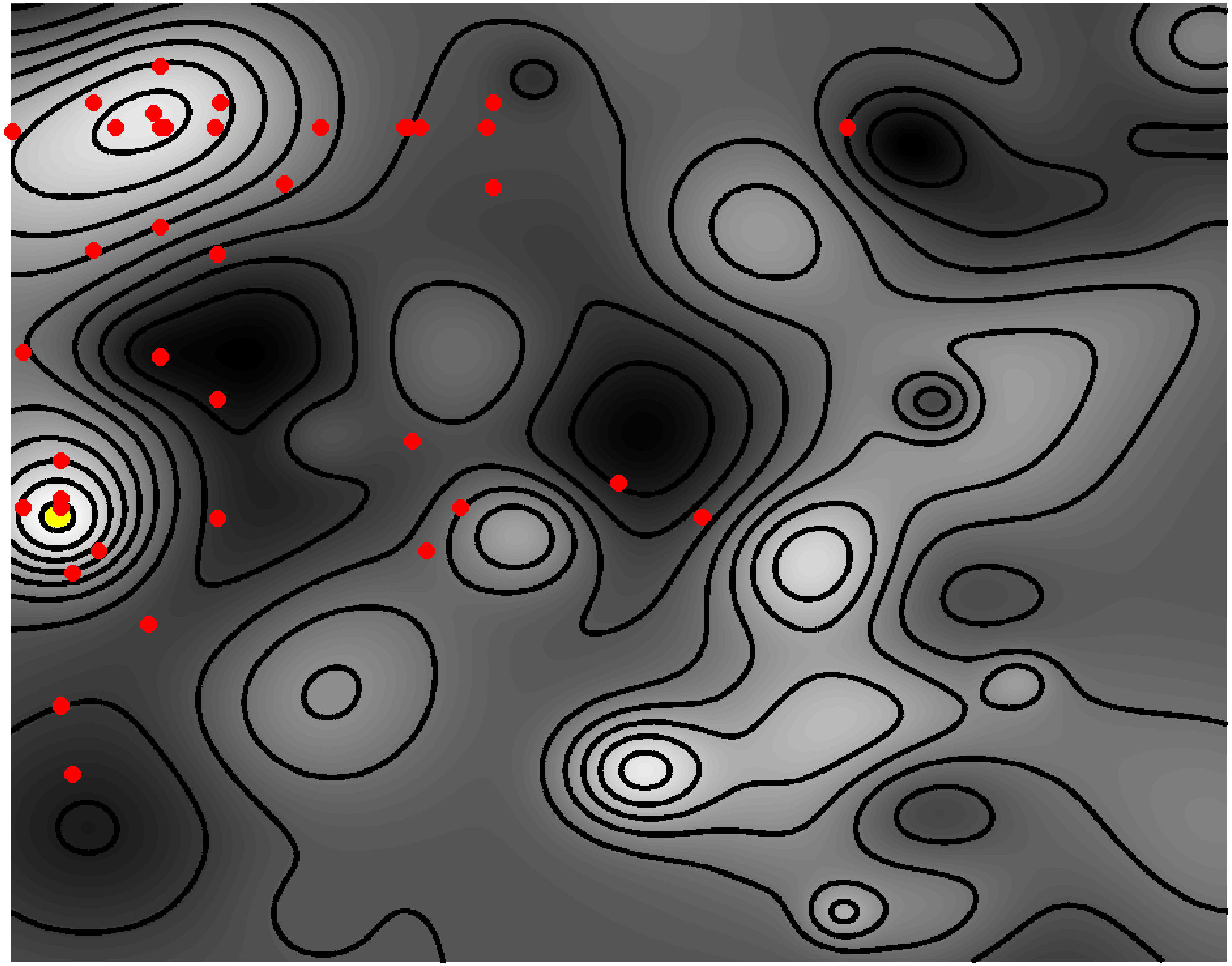
$n = 5$



Machine learning control

Duriez, Brunton & Noack 2017 Springer, Gautier et al. 2015 JFM

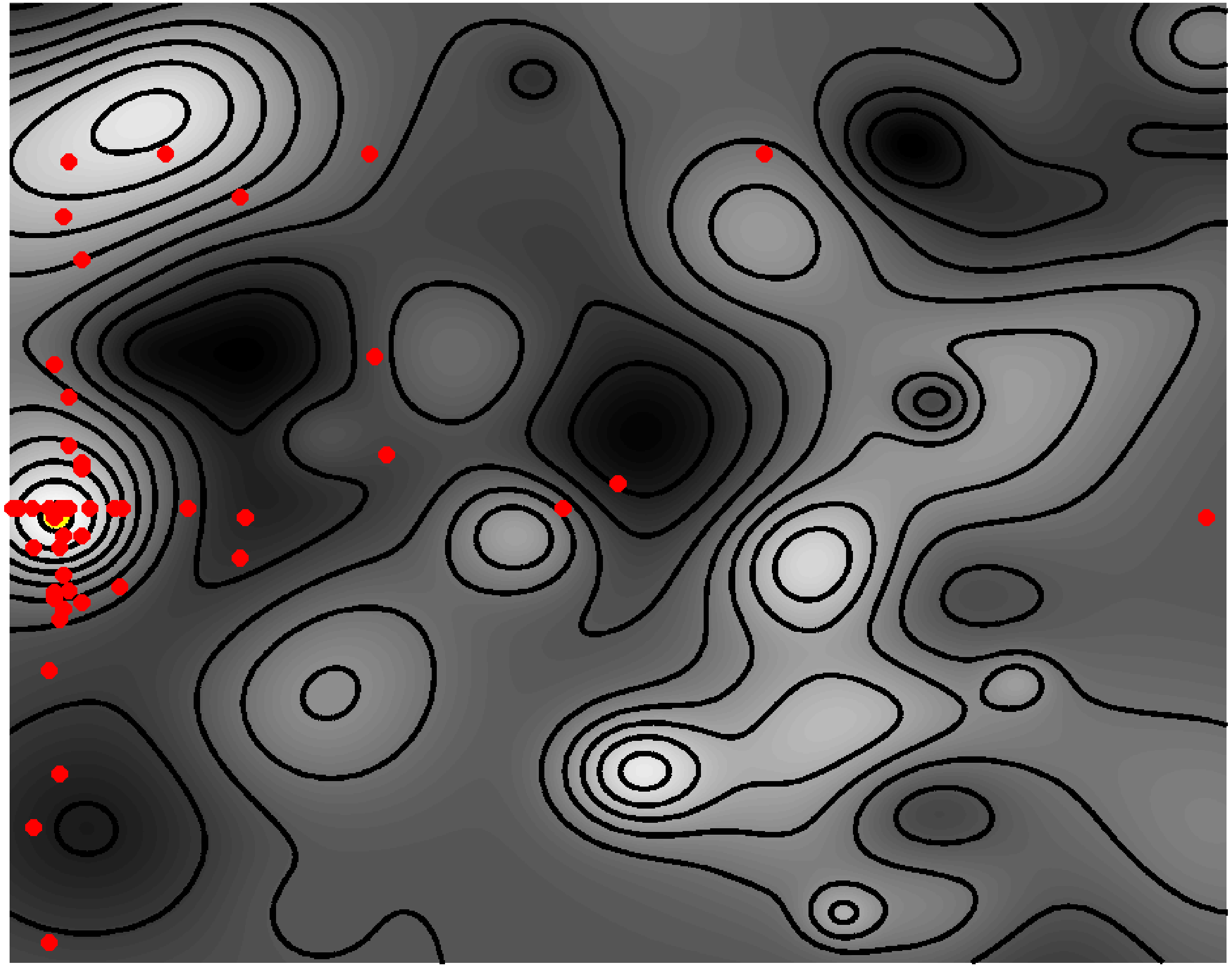
$n = 10$



Machine learning control

≡ Duriez, Brunton & Noack 2017 Springer, ≡ Gautier et al. 2015 JFM

$n = 20$



Drag reduction of simplied car model

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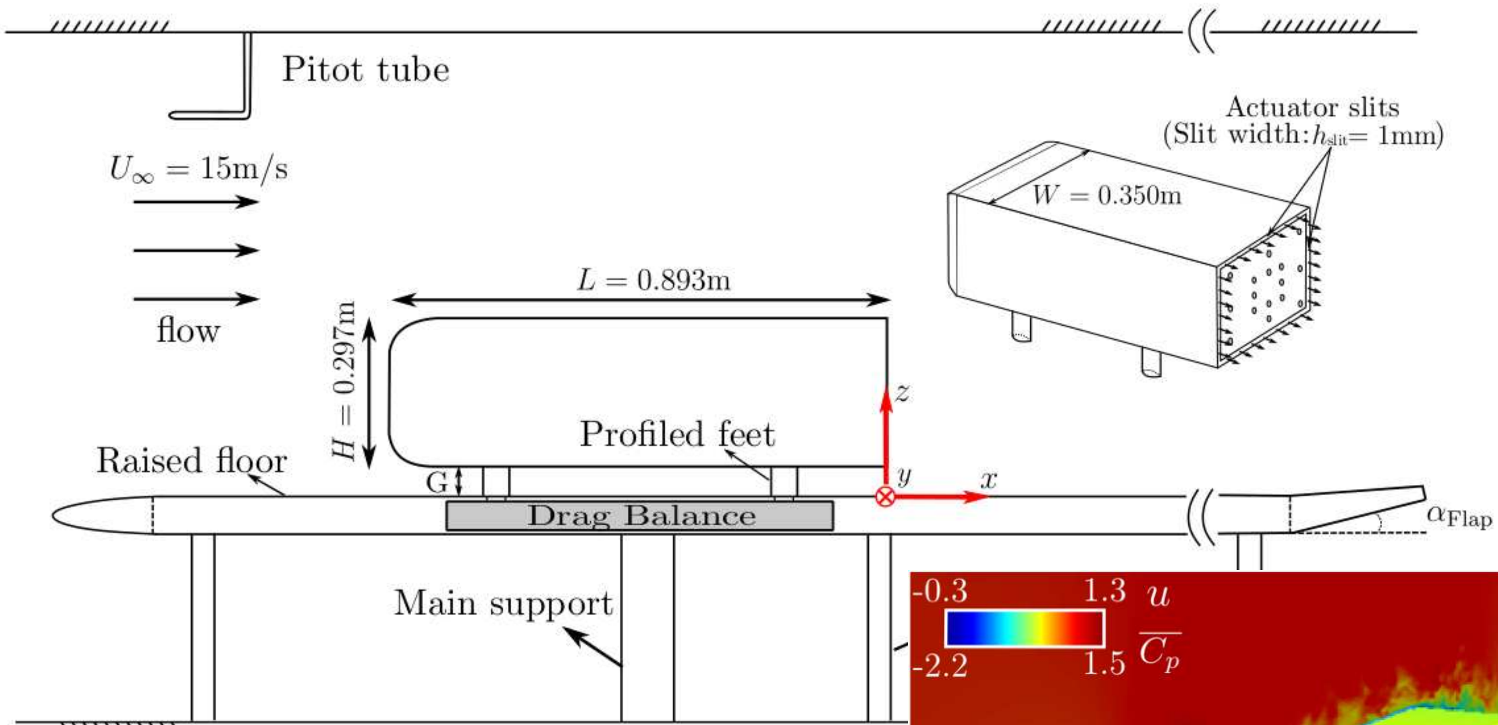

LES simulation
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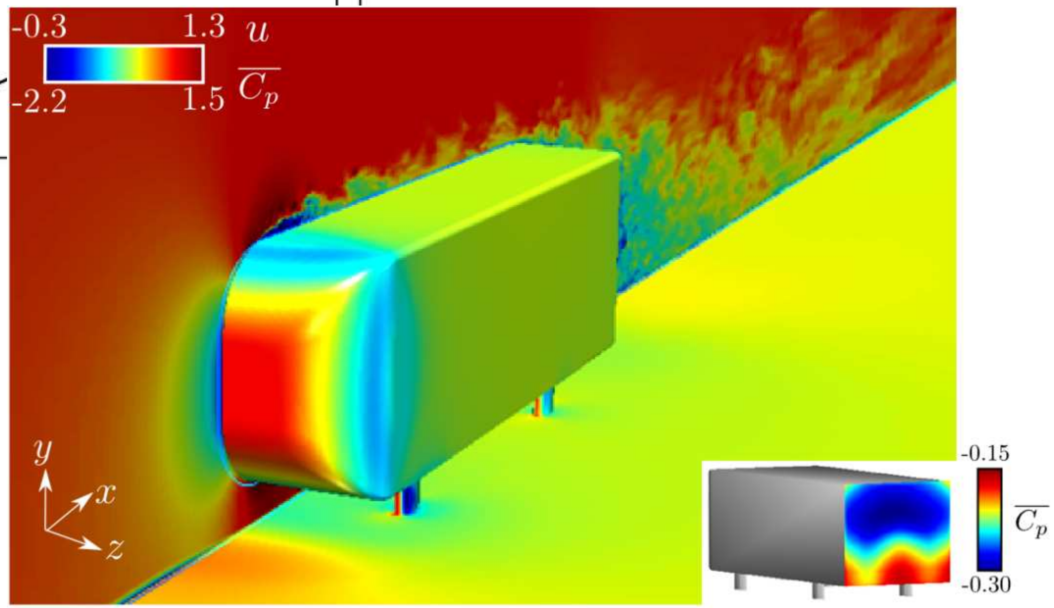
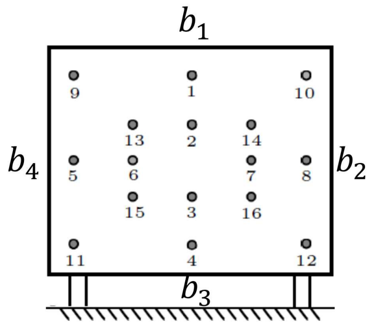


MLC-based drag reduction

Li+ 2017 EF & Barros+ 2016 JFM



Experiment: $Re = 3 \times 10^5$

MIMO control problem:

Ansatz $\boldsymbol{b} = \boldsymbol{K}(\boldsymbol{s})$

Drag reduction: 22%

Energy investment: 3%

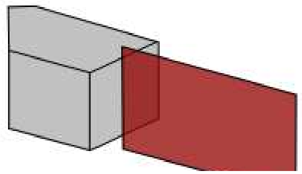
MLC application

Testing time < 1 hour

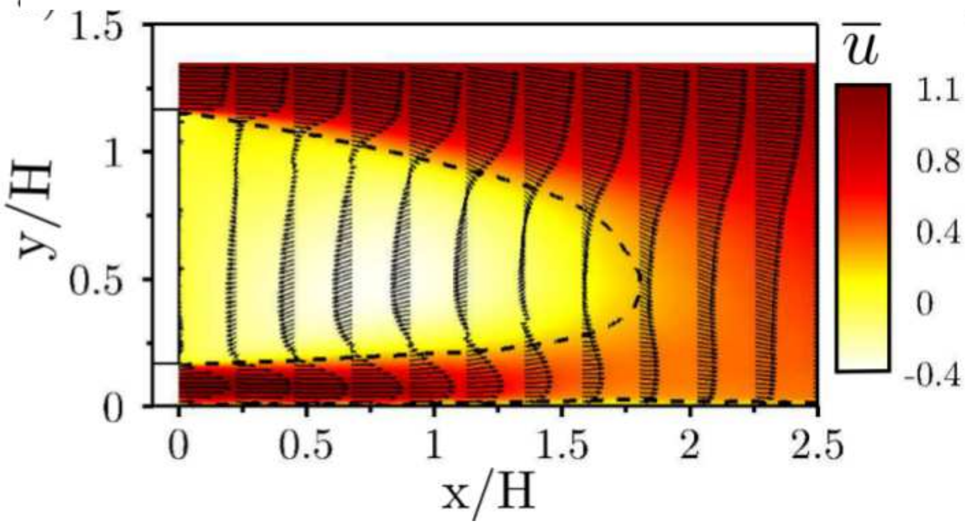
MLC law:

$b_1 = b_2 = b_3 = b_4 = b$

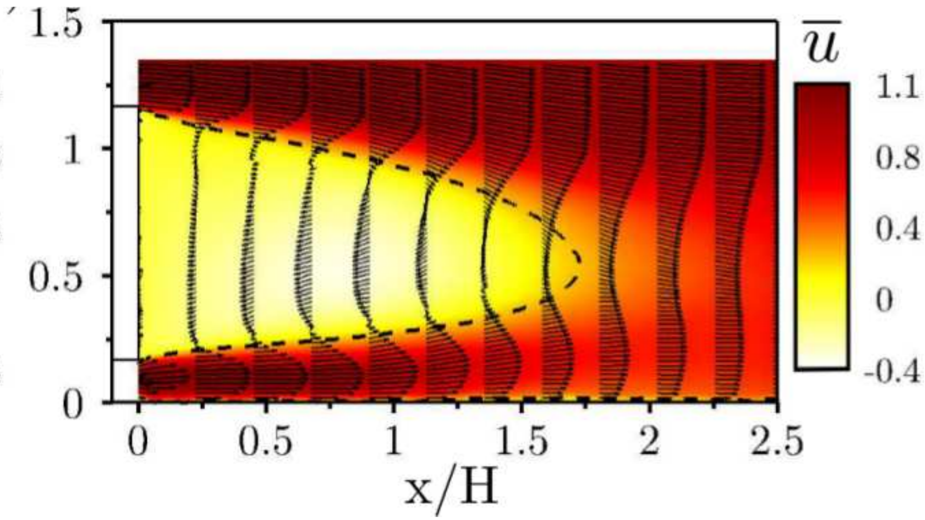
$b = H \left[\tanh \tanh(s'_4 - 0.1)\right]$



Unforced

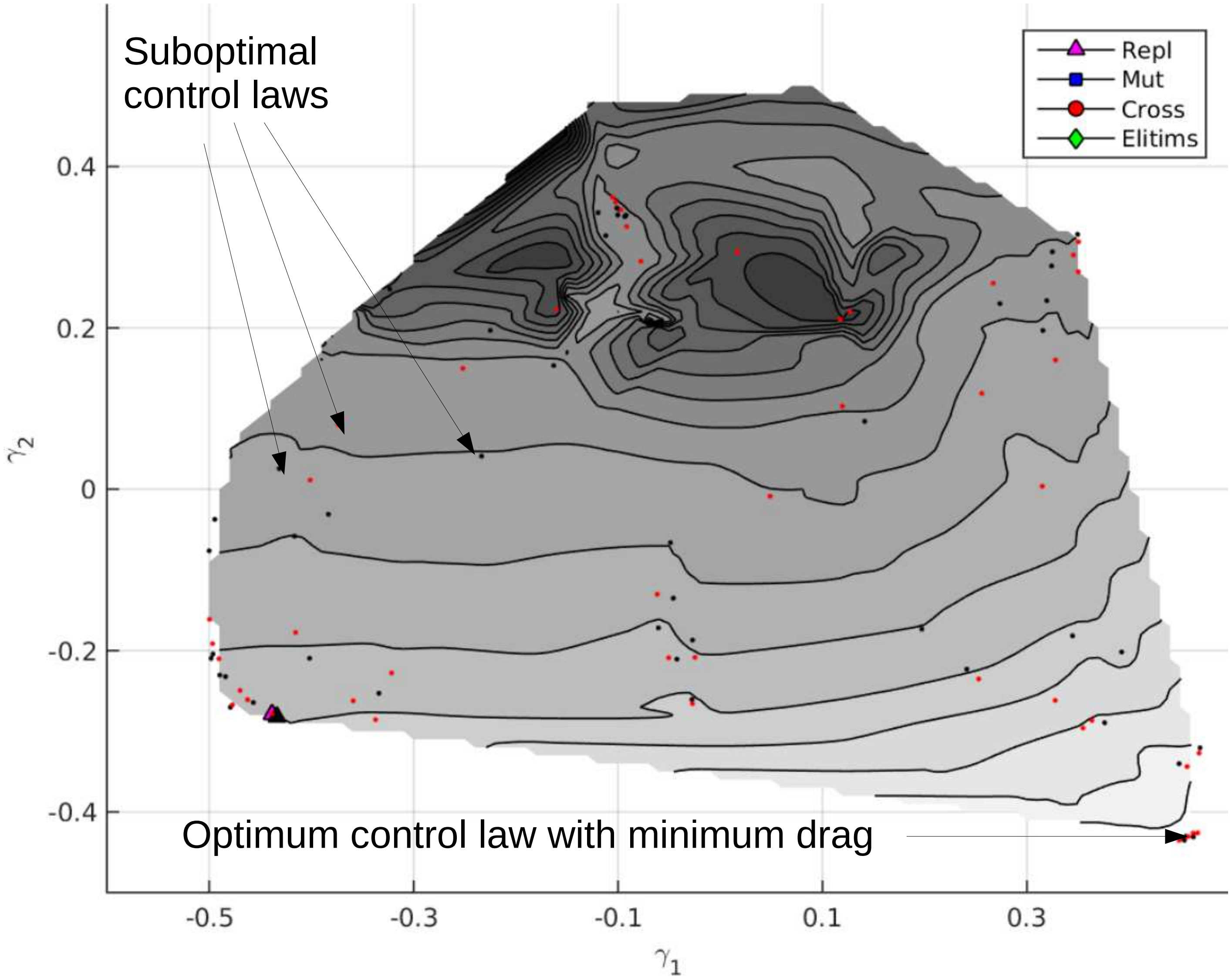


MLC controlled



Proximity plot for MLC of car model

2017 Kaiser+ FSSIC *2016 Kaiser+ TCFD*



MLC with 5 generations with 50 control laws each.

More

AI / Machine Learning Control Experiments

Brunton & Noack 2015 AMR; Duriez+ 2016 Springer; Noack 2019 FSSIC

- **Drag reduction of an Ahmed body** — Li+ 2017 EF
  Multi-frequency forcing beats opt. periodic forcing (PF)
- **Mixing enhancement in shear layer** — Parezanovic+ 2016 JFM
  Feedback phaser control; linear models invalidated
- **Separation control over a BFS** — Gautier+ 2015 JFM
  Feedback low-freq. forcing beats opt. PF
- **Separation mitigation of a TBL $Re = 13,000$**
  High-freq.feedback beats opt. PF — Debien+ 2016 EF
- **Jet mixing with 6 actuators** — Zhou+ 2020 JFM
- **Drag reduction of a TBL** — Yu+ 2021 AMS
- **Many more experiments and simulations**

MLC has outperformed exisiting optimized control.

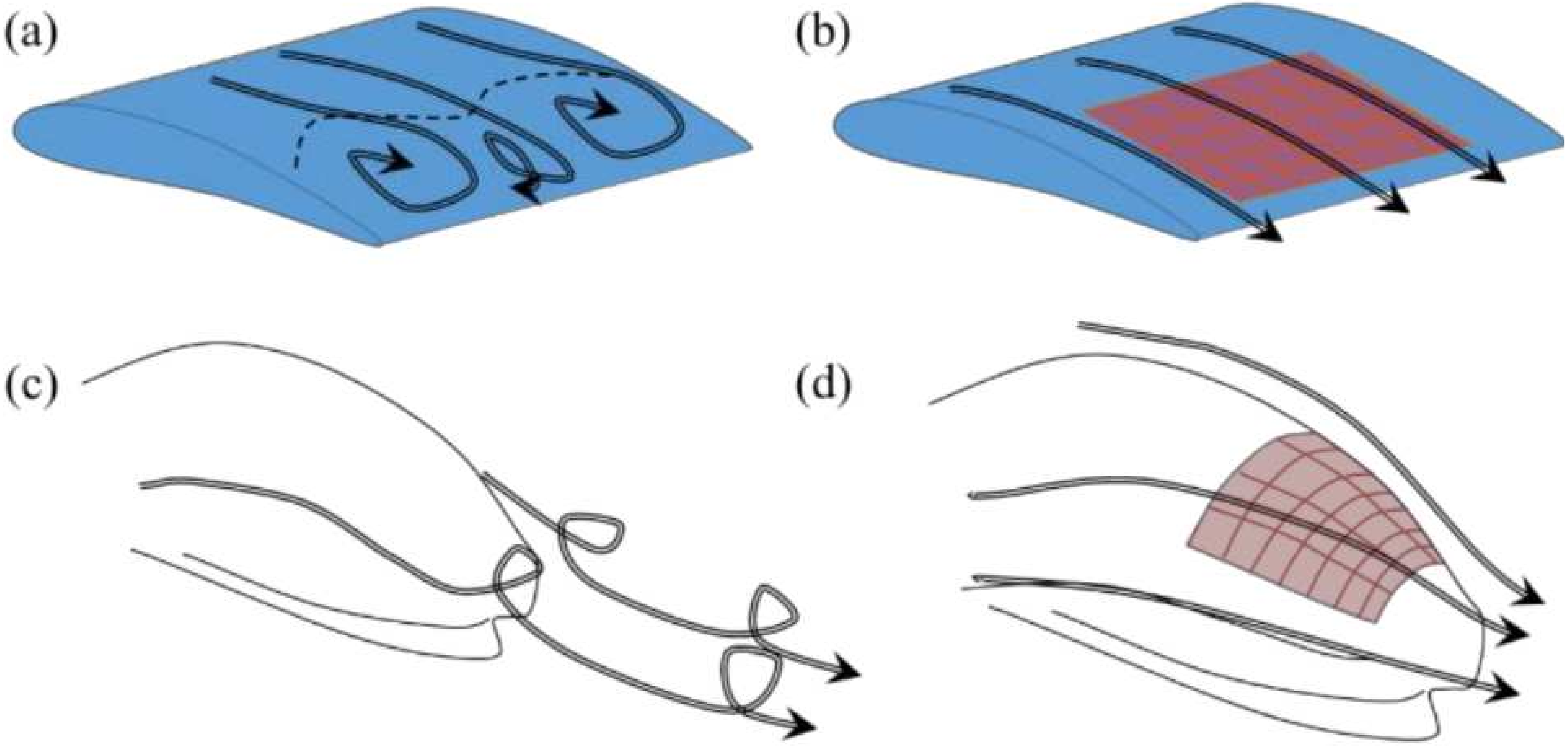
MLC selects sensors + actuators.

Small chances for modeling-based control.

Actuation mechanisms often used unexpected frequencies, unexpected frequency crosstalk and multi-freq. forcing

Smart skin concept

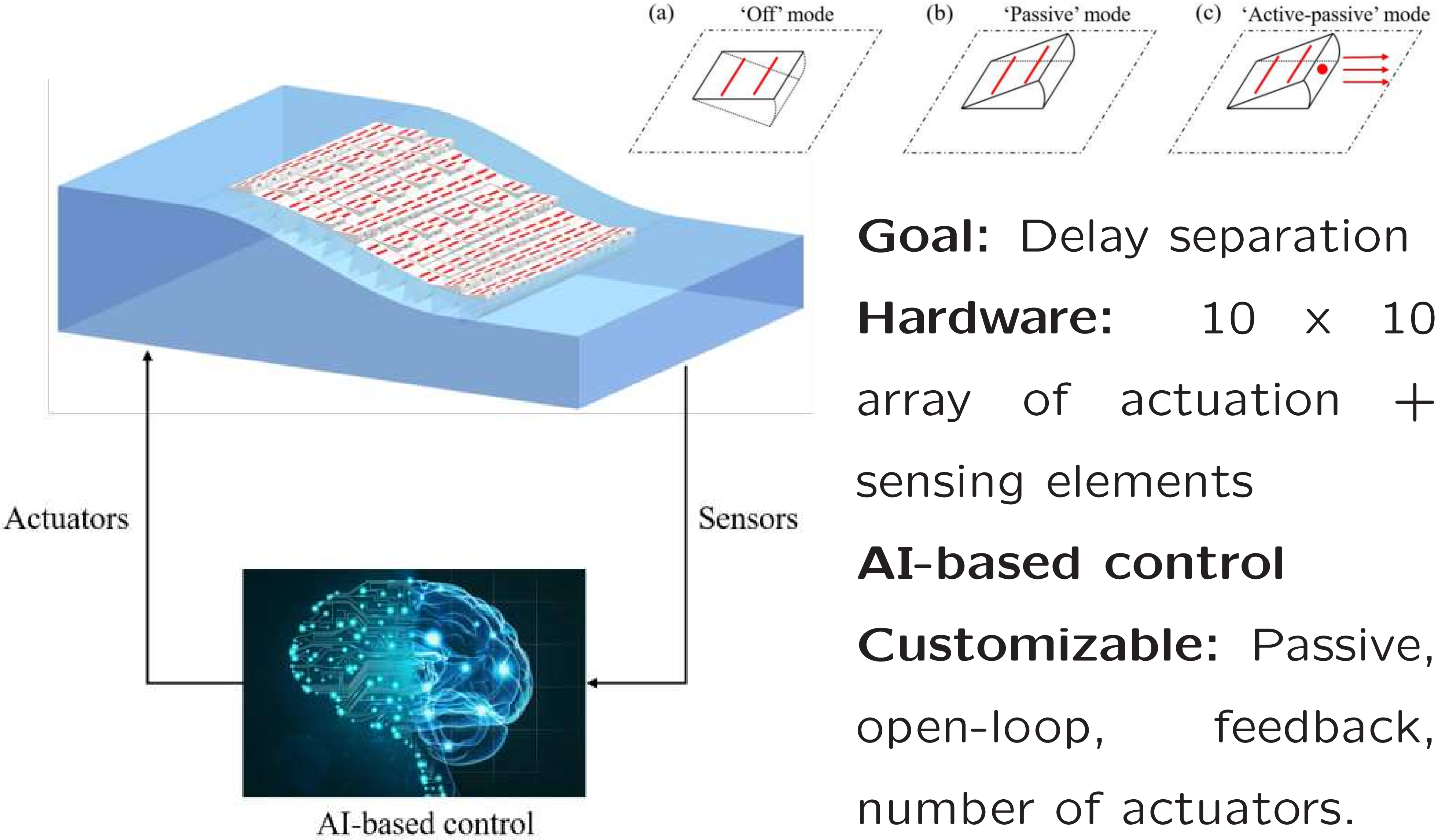
S.L. Brunton & B.R. Noack 2015 AMR



Targeted actuation near sensed point of separation with AI-based control.

Smart skin concept

S.L. Brunton & B.R. Noack 2015 AMR



Goal: Delay separation

Hardware: 10 x 10 array of actuation + sensing elements

AI-based control

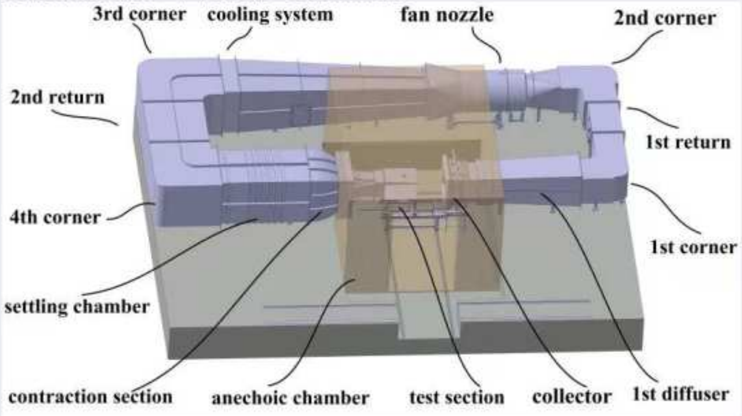
Customizable: Passive, open-loop, feedback, number of actuators.

Smart skin separation control experiment

— Work in progress —

Wind Tunnels

- Anechoic Wind Tunnel:



- Low-speed wind tunnel:

Ramp demonstrator

Actuators for hybrid control algorithms:

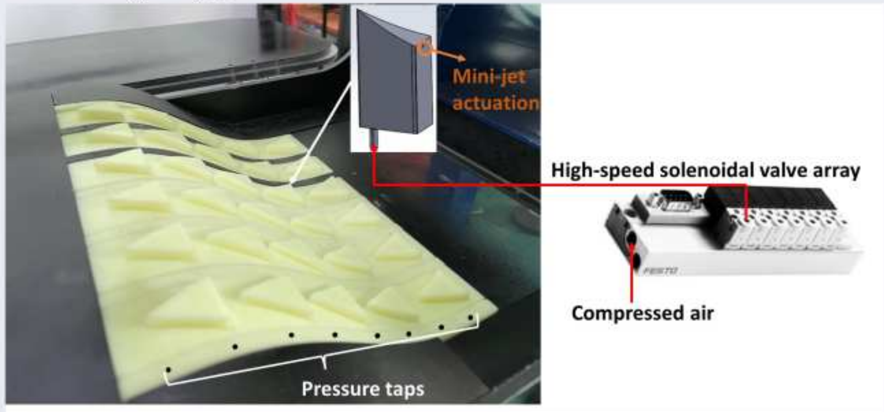
- Passive control: Height-adjustable vortex generators 5 (streamwise)×6 (spanwise).
- Active: Mini-jets actuation (up to 500Hz).

Sensors: 8×7 pressure taps.

Cost function: $J = J_a + \gamma J_b$, $\gamma = 0.2$.

$J_a = U_\infty \int (p_\infty - \bar{p}) d\boldsymbol{x}$ (pressure recovery)

$J_b = \sum \frac{1}{2} \rho u_{\text{jet}}^3 dA$ (energy input)



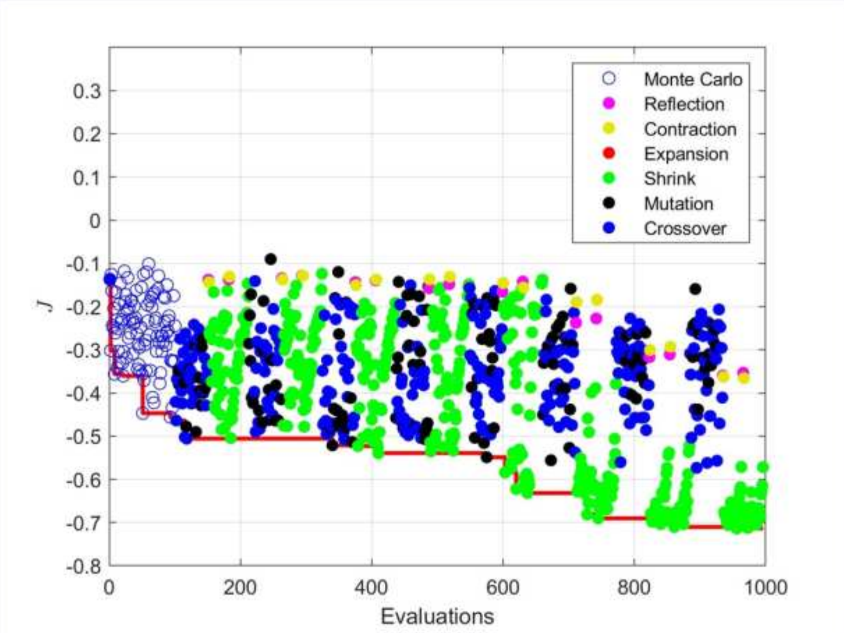
U_∞ =5 m/s; H =5cm; δ_{99} = 1cm; Re_H =33,000;
U_{jet} =15-20 m/s; actuator/sensor element 2 cm × 5 cm.

Smart skin + gMLC: Learning curve

— Work in progress —

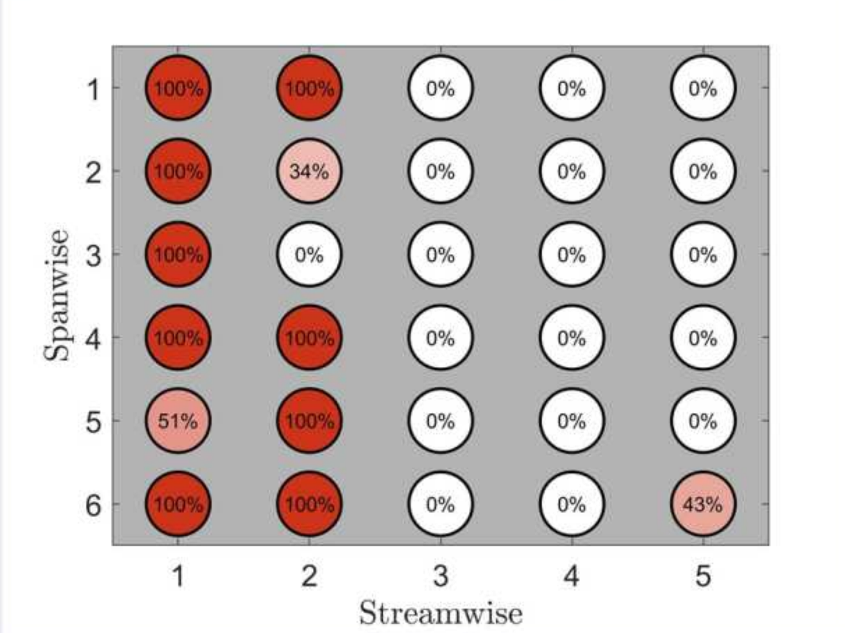
Learning curve

- Optimization problem: $\underset{\boldsymbol{K}\in\mathcal{K}}{\operatorname{argmin}} J(\boldsymbol{K})$.



Optimized actuation

- Equivalent duty cycles of the best control law

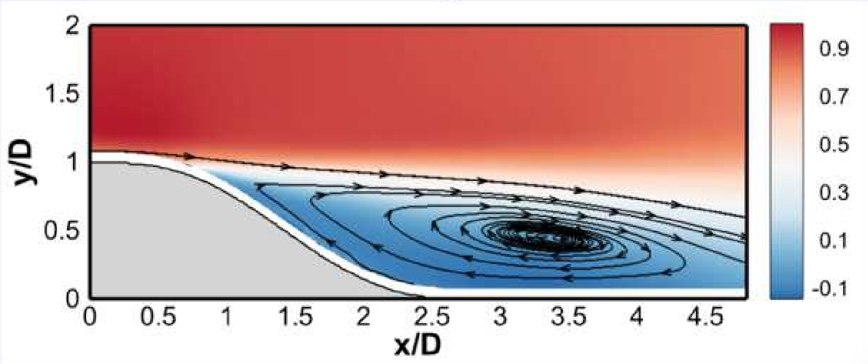


Smart skin + gMLC: Flows

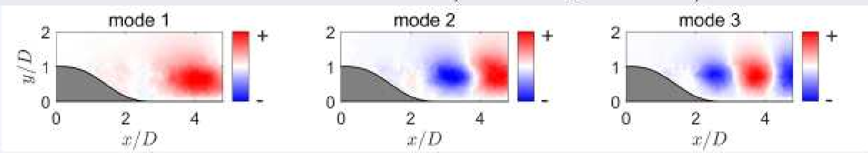
— Work in progress —

Uncontrolled flow

- Mean streamwise velocity:



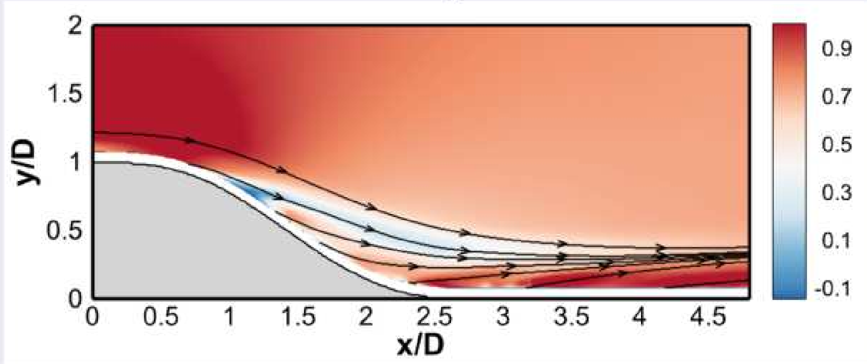
- First three POD modes (v component):



- Dominant turbulent modes: coherent structures from flow separation.

Controlled flow

- Mean streamwise velocity:



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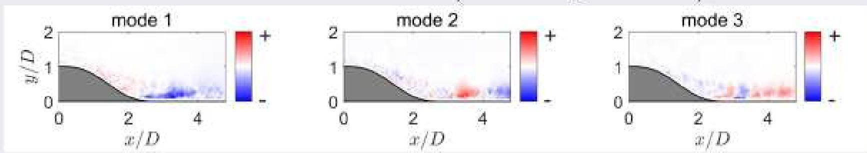

- Dominant turbulent modes: smaller structures from jet actuation.

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Cluster-based feedback control

A.G. Nair, C.-A. Yeh, E. Kaiser, B.R. Noack, S.L. Brunton & K. Taira 2019 JFM

LES, NACA0012: $Re = U_\infty L/\nu = 23,000$, $\alpha = 9^\circ$

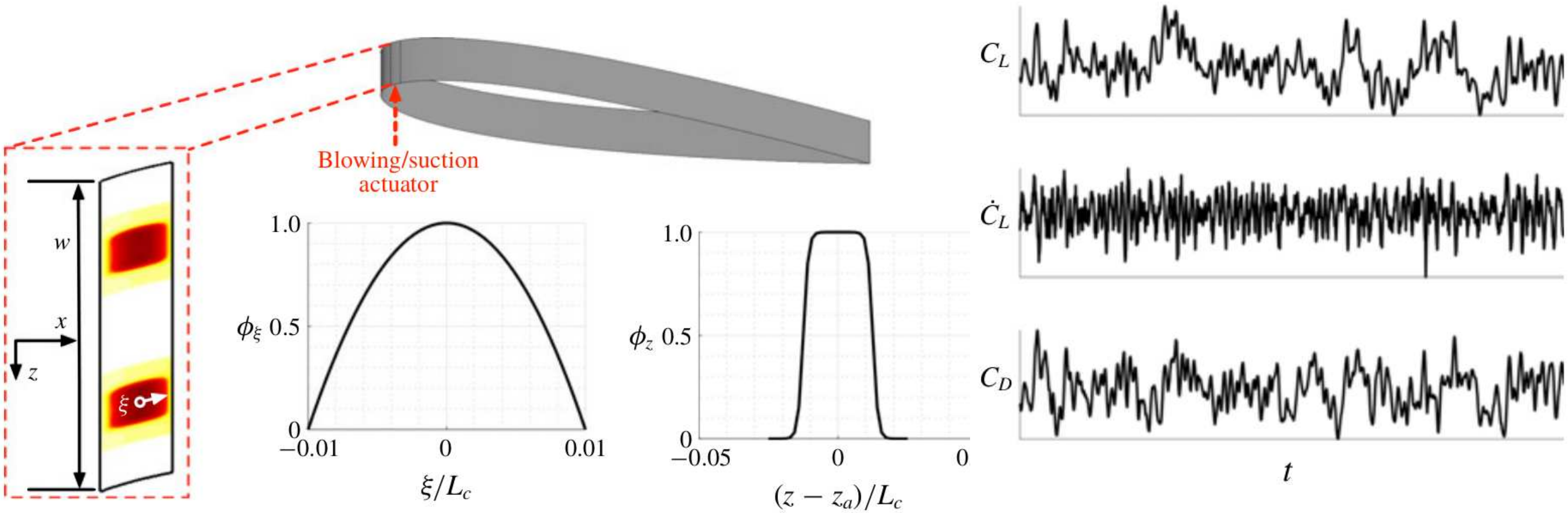
Single-input: b, Amplitude of spanwise periodic jets

Multiple-input: $\boldsymbol{s} = [C_D(t), C_L(t), dC_L/dt(t)]^\dagger$

Control law: $b = K(\boldsymbol{s})$;

Cost function: $J =$ flight endurance $\sim$ drag

(propulsion energy per unit mass and unit le



Cluster-based feedback control

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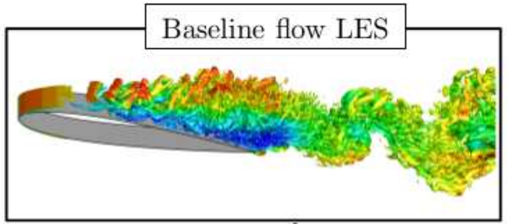
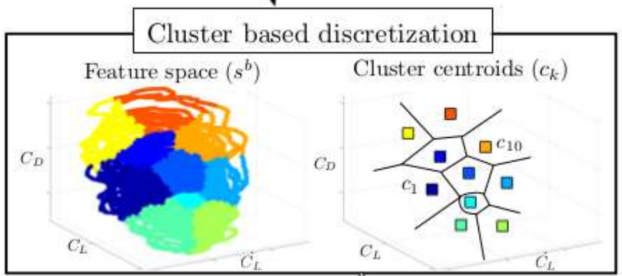
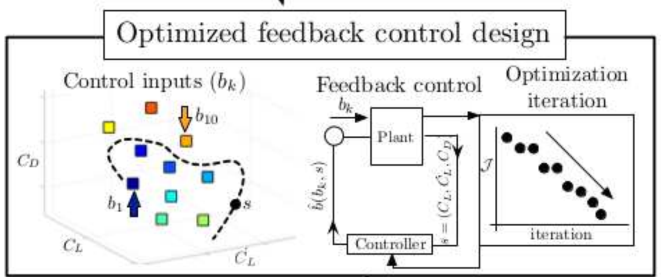


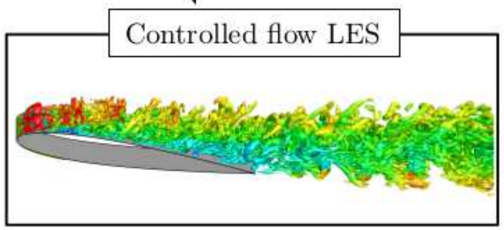
- 3D (2D) LES of baseline flow
  $Re = 23000, Ma_\infty = 0.3, \alpha = 9°$
  (Section 2.1)



- Collect feature-space baseline data
  $s^b = (C_L, \dot{C}_L, C_D)$
- Cluster-based discretization
  $\{c_k\}_K = k\text{-}means\ (s^b)$
  (Section 2.3)



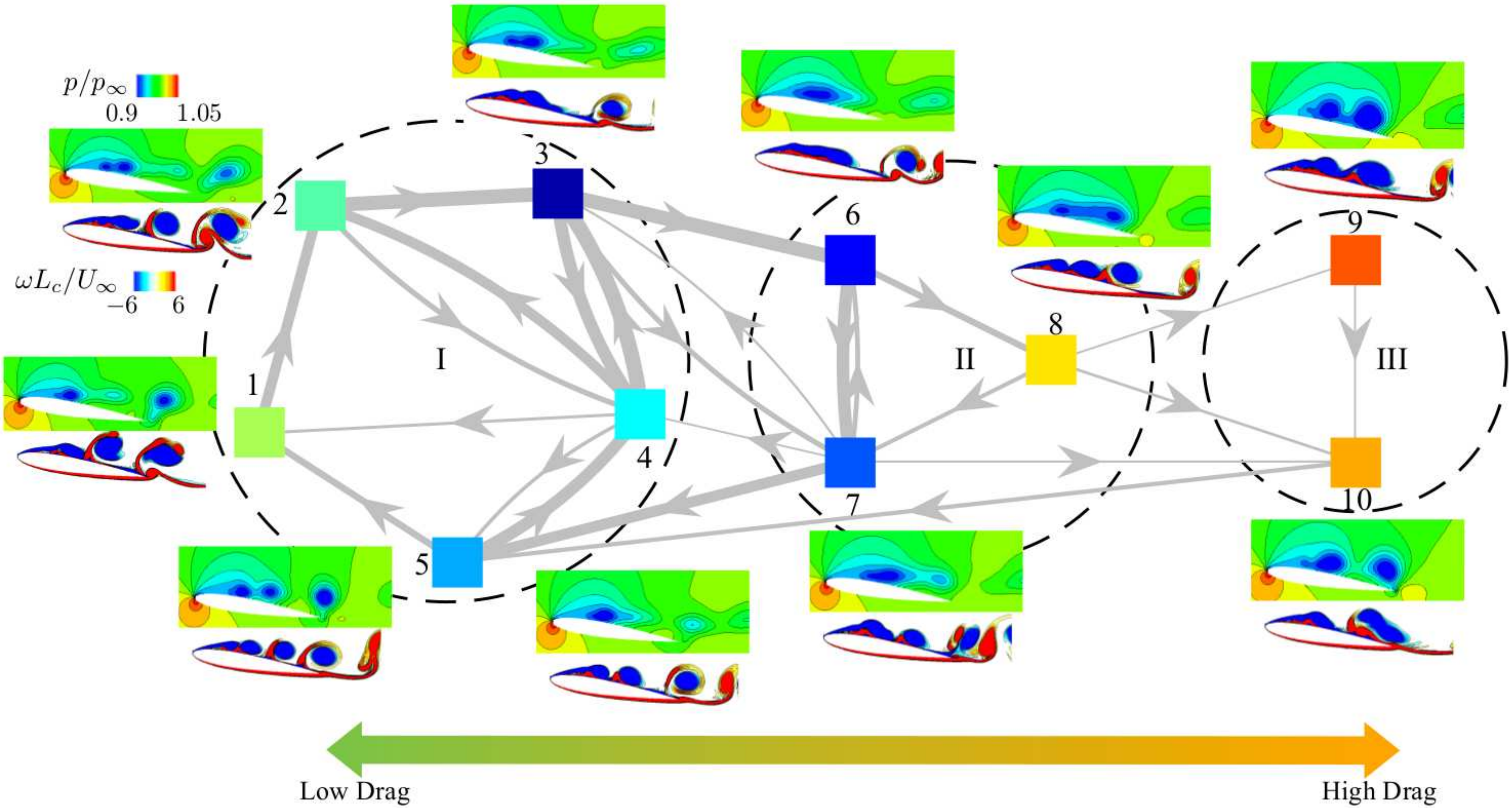
- Cluster-based feedback control
  $\hat{b}(b_k, s) = \dfrac{\sum_{k=1}^{K} b_k\, e^{-||s-c_k||^2/\sigma^2}}{\sum_{k=1}^{K} e^{-||s-c_k||^2/\sigma^2}}$
- Data-driven optimization
  $\underset{b_k}{minimize}\ \ \mathcal{J} = P_a + P_b$
  (Section 2.4)



- 3D (2D) LES of controlled flow
  (Section 3 and 4)

Cluster-based feedback control

≡ *A.G. Nair, C.-A. Yeh, E. Kaiser, B.R. Noack, S.L. Brunton & K. Taira 2019 JFM*



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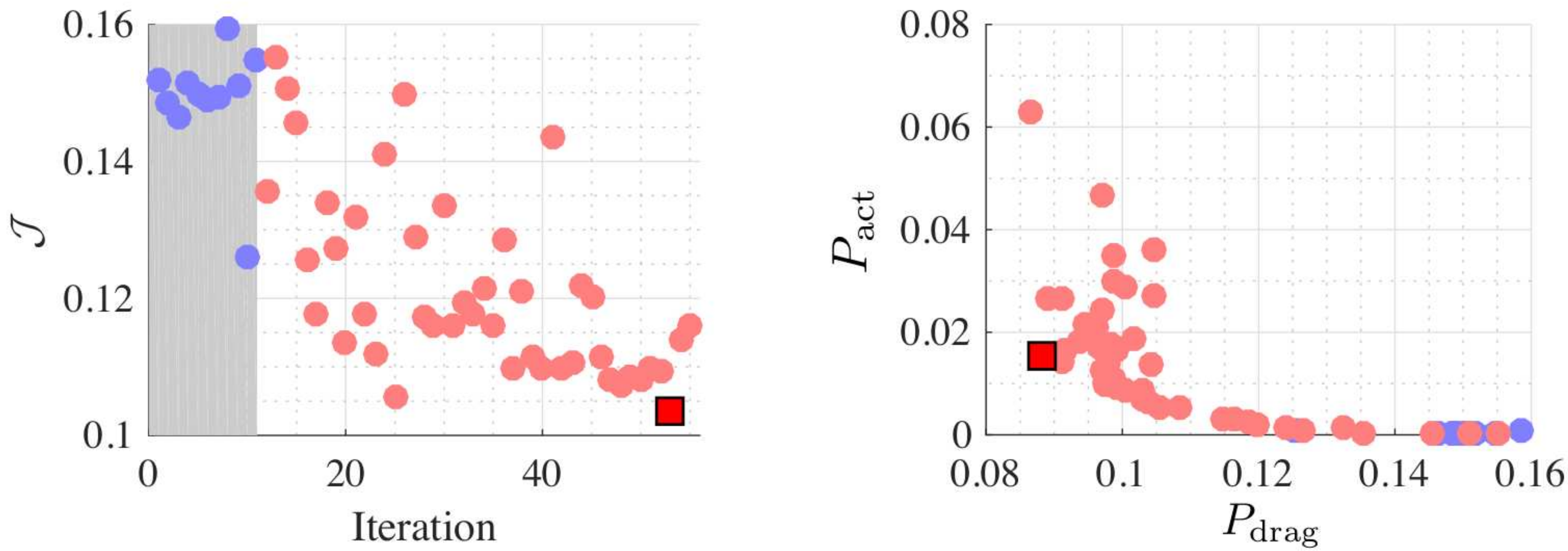

Cost function $J = J_{drag} + J_{act}$ where

$J_{\mathrm{drag}} = c_D^a \left(c_L/c_L^a\right)^{3/2}$ (flight endurance); J_{act}=act. power

Simplex optimization of cluster-based control law:

Lift preserved, drag reduced by 41 %

Cluster-based feedback control

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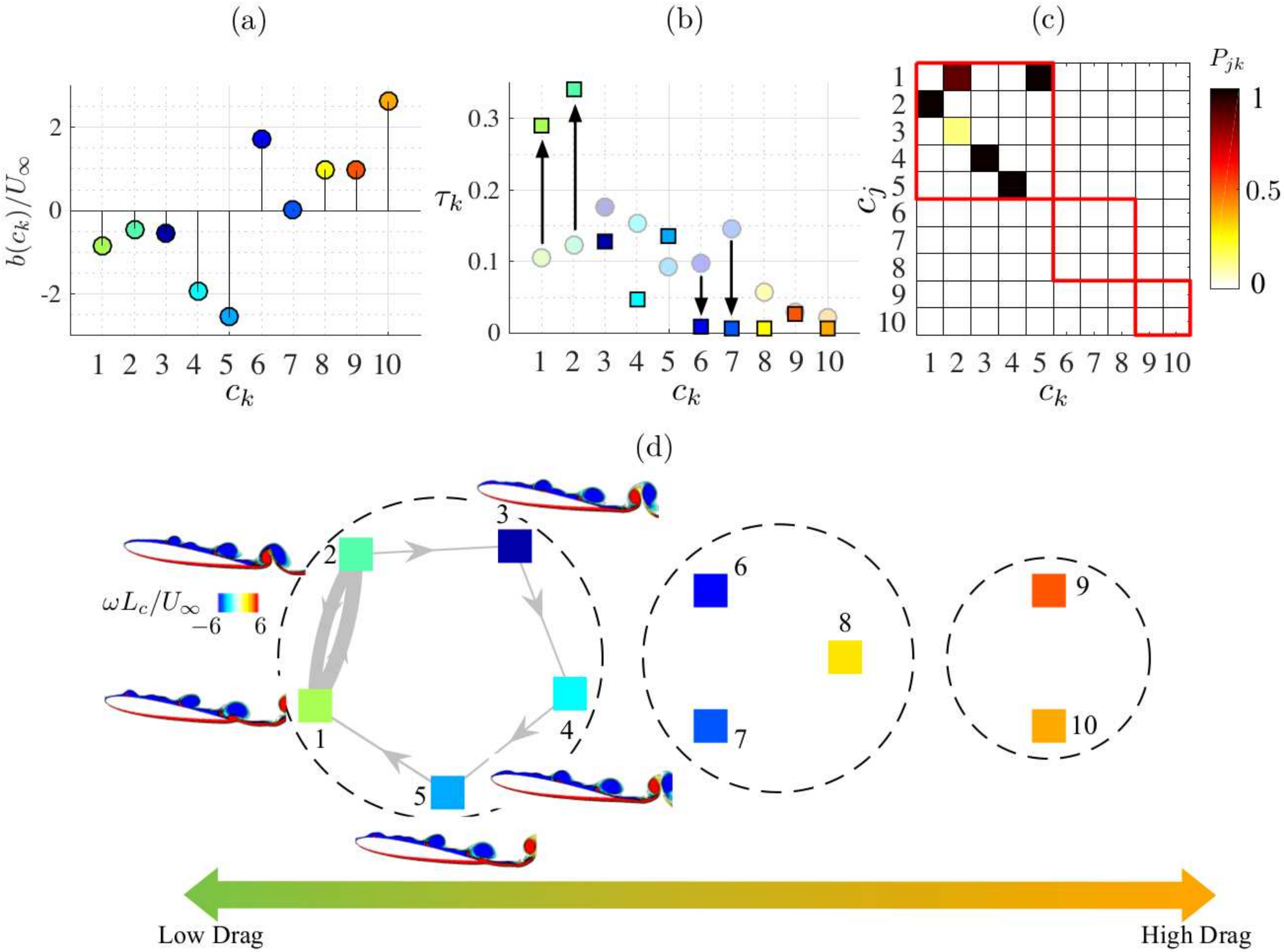
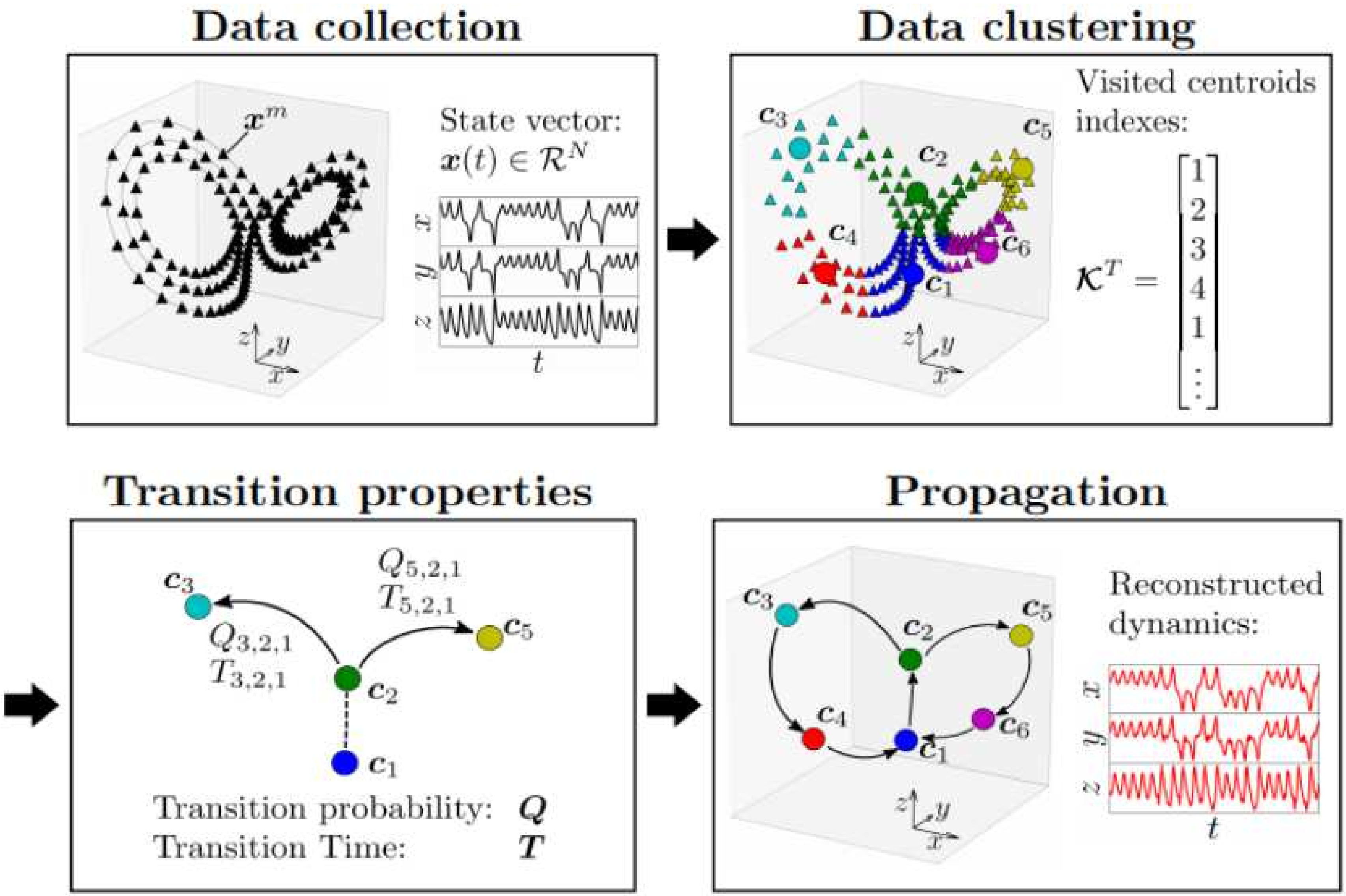


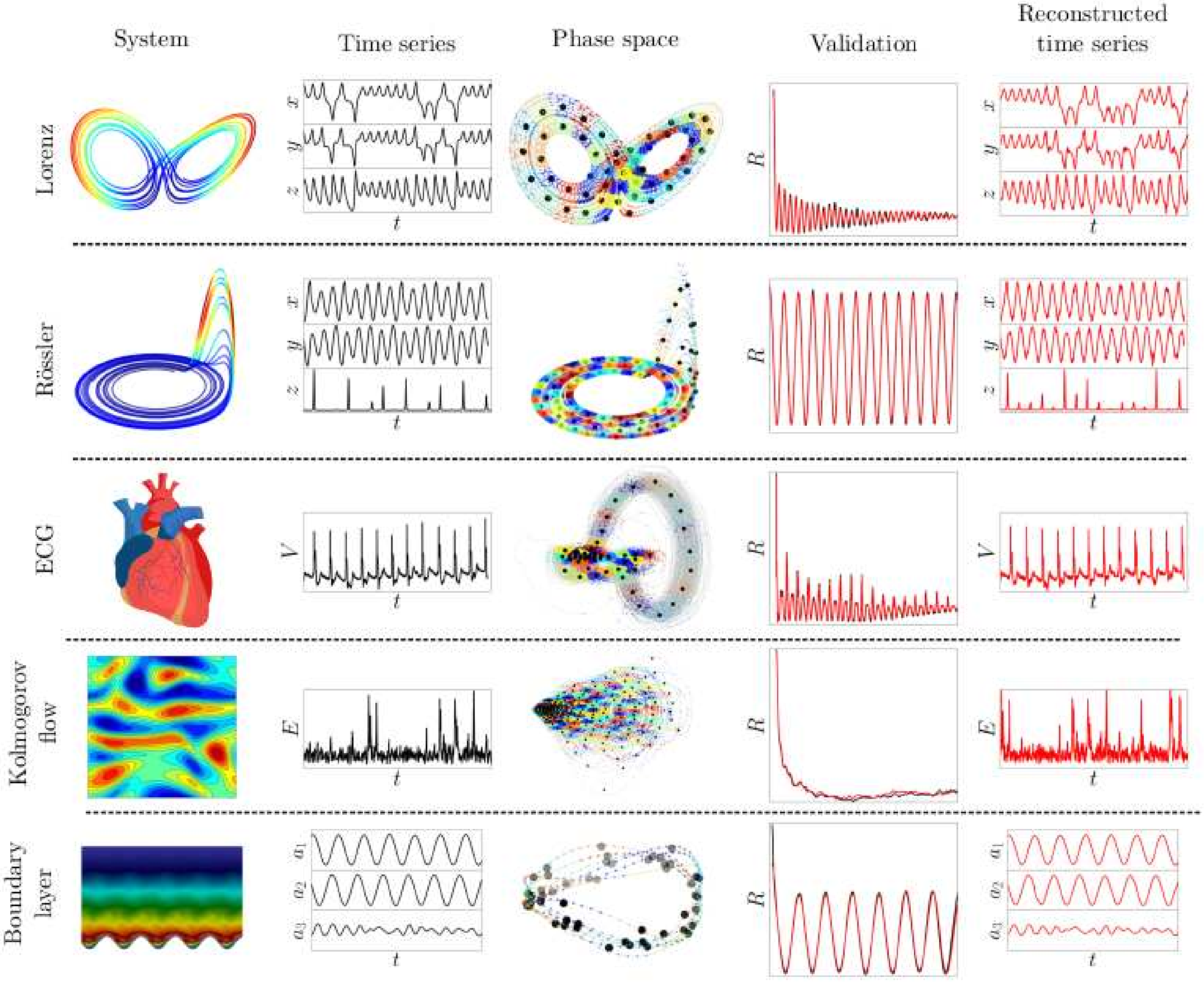
Cluster-based network model

≡ *Fernex et al 2021 Sci Adv*, ≡ *H. Li et al. 2020 JFM*



Cluster-based network model

Fernex et al 2021 Sci. Adv.



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Toolbox for turbulence control

≡ *S. Brunton, B.R. Noack & P. Koumoutsakos 2020 ARFM*

(1) **Response model** . . . . $\boldsymbol{b} \mapsto J$

(2) **Parametric optimizer** . . . . $\boldsymbol{b}^\star = \arg\min J(\boldsymbol{b})$

EGM, BO, PSO, . . . ▷ 11:45 talk of Anne LI

(3) **Feedback learner** . . . . $\boldsymbol{K}^\star(\boldsymbol{s}) = \arg\min J(\boldsymbol{K}(\boldsymbol{s}))$

▷ 11:15 talk of Guy CORNEJO MACEDA

(4) **Automatable reduced order model**

$$\frac{d\boldsymbol{a}}{dt} = \boldsymbol{f}(\boldsymbol{a},\boldsymbol{b}), \boldsymbol{u}(\boldsymbol{x}) = \boldsymbol{h}(\boldsymbol{a},\boldsymbol{b},\boldsymbol{x})$$

(5) **Handcrafted model** ▷ 11:00 talk of Nan DENG

$$\frac{d\boldsymbol{a}}{dt} = \boldsymbol{f}(\boldsymbol{a},\boldsymbol{b}), \boldsymbol{u}(\boldsymbol{x},t) = \sum a_i(t)\boldsymbol{u}_i(\boldsymbol{x})$$

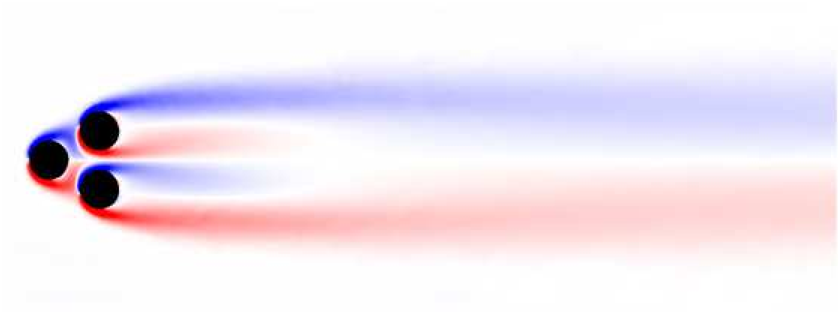
(6) **Full-state estimator** ▷ 11:30 talk of Songqi LI

$$\boldsymbol{u}(\boldsymbol{x}) = \boldsymbol{g}(\boldsymbol{s},\boldsymbol{b},\boldsymbol{x})$$

Fluidic pinball—A modeling benchmark

≡ *N. Deng, B. R. Noack, M. Morzyński & L. Pastur 2020 & 2021 JFM*

Reynolds number $\mathrm{Re} = \frac{U_\infty D}{\nu} = 100$



Fluidic pinball:

- $Re = 18$ Onset of vortex shedding
- $Re = 68$ Supercritical pitchfork bifurcation
- $Re = 104$ Second Hopf bifurcation
- $Re = 115$ Chaos

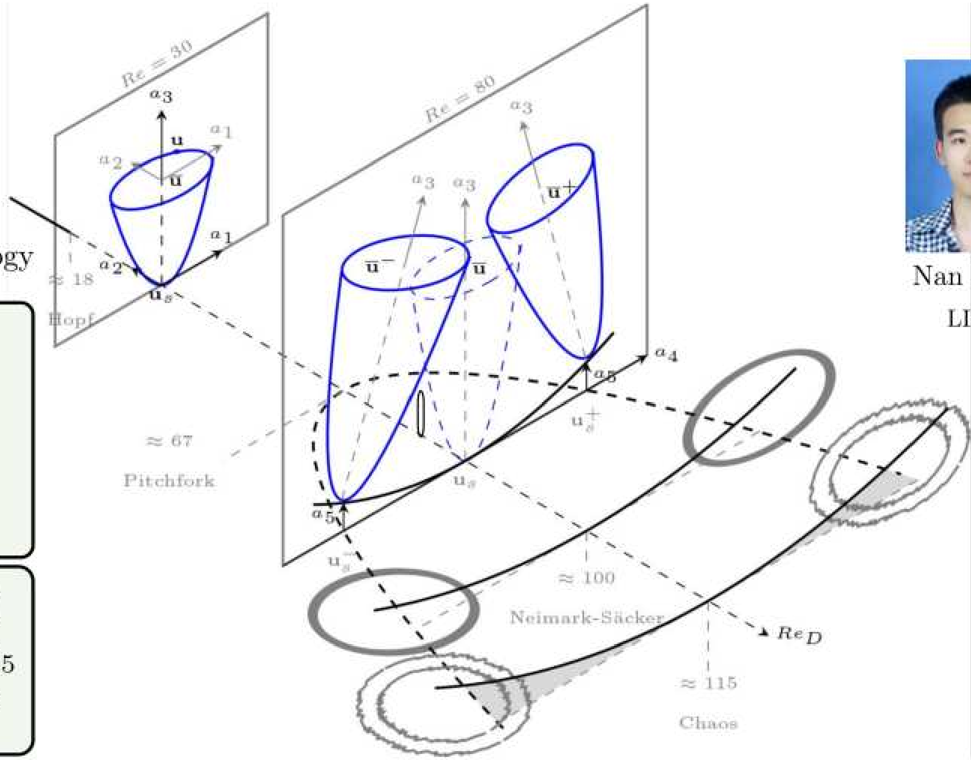
Marek Morzyński
Poznań University of Technology

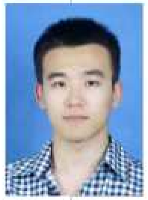
Hopf (Re ≈ 18)

$$da_1/dt = \sigma a_1 - \omega a_2$$
$$da_2/dt = \sigma a_2 + \omega a_1$$
$$da_3/dt = \sigma_3 a_3 + \beta_3 r^2$$

+ **Pitchfork** (Re ≈ 68)

$$da_4/dt = \sigma_4 a_4 - \beta_4 a_4 a_5$$
$$da_5/dt = \sigma_5 a_5 + \beta_5 {a_4}^2$$



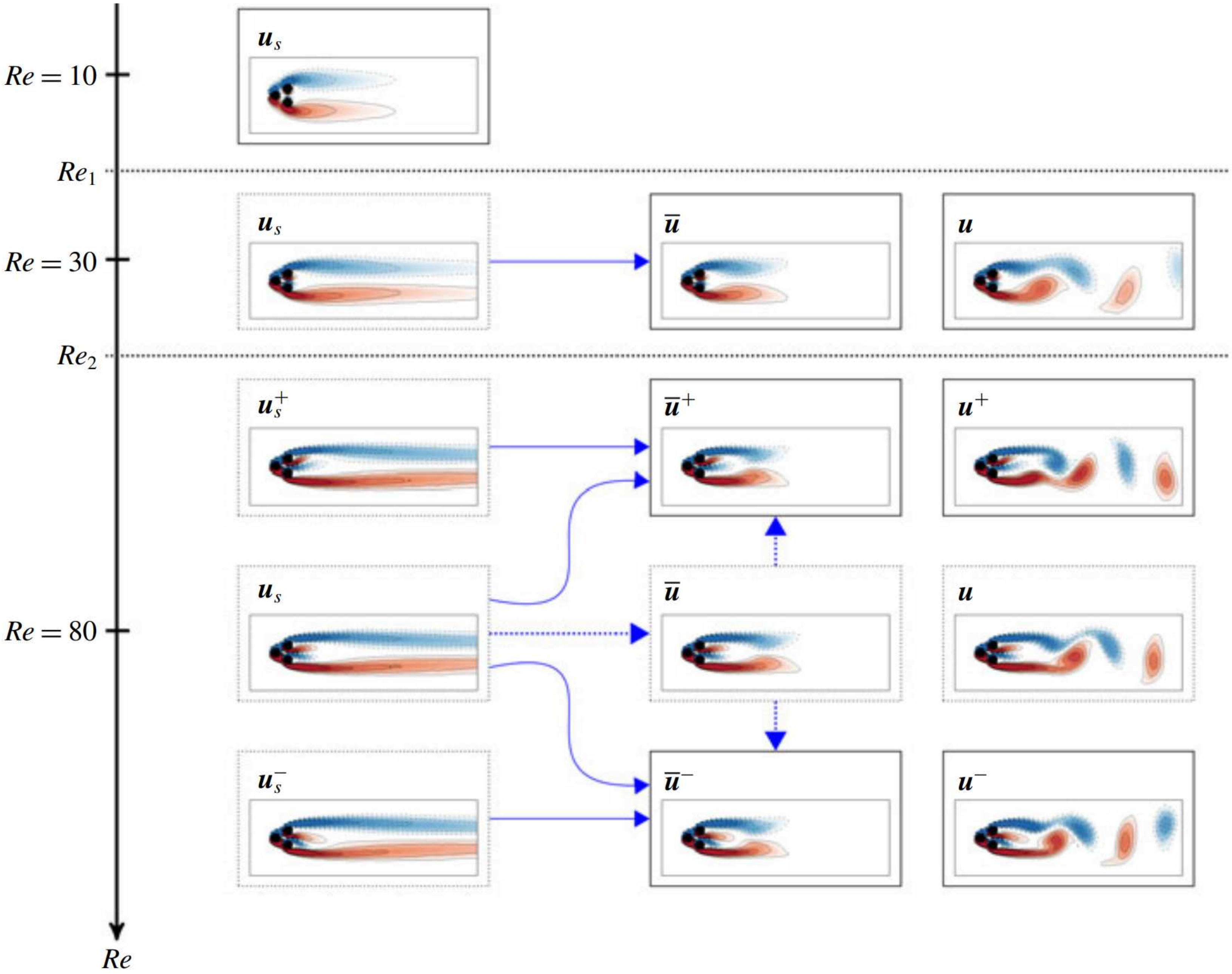


Nan Deng
LISN

Luc Pastur
ENSTA

Fluidic pinball—Successive bifurcations

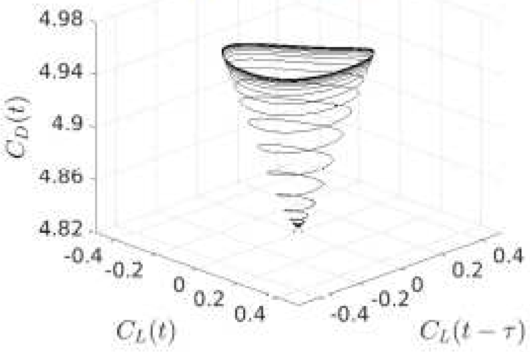
≡ Deng et al. 2020 JFM, ≡ Deng et al. 2021 JFM, ≡ Deng et al. 2021 EPL



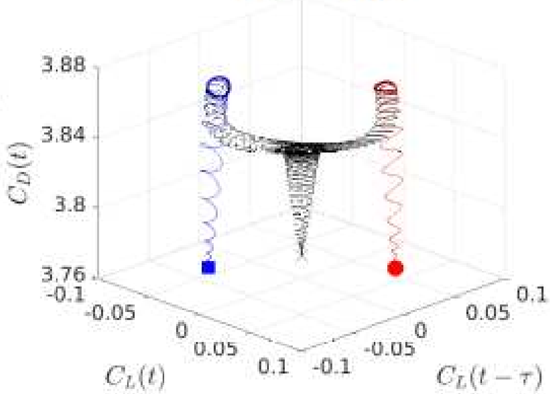
Fluidic pinball—Phase portraits

≡ *Deng, Noack, Morzyński & Pastur 2020 JFM*

Re = 30



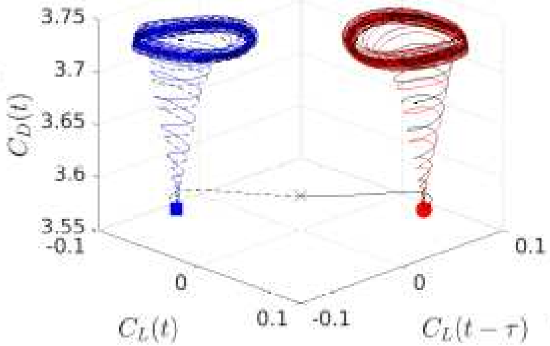
Re = 80



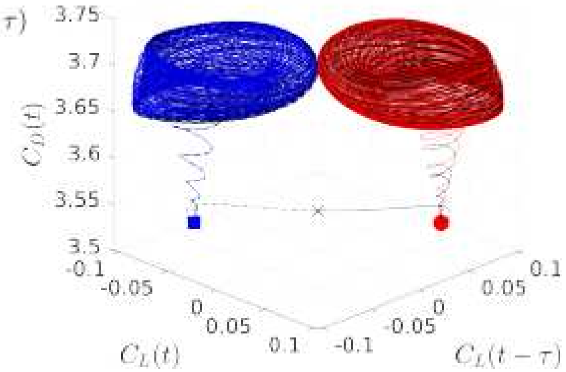
The drag and lift coefficients:

$$C_D(t) = \frac{2F_D(t)}{\rho U^2}, \qquad C_L(t) = \frac{2F_L(t)}{\rho U^2}.$$

Re = 100



Re = 105



$$\mathrm{Re} = \frac{UD}{\nu}$$

POD Galerkin method — Summary

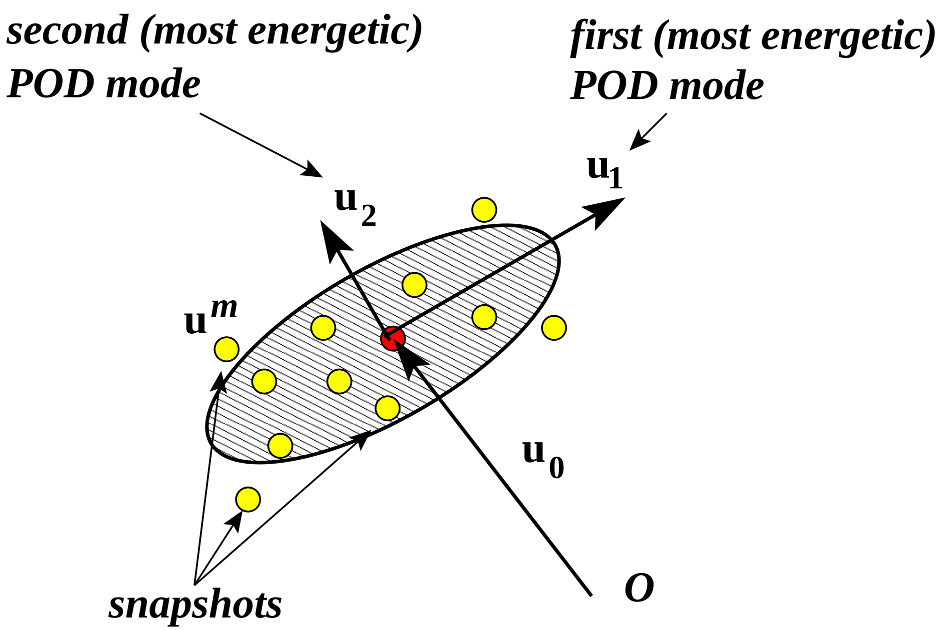
— Holmes, Lumley, Berkooz & Rowley 2012 Cambridge —

Galerkin method

$$
\begin{array}{ccccccc}
\mathbf{u} & \rightarrow & \partial_t \mathbf{u} & = \nu \triangle \mathbf{u} & -\nabla(\mathbf{u}\mathbf{u}) & -\nabla p \\
\downarrow & & \downarrow & \downarrow & \downarrow & \downarrow \\
\mathbf{u} = \sum_{i=0}^{N} a_i \mathbf{u}_i & \rightarrow & \frac{da_i}{dt} & = \nu \sum_{j=0}^{N} l_{ij}^{\nu} a_j & + \sum_{j,k=0}^{N} (q_{ijk}^{c} & + q_{ijk}^{p})\, a_j\, a_k
\end{array}
$$

Galerkin approximation

(Proper orthogonal decomposition, principal axes)



Galerkin projection

$$(\mathbf{u}, \mathbf{v})_\Omega := \int dV\, \mathbf{u} \cdot \mathbf{v}$$

$$
\begin{aligned}
(\mathbf{u}_i, \partial_t \mathbf{u})_\Omega &= \int dV\, \mathbf{u}_i \cdot \partial_t \left(\sum_{j=0}^{N} a_j \mathbf{u}_j \right) \\
&= \sum_{j=1}^{N} \frac{da_i}{dt} \int dV\, \mathbf{u}_i \cdot \mathbf{u}_j \\
&= \frac{d}{dt} a_i
\end{aligned}
$$

Fluidic pinball—Galerkin model for $Re = 80$

Deng, Noack, Morzyński & Pastur 2020 JFM

$$\boldsymbol{u}(\boldsymbol{r},t) \approx \underbrace{\boldsymbol{u}_s(\boldsymbol{r})}_{Steady\ solution} + \underbrace{a_1\boldsymbol{u}_1(\boldsymbol{r}) + a_2\boldsymbol{u}_2(\boldsymbol{r}) + a_3\boldsymbol{u}_3(\boldsymbol{r})}_{Hopf\ bifurcation} + \underbrace{a_4\boldsymbol{u}_4(\boldsymbol{r}) + a_5\boldsymbol{u}_5(\boldsymbol{r})}_{Pitchfork\ bifurcation}$$

Dynamical system with 5 d.o.f.

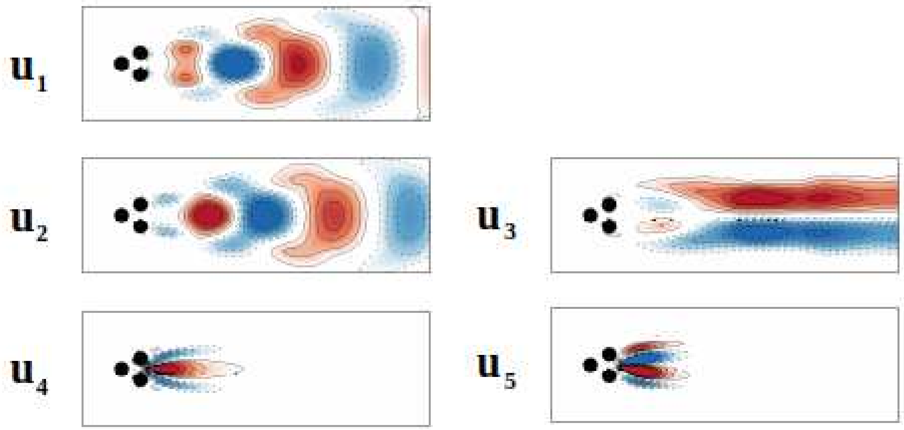
Hopf

$$\dot{a}_1 = \sigma(a_3)a_1 - \omega(a_3)a_2,$$
$$\dot{a}_2 = \sigma(a_3)a_2 + \omega(a_3)a_1,$$
$$\dot{a}_3 = \sigma_3 a_3 + \beta_3(a_1^2 + a_2^2),$$

PF

$$\dot{a}_4 = \sigma_4 a_4 - \beta_4 a_4 a_5,$$
$$\dot{a}_5 = \sigma_5 a_5 + \beta_5 a_4^2,$$

Elementary d.o.f



Identification of the coefficients from linear stability analysis and asymptotic dynamics.

σ_1	5.22×10^{-2}	β	1.31×10^{-2}
ω_1	5.24×10^{-1}	γ	2.95×10^{-2}
σ_3	-5.22×10^{-1}	β_3	1.53×10^{-1}
σ_4	2.72×10^{-2}	β_4	2.45×10^{-1}
σ_5	-2.72×10^{-1}	β_5	2.14×10^{-1}

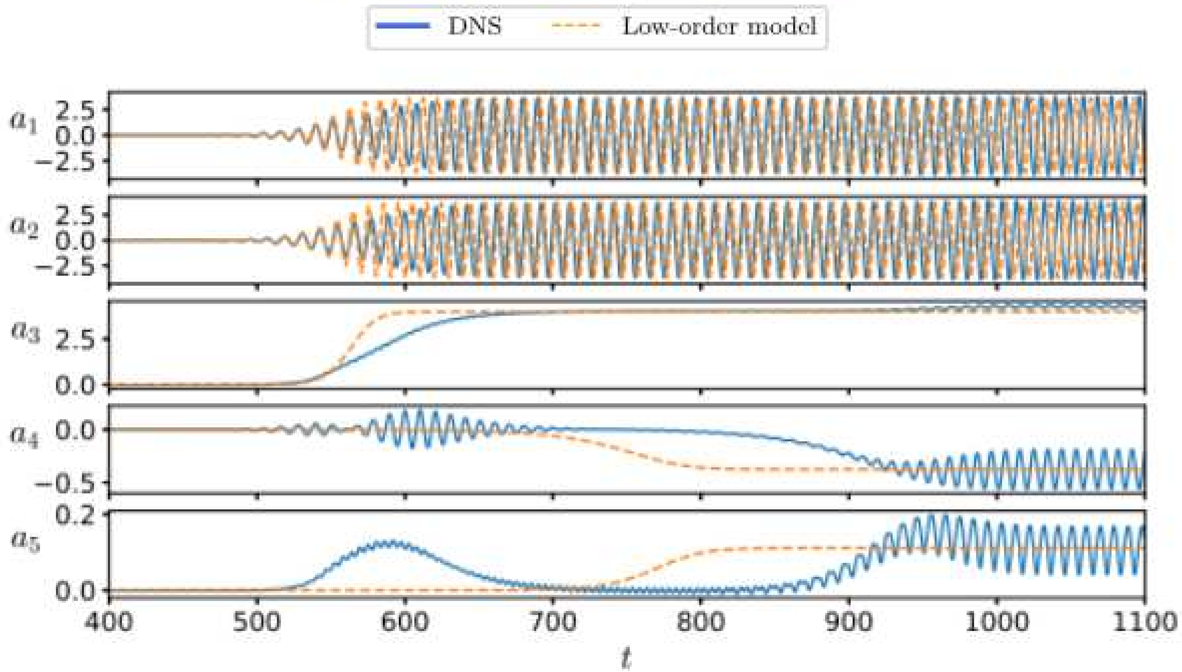


Figure : Comparison of DNS with R.O.M.

Fluidic pinball—Galerkin model for $Re = 80$

Deng, Noack, Morzyński & Pastur 2020 JFM

$$\boldsymbol{u}(\boldsymbol{r},t) \approx \underbrace{\boldsymbol{u}_s(\boldsymbol{r})}_{Steady\ solution} + \underbrace{a_1\boldsymbol{u}_1(\boldsymbol{r}) + a_2\boldsymbol{u}_2(\boldsymbol{r}) + a_3\boldsymbol{u}_3(\boldsymbol{r})}_{Hopf\ bifurcation} + \underbrace{a_4\boldsymbol{u}_4(\boldsymbol{r}) + a_5\boldsymbol{u}_5(\boldsymbol{r})}_{Pitchfork\ bifurcation}$$

Dynamical system with 5 d.o.f. :

Hopf:

$$\dot{a}_1 = \sigma(a_3)a_1 - \omega(a_3)a_2,$$
$$\dot{a}_2 = \sigma(a_3)a_2 + \omega(a_3)a_1,$$
$$\dot{a}_3 = \sigma_3 a_3 + \beta_3(a_1^2 + a_2^2),$$

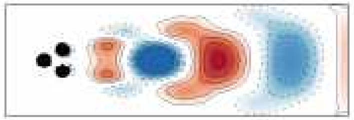
PF:

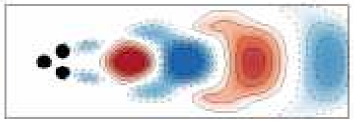
$$\dot{a}_4 = \sigma_4 a_4 - \beta_4 a_4 a_5,$$
$$\dot{a}_5 = \sigma_5 a_5 + \beta_5 a_4^2,$$

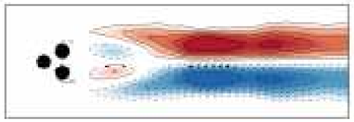
Cross terms

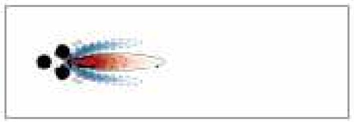
- **Identify the coefficients from the L.S.A. and asymptotic dynamics.**
- **Identify the cross terms.**
  [SINDy algorithm (Brunton et al. 2016)]

Elementary d.o.f :

$\mathbf{u}_1$ 

$\mathbf{u}_2$ 

$\mathbf{u}_3$ 

$\mathbf{u}_4$ 

$\mathbf{u}_5$ 

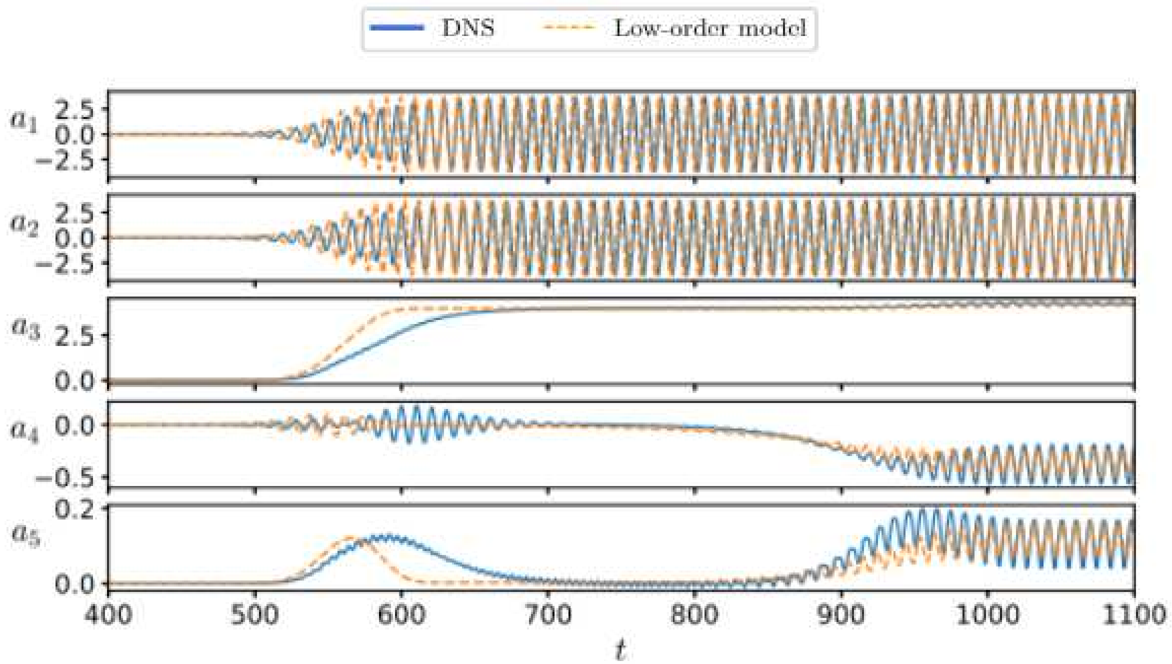
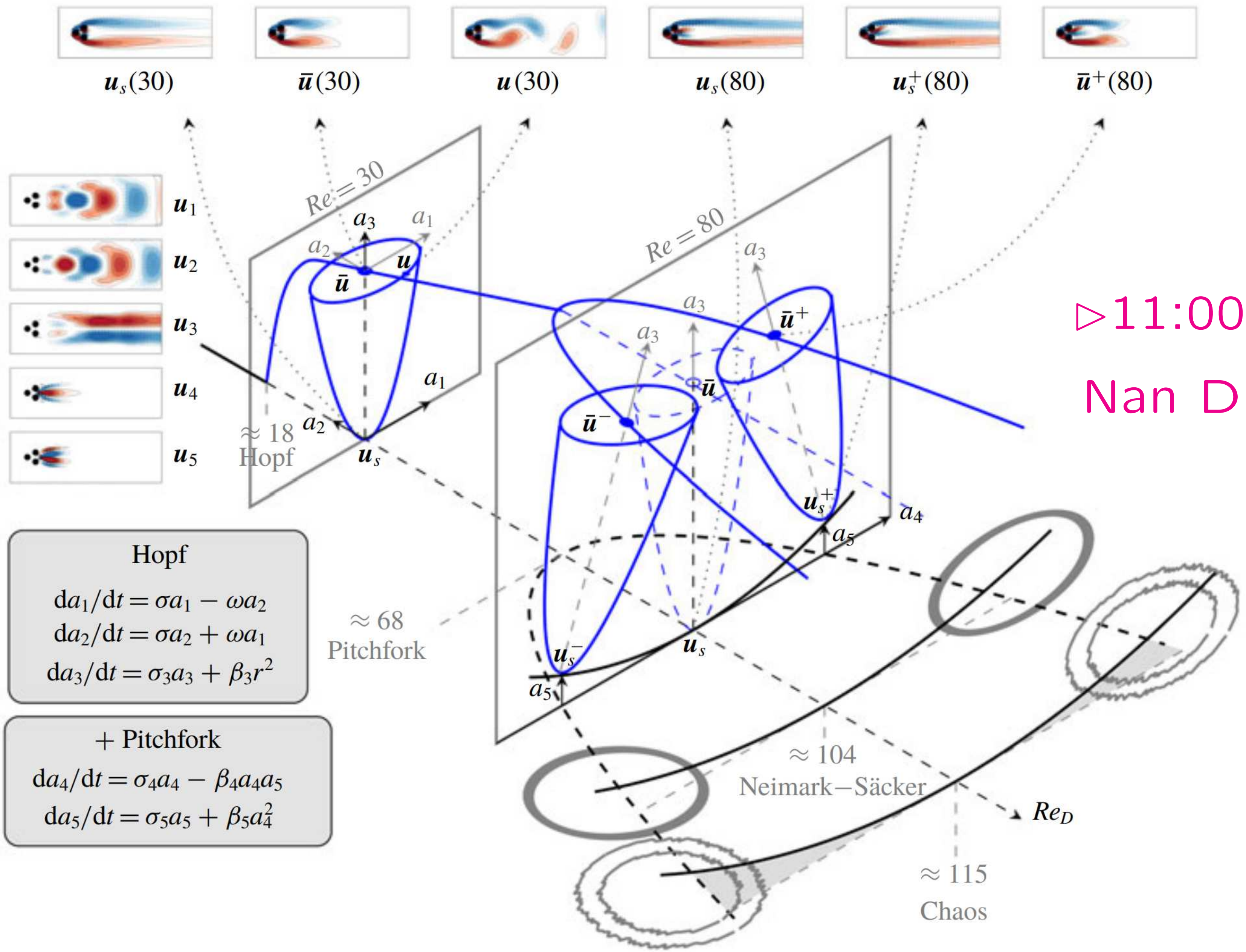


Figure : Comparison of DNS with R.O.M.

Fluidic pinball—Galerkin model bifurcations

☰ *Deng, Noack, Morzyński & Pastur 2020 JFM*



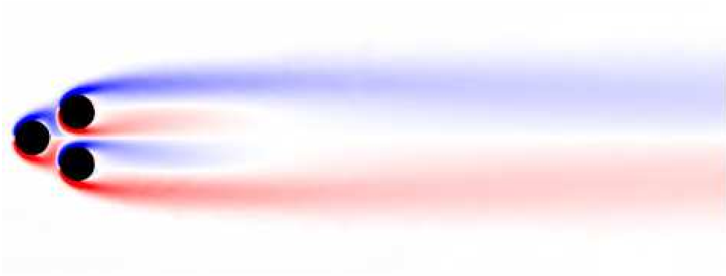
▷11:00 talk

Nan DENG

Fluidic pinball—A control benchmark

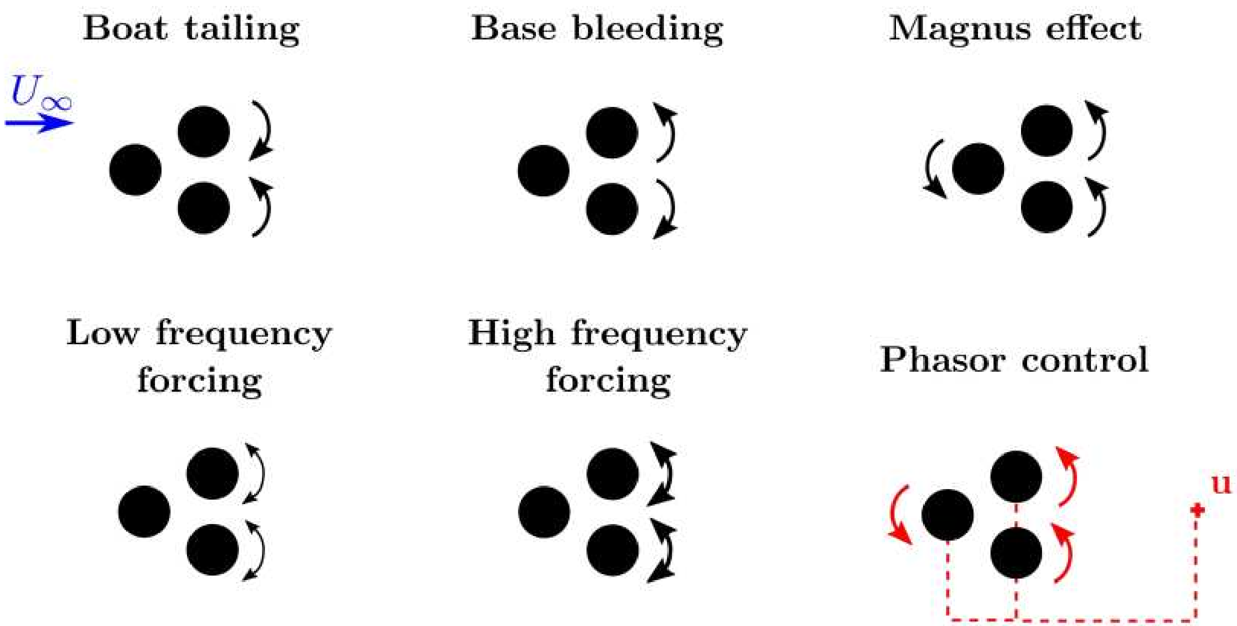
G.Y. Cornejo Maceda, Y. Li, F. Lusseyran, M. Morzynski & B.R. Noack 2021 JFM

Reynolds number $\mathrm{Re} = \frac{U_\infty D}{\nu} = 100$



Fluidic pinball community:

- **Model predictive control** by Steve Brunton (University of Washington)
- **Deep reinforcement learning control** by Jean Rabault (University of Oslo) and Thibaut Guégan & Laurent Cordier (Pprime Institute) and
- **Experiments** in the University of Calgary lead by Robert Martinuzzi and LISN/CNRS lead by François Lusseyran
- **Myriad of regimes** (Chen *et al.*, 2020 *JFM*)



Stablization of the fluidic pinball at $Re = 100$

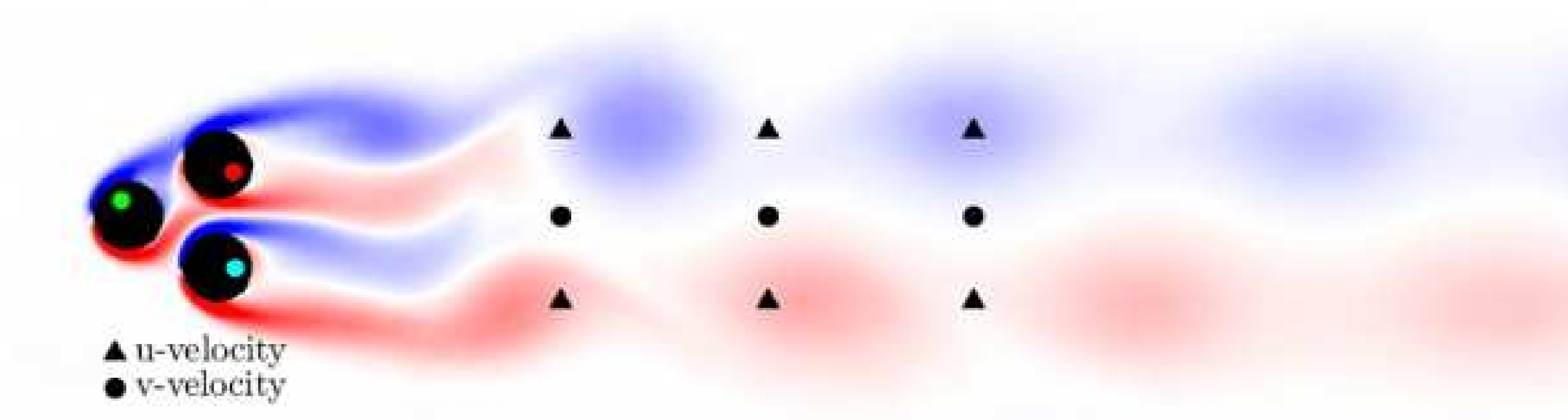
G. Cornejo-Maceda, Y. Li, F. Lusseyran, M. Morzyński & B. R. Noack 2021 JFM

Plant: 3 rotating cylinders $\boldsymbol{b}$ + 9 sensors $\boldsymbol{s}$

Control law: $\boldsymbol{b} = \boldsymbol{K}(\boldsymbol{a})$, $\boldsymbol{a}(t) = [\boldsymbol{s}(t), \boldsymbol{s}(t-\tau), \ldots, \boldsymbol{s}(t-3\tau)]$

Cost function: $J_a = \sqrt{\|\boldsymbol{u}(\boldsymbol{x},t) - \boldsymbol{u}_s(\boldsymbol{x})\|^2}$

Actuation penalty: J_b = power to rotate the cylinders



Stabilizing the fluidic pinball

≡ *G. Cornejo Maceda, Y. Li, F. Lusseyran, M. Morzyński & B.R. Noack 2021 JFM*

Distance to the symmetric steady solution

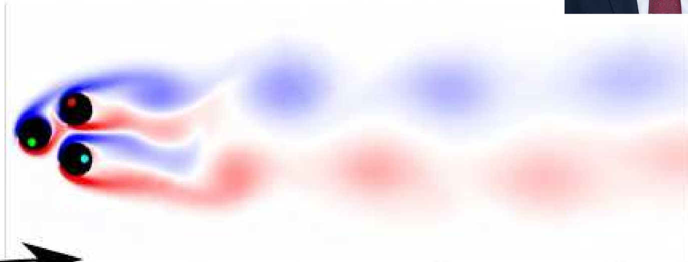
$$J_a = \frac{1}{T_{ev}} \int_{t_0}^{t_0+T_{ev}} \|\boldsymbol{u_b}(t) - \boldsymbol{u}_s\|_\Omega^2 \, \mathrm{dt}$$

Actuation power

$$J_b(\boldsymbol{b}) = \frac{1}{T_{ev}} \int_{t_0}^{t_0+T_{ev}} \sum_{i=1}^{3} \mathcal{P}_{\mathrm{act,i}} \, \mathrm{dt}$$

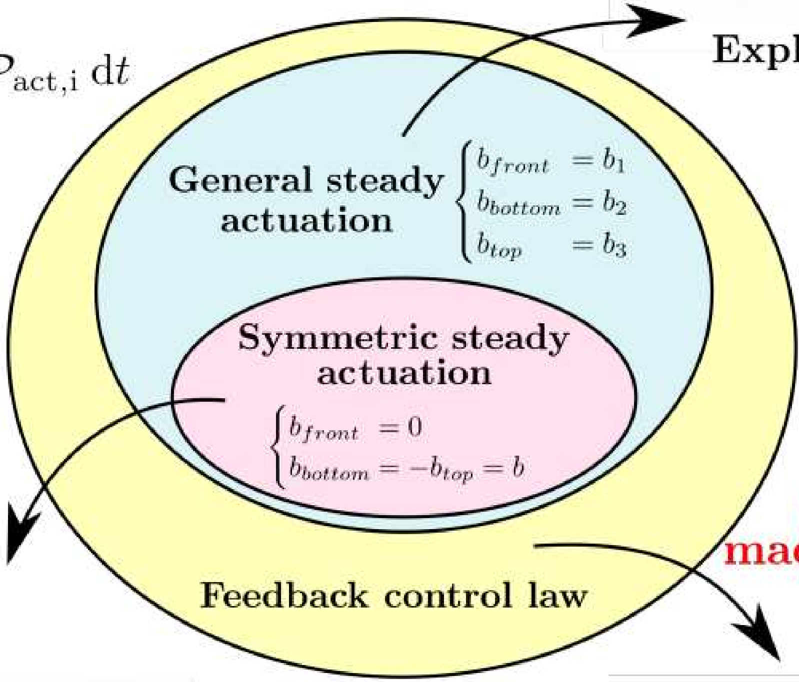
$J_a/J_0 \downarrow$ **72%**

$J_b =$ **0.12**



Optimization problem

$$\mathbf{K} = \arg \min_{\mathbf{K} \in \mathcal{K}} J_a(\mathbf{K})$$



Explorative gradient method

Y. Li 2021 JFM *submitted*

$$\begin{cases} b_{front} = 1.11 \\ b_{bottom} = -0.20 \\ b_{top} = -0.16 \end{cases}$$

Parametric study

$$\begin{cases} b_{front} = 0 \\ b_{bottom} = -b_{top} = -0.375 \end{cases}$$

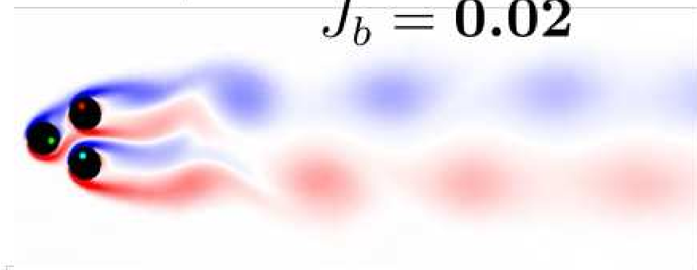
$J_a/J_0 \downarrow$ **49%**

$J_b =$ **0.03**

gradient-enriched machine learning control

$J_a/J_0 \downarrow$ **80%**

$J_b =$ **0.02**



Optimal stabilization = asymm. boat tailing actuation + phasor control

Learning time: ∼ 500 simulations. ▷ Talk of Guy CORNEJO MACEDA

Overview

1. An eldorado of engineering applications
. . . . The need for closed-loop turbulence control

2. Machine learning control
. . . . Complex MIMO laws in ∼1h wind-tunnel test

3. Cluster-based control
. . . . Simple feedback laws in few dozen simulations

4. Tool development with fluidic pinball
. . . . A new benchmark for modeling + control

5. Summary and outlook of turbulence control
. Paradigm change by machine learning

Conclusions

Brunton+ 2015 AMR; Duriez+ 2016 Springer; Brunton+ 2020 ARFM

- **Machine learning control $\mapsto$ Car+**

  Complex MIMO feedback ∼1 hour wind-tunnel time

- **Cluster-based control $\mapsto$ Airfoil+**

  Simple full-state feedback ∼ few dozen simulations

- **Smart skin drag reduction $\mapsto$ customizable control**

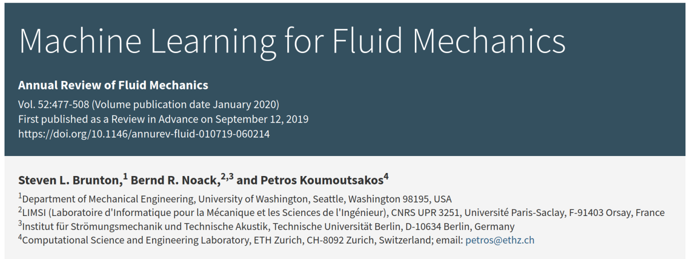
  Distributed actuation + sensing $\mapsto$ Next big opportunity

- **Fluidic pinball = modeling + control benchmark**

  Rich unforced dynamics, many actuation mechanisms

  ▷ Talks of Anne, Guy, Nan and Songqi 11:00–12:00

Books and reviews


Machine Learning for Fluid Mechanics

Annual Review of Fluid Mechanics

Vol. 52:477-508 (Volume publication date January 2020)
First published as a Review in Advance on September 12, 2019
https://doi.org/10.1146/annurev-fluid-010719-060214

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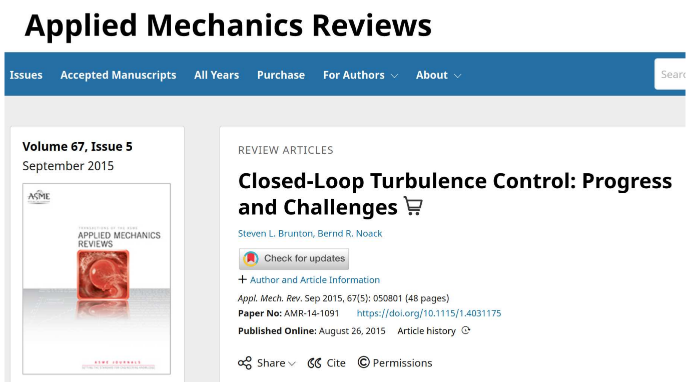
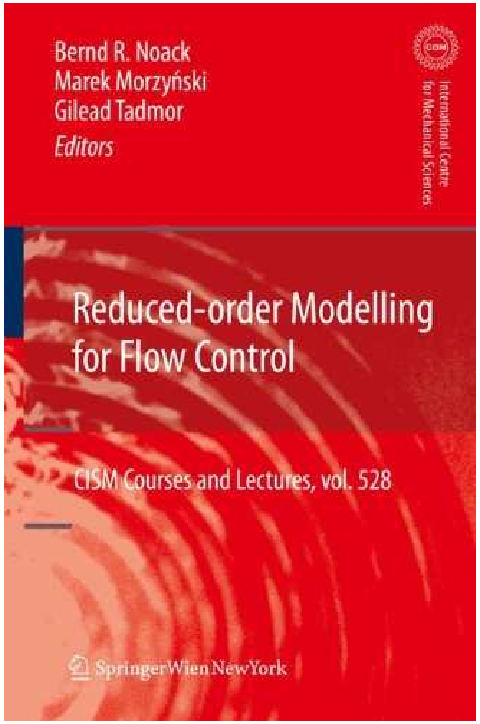
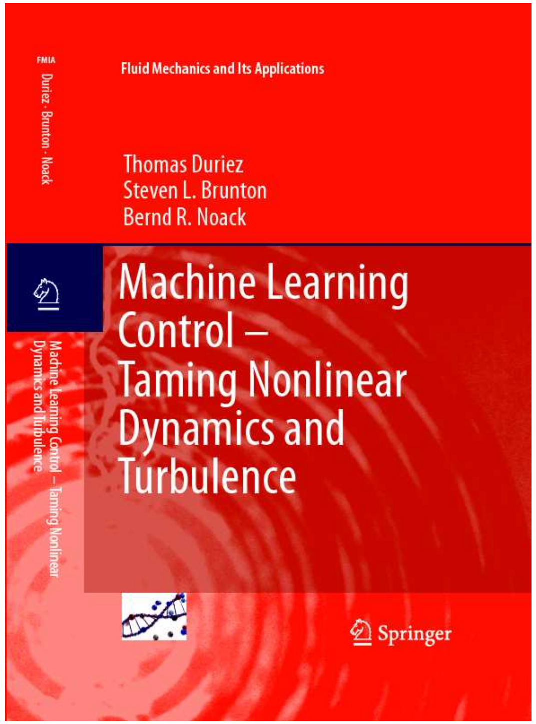
2020 ARFM



2015 AMR



2011 Springer



2017 Springer

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- *Gust mitigation and flight control.*
- *Computational fluid dynamics and aeroacoustics.*
- *Experimental fluid dynamics and aeroacoustics.*
- *Machine learning and artificial intelligence.*

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bernd.noack@hit.edu.cn