

# Heat-Transfer Flow-control applications using infrared thermography and a Python toolbox

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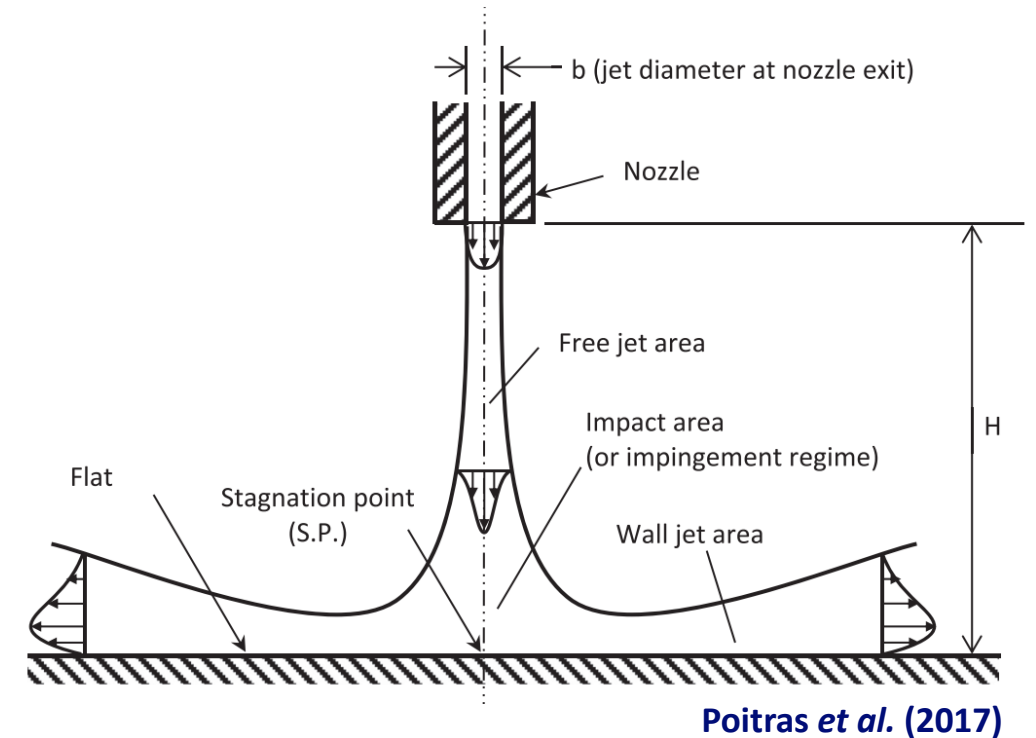
# Towards enhanced convective heat transfer

## » What is the target? **Convective heat transfer enhancement by jet mixing in an impinging jet**

- » Mini-jet pulsation to an impinging jet. Liu et al. (1996); Mladin et al. (1997)
- » Performance feedback from a heated-thin-foil (HTF). Astarita and Carlomagno (2012)

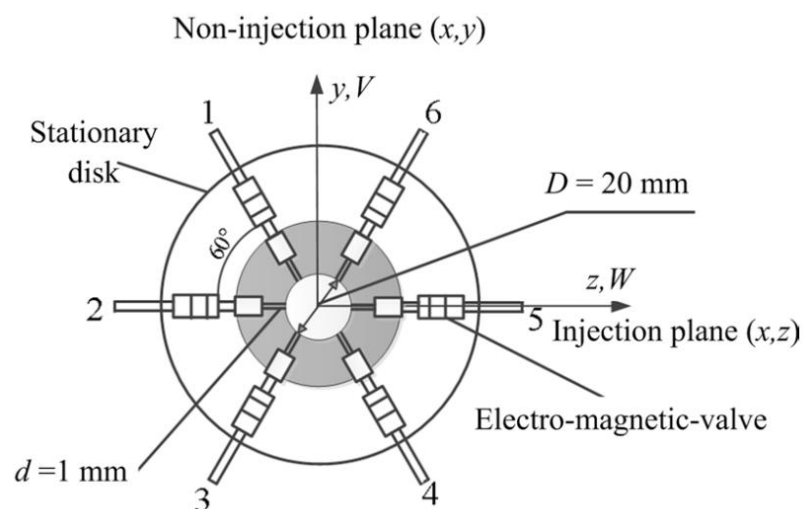
## » Why using impinging jets for heat transfer?

- » Controllable and localized action.
- » High local heat transfer coefficients due to stagnation point flow.
- » Traditionally used for cooling (i.e., aerospace industry), with recent opportunities (AI, GPUs, etc).

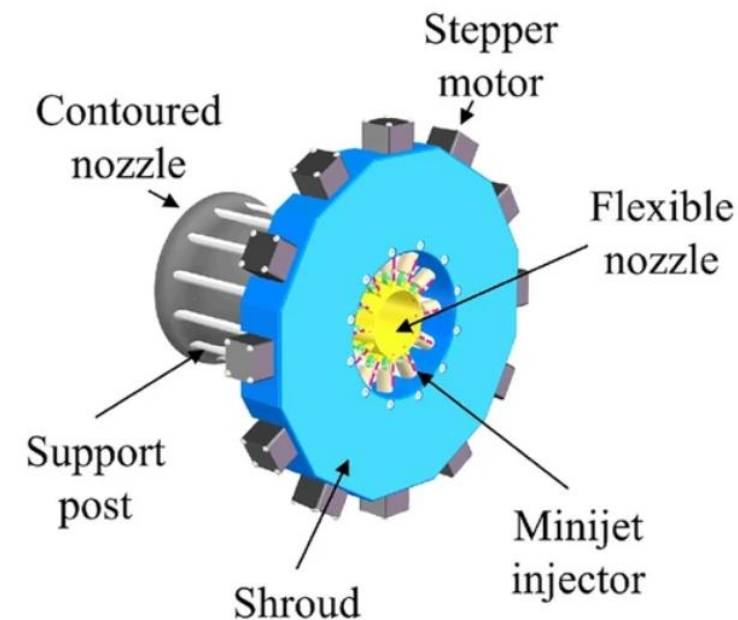


# Jet mixing control

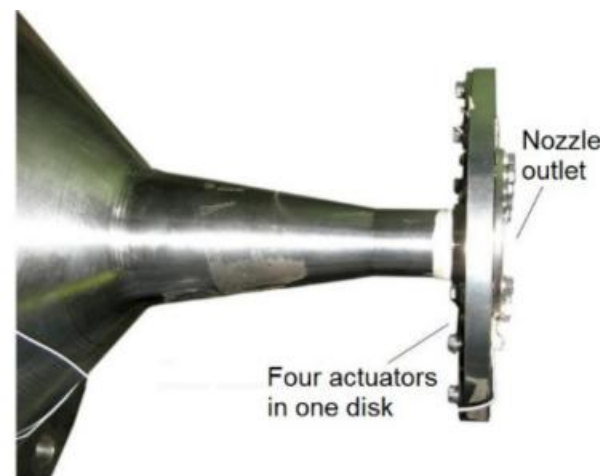
- » Improving mixing can be, somehow, easy
  - » Not able to adapt to varying conditions!
- » Solution: **jet mixing control**
  - » Enhances heat transfer beyond the stagnation point
  - » Enables active or passive control.



Wu et al. (2018)

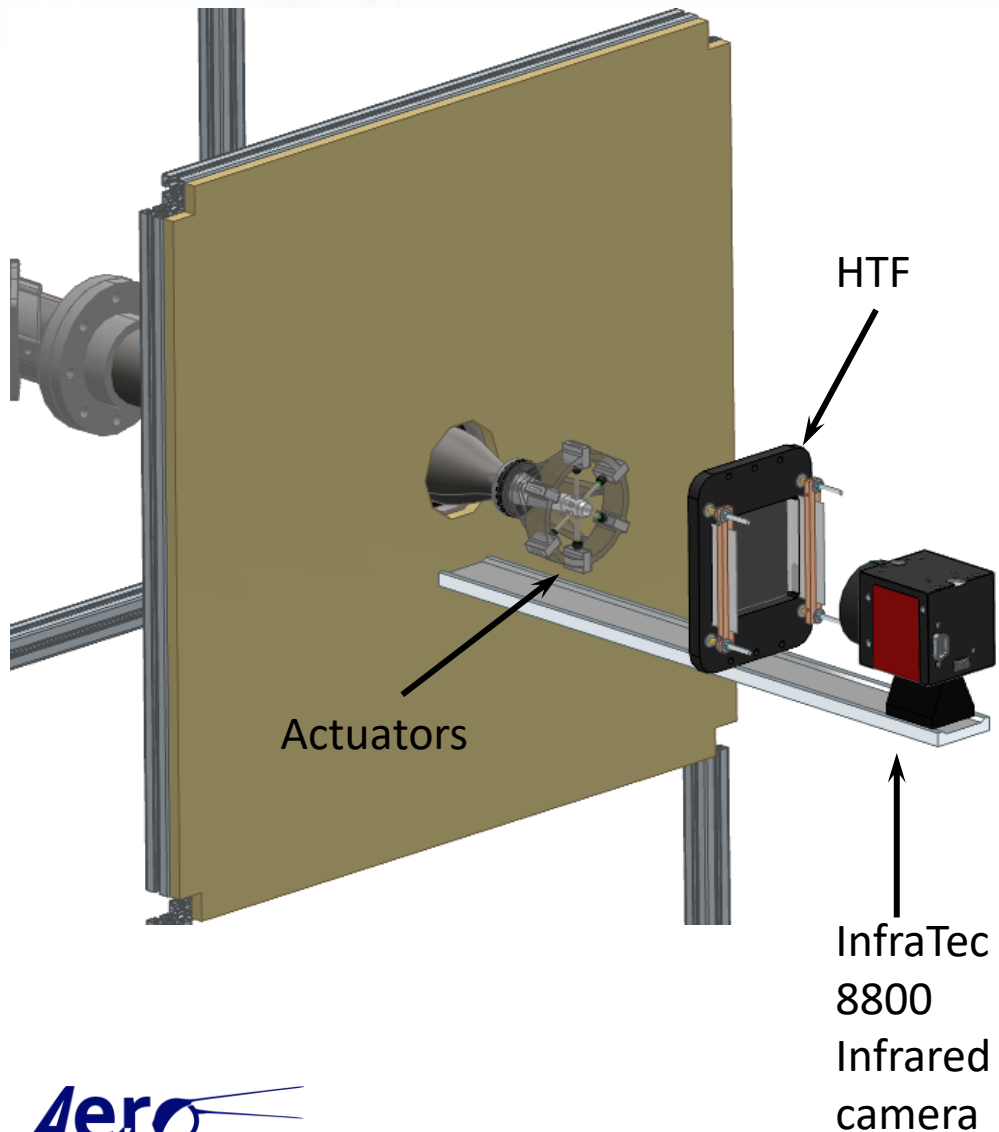


Shaqarin et al. (2024)



Zhang et al. (2021)

# Objective



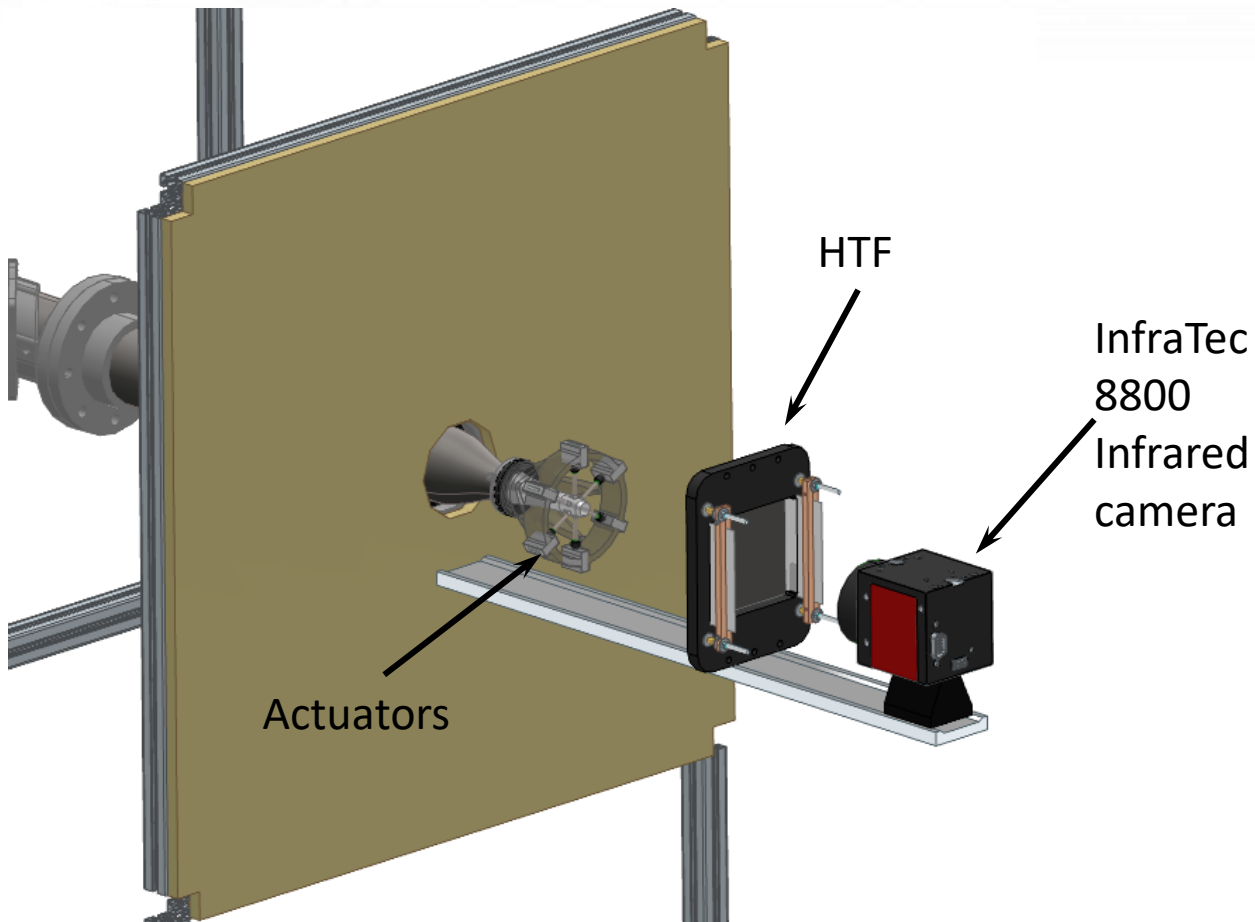
Optimization of the convective heat transfer in an impinging jet using hybrid genetic algorithms.

Experimental setup:

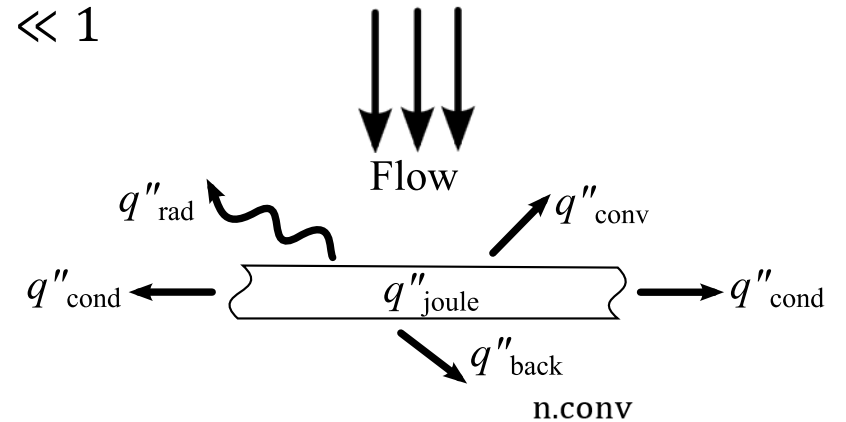
- Nozzle diameter  $D_h$  30mm.
- Six fast-actuating valves placed radially at 60°. Exit diameter  $d_h = 1mm$ .
- $Re \approx 12000$



# Heat transfer measurements



- » Infrared camera Infratec 8800
- » **Heated thin foil** sensor placed at a distance  $3D_h$  from the jet exit.
- »  $Bi \ll 1$



- » Images with  $q''_{\text{joule}} = 0 \rightarrow T_{\text{aw}}$ .
- » Images with  $q''_{\text{joule}} \neq 0 \rightarrow T_w$ .

$$q''_{\text{conv}} = q''_{\text{joule}} - q''_{\text{rad}} - q''_{\text{cond}} - q''_{\text{n.conv}} = h(T_w - T_{\text{aw}})$$

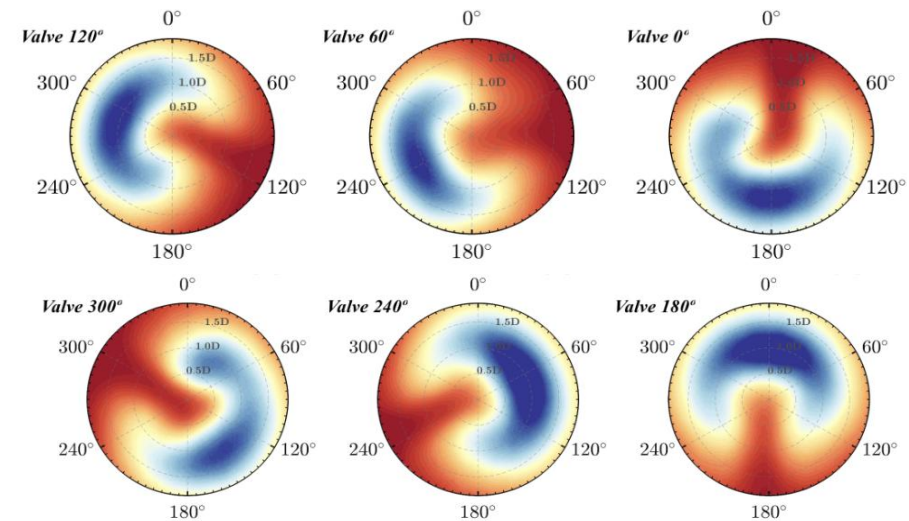
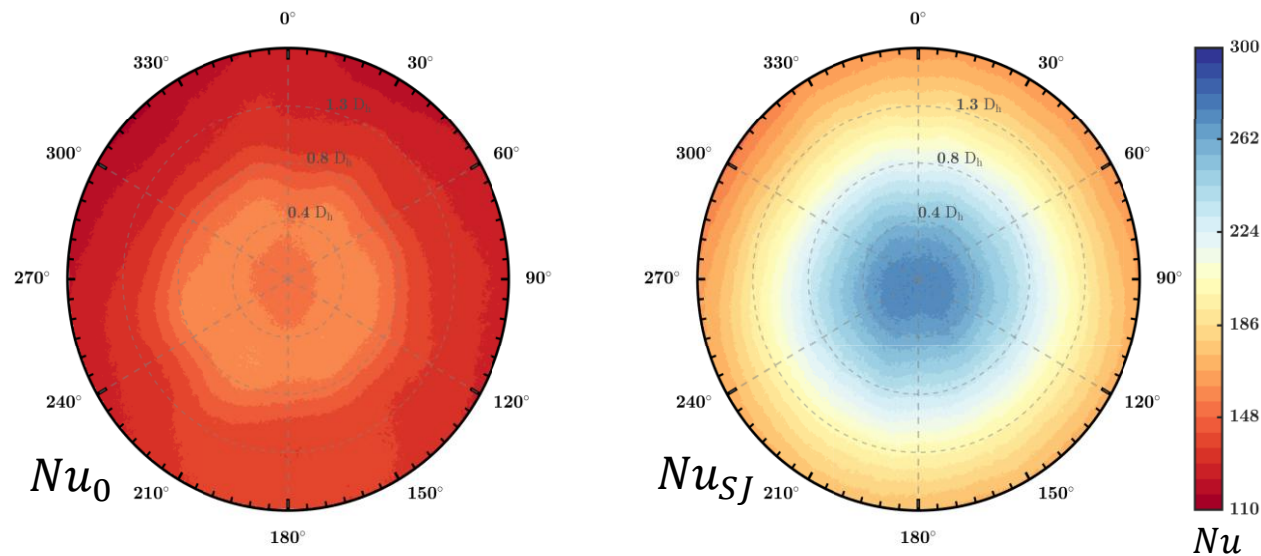
$$h \approx \frac{q''_{\text{joule}} - q''_{\text{rad}}}{(T_w - T_{\text{aw}})}$$

# Reference conditions, performance metrics

» Nusselt number  $Nu = \frac{h \cdot D_h}{k}$

» Reference conditions:

- » Non-actuated flow (all valves closed, subindex 0).
- » Steady-jet (all valves open, subindex SJ). 22%  $\dot{m}_{Jet}$



# Objective function

» Cost function based on Performance Evaluation Criteria **Castellanos (2023)**

» Quantification of heat transfer enhancement.

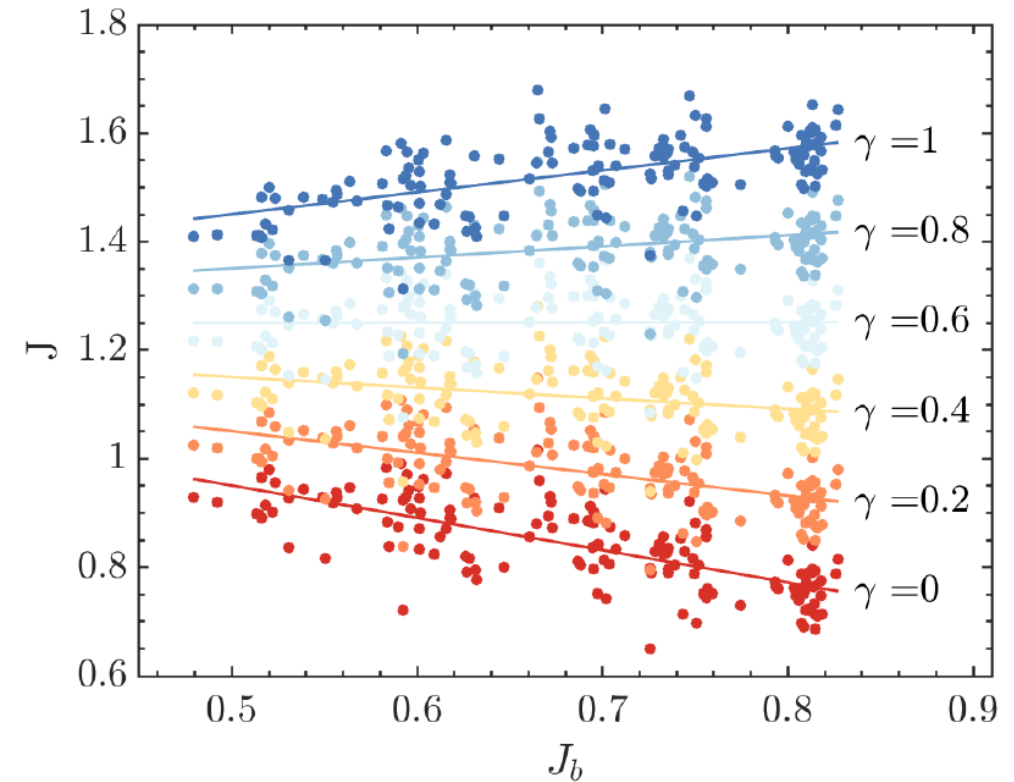
$$J_a = 1 - E = 1 - \left( \frac{\overline{Nu}}{\overline{Nu}_0} - 1 \right)$$

» Penalization based on power requirement.

$$J_b = \left( \frac{\dot{m}}{\dot{m}_{SJ}} \right)$$

» Global cost function.

$$J = J_a + \gamma J_b$$



# Solving the flow control problem...

- » Apply machine-learning algorithm in an experimental environment
  - » Hybrid Genetic Algorithms
  - » Using sophisticated measurement techniques → IR thermography to evaluate the state
- » Actuators → 6 jets in crossflow
  - » Actuated independently
- » Control parameters →  $\theta = [f_1, DC_1, \Phi_1, \Phi_2, \Phi_3, \Phi_4, \Phi_5]$ 
  - » Frequency →  $f_1 \in [10 - 350]Hz$
  - » Duty cycle →  $DC_1 \in [20, 30, 40, 50]\%$
  - » Phase →  $\Phi_1, \Phi_2, \Phi_3, \Phi_4, \Phi_5 \in [0 - 2\pi]$
- » Determine  $\theta^*$  → maximize heat transfer

# Training loop

» Algorithm: Genetic Algorithm + Downhill Simplex

» Hybrid Genetic Optimiser (HYGO) [Robledo et al. \(2025\)](#)

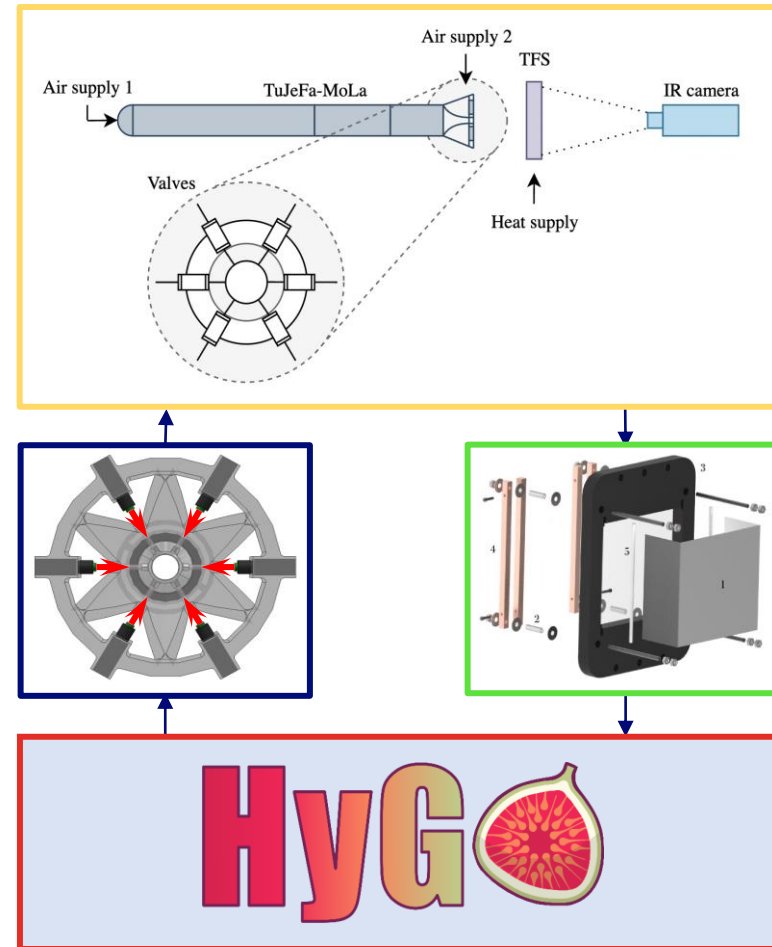
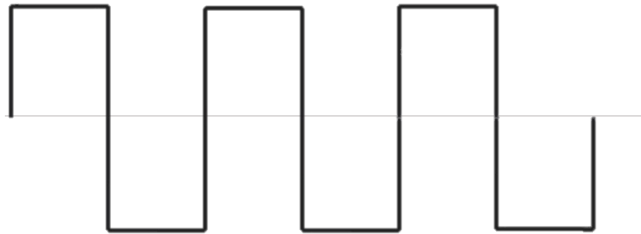
» Control laws

$$b_1(t) = H(\sin(2\pi f_1 t) + k(DC_1))$$

$$b_i(t) = H(\sin(2\pi f_1 t + \Phi_i) + k(DC_1))$$

$H(\ ) \rightarrow$  Heaviside function

$k \in [-1, 1] \rightarrow$  Scaling

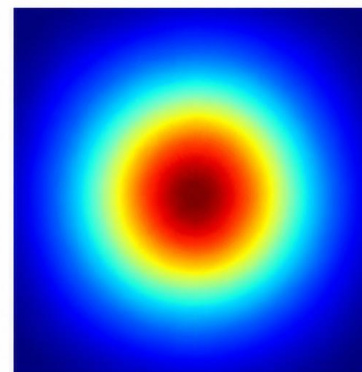


# Why an InfraTec scientific IR camera?

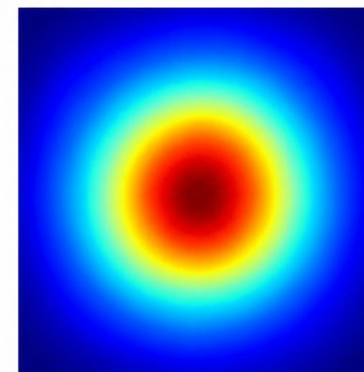
In optimisation, the IR camera is not only for visualisation. It is the sensor that defines the cost function.

- » Optimisation ranks many candidate actuation laws,  $\theta$ .
- » Different  $f$ , DC and phase patterns can produce almost identical IR maps.
- » Useful effects may be small  $\Delta T$ , so thermal sensitivity and stability are critical.
- » Accurate maps make  $J(\theta)$  repeatable enough to separate physics from noise.
- » Python SDK: set actuation  $\rightarrow$  wait  $\rightarrow$  acquire  $T_{\text{cold}}/T_{\text{hot}} \rightarrow$  compute  $Nu$  and  $J$ .

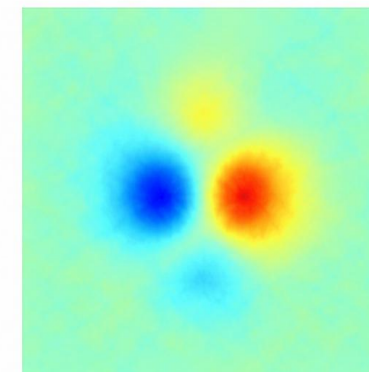
## Example: nearly indistinguishable thermal footprints



Individual  $\theta_1$



Individual  $\theta_2$



Difference  $\Delta T$

Small temperature differences can decide the ranking.

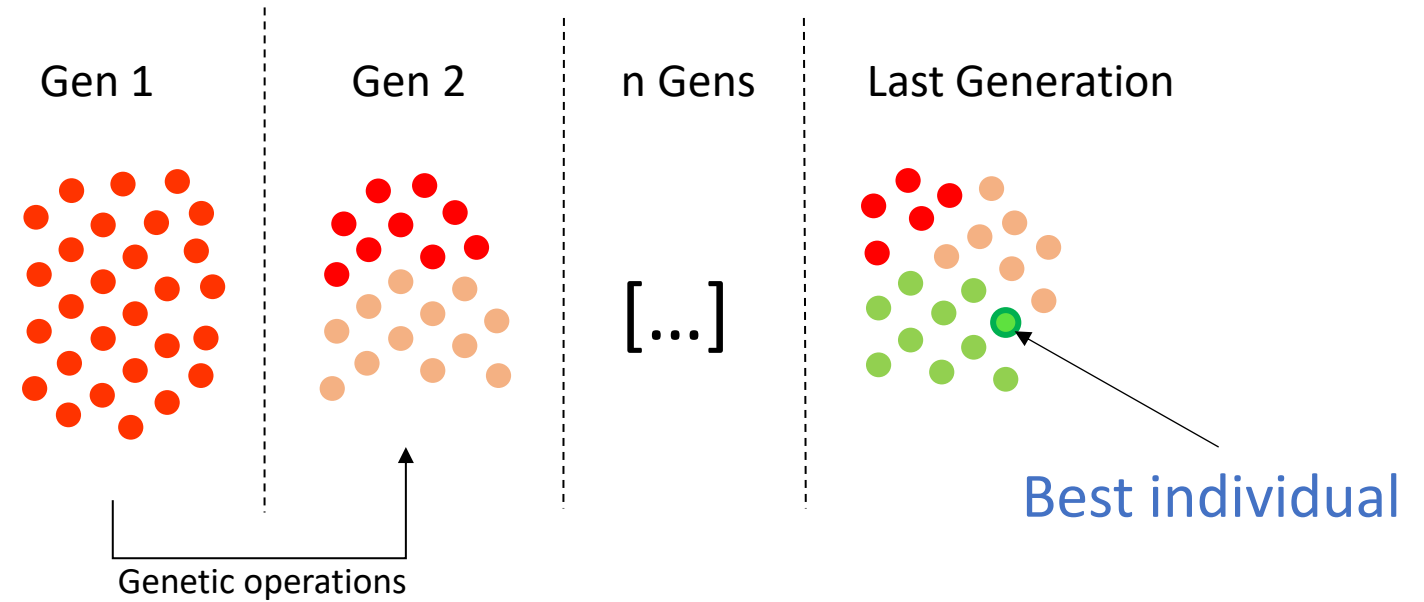
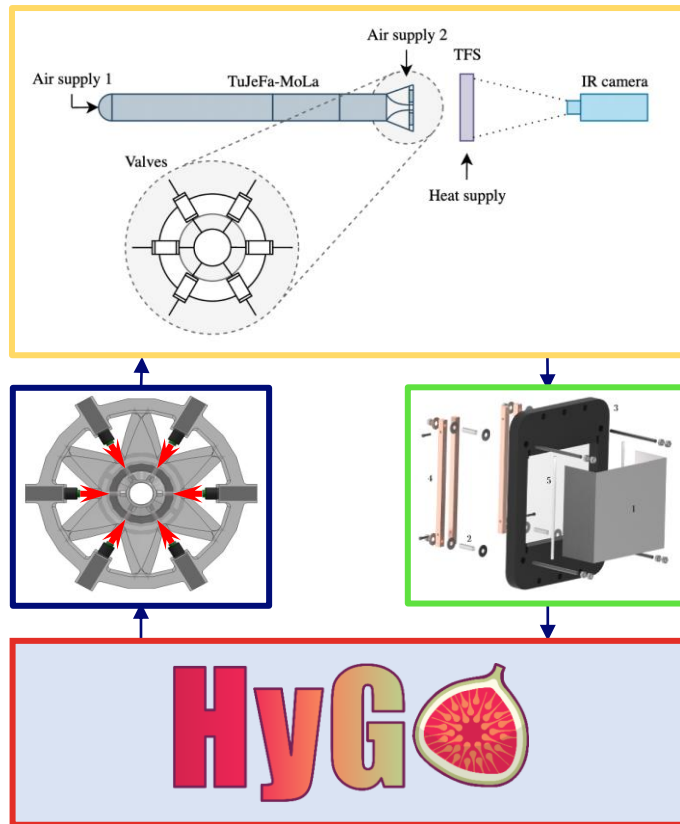
Automatic SDK control keeps acquisition repeatable and logged.

Scientific IR  $\rightarrow$  reliable full-field feedback for optimisation, not just qualitative thermal images

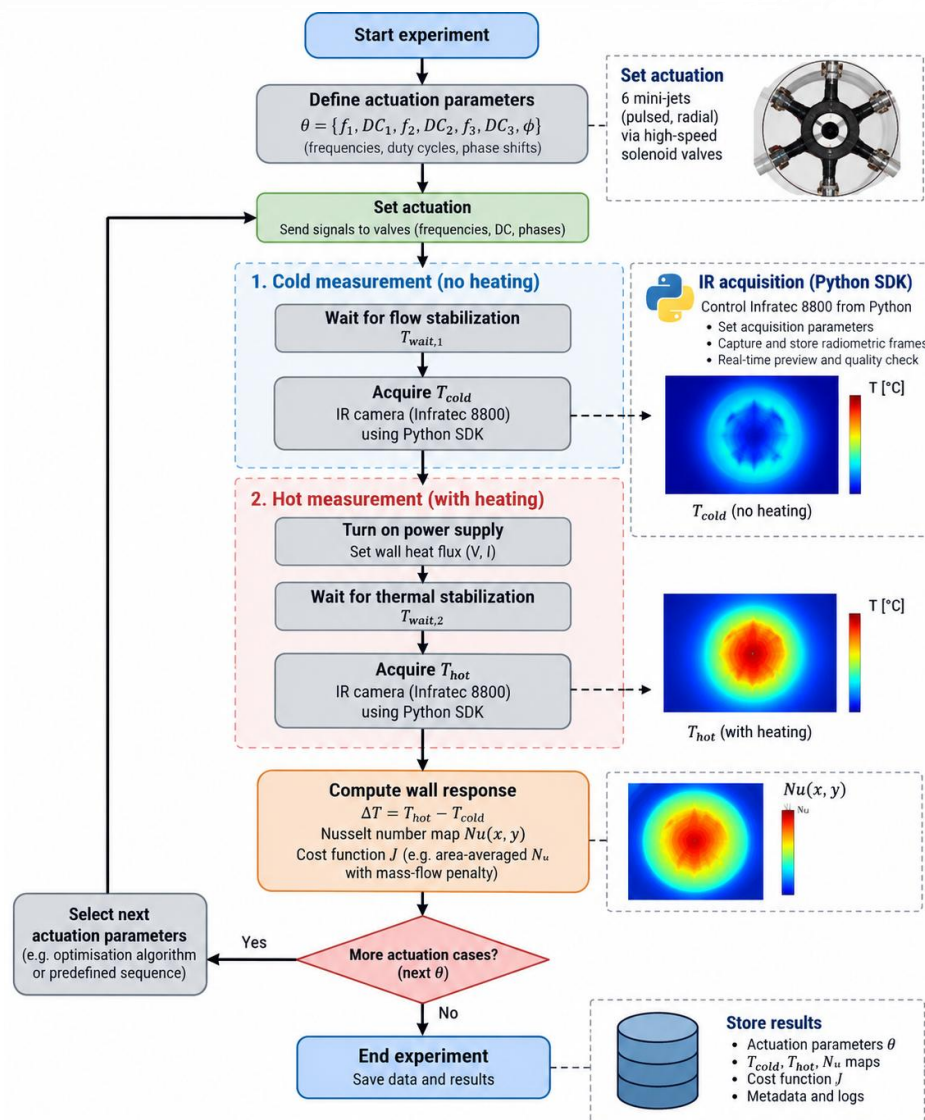
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# Using InfraTec Python SDK to automatize



# Distribution of results

## » Preferred frequency

»  $f = 114\text{Hz}$

»  $St = 0.54$

Recall,  $St = \frac{f \cdot D_h}{V_{jet}}$

## » Preferred Duty cycles

»  $DC = 30, 40\%$

## » Preferred phases

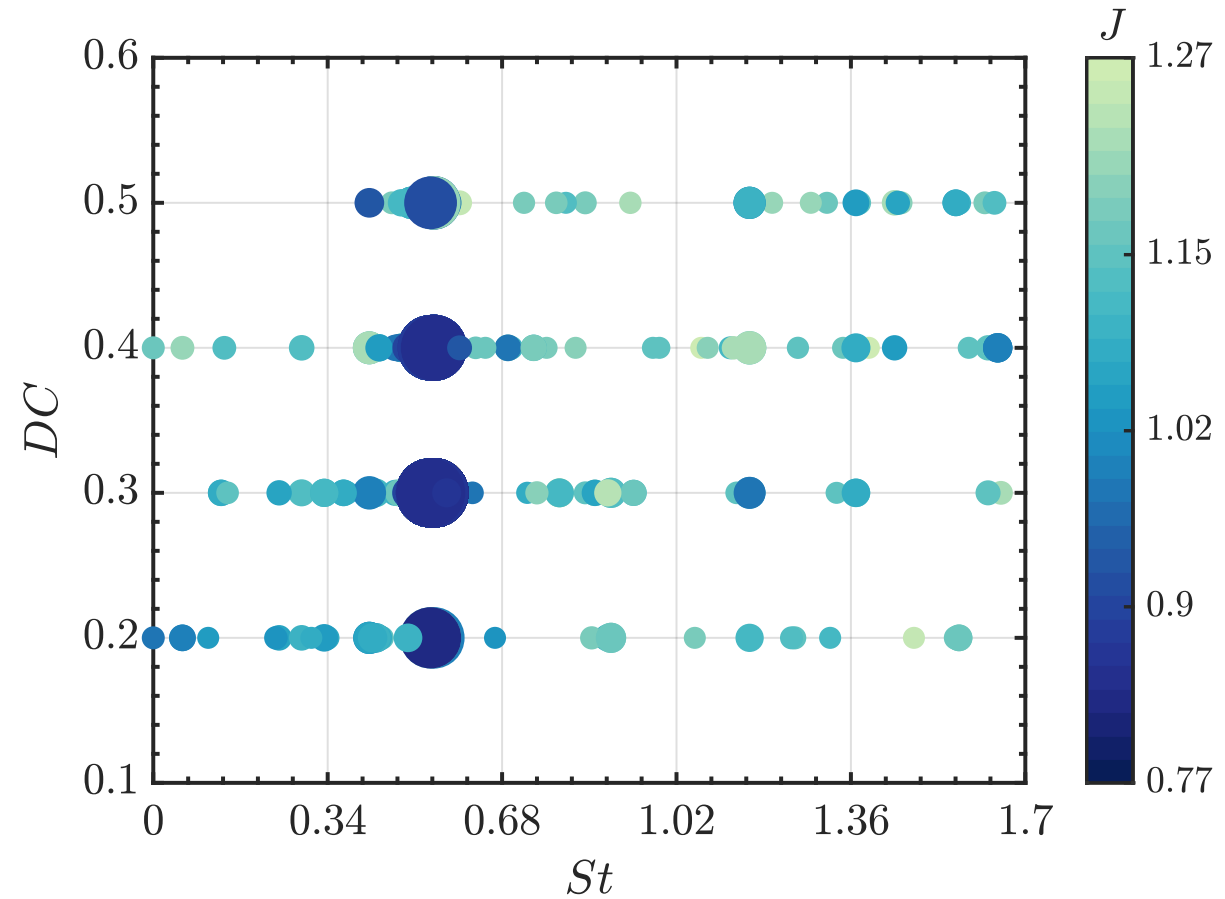
»  $\Phi_1 \approx \frac{25\pi}{18}$

»  $\Phi_2 \approx \frac{5\pi}{9}$

»  $\Phi_3 \approx \frac{5\pi}{18}$

»  $\Phi_4 \approx \frac{35\pi}{18}$

»  $\Phi_5 \approx \frac{10\pi}{9}$



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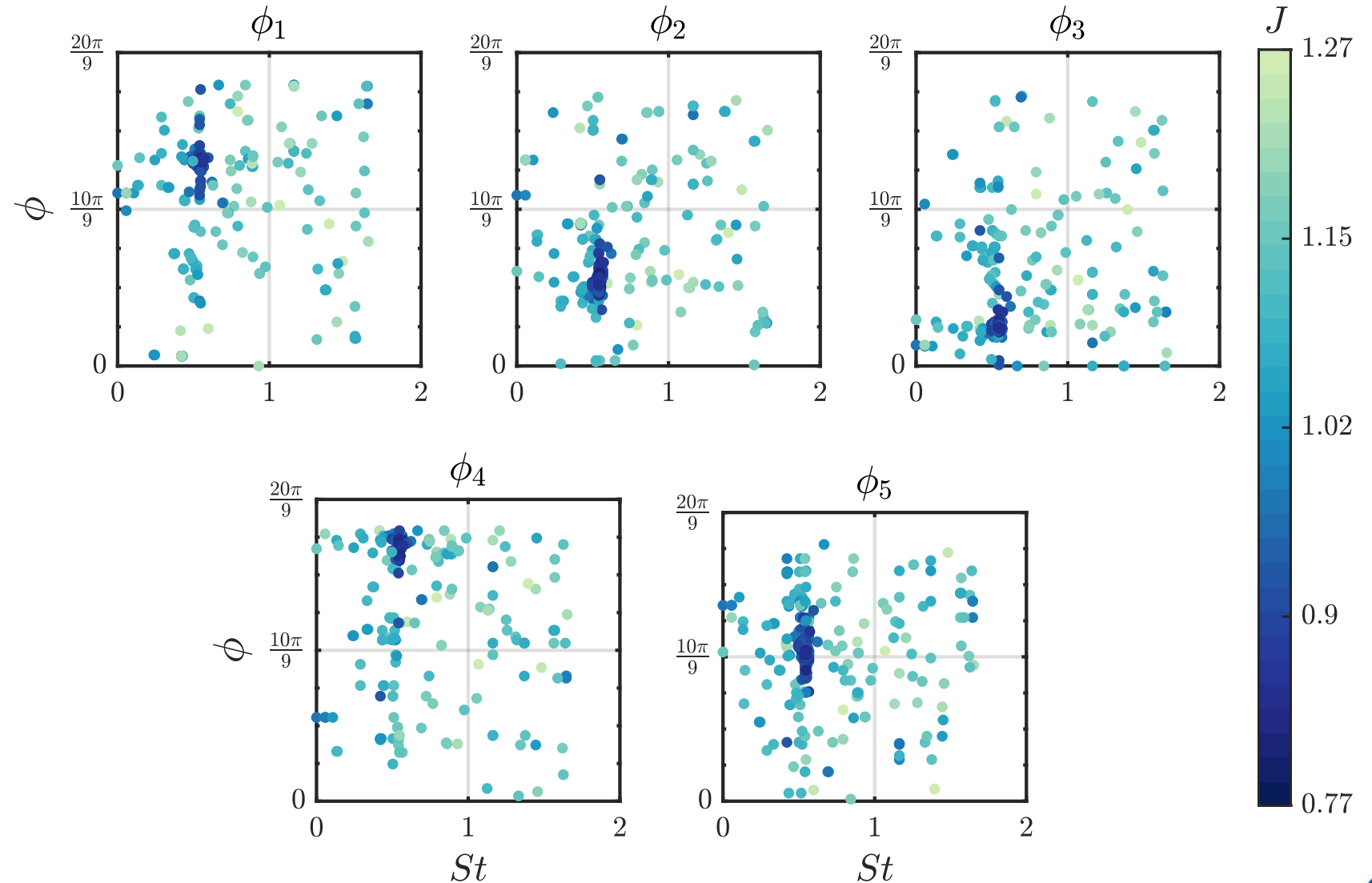
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# Training evolution and results

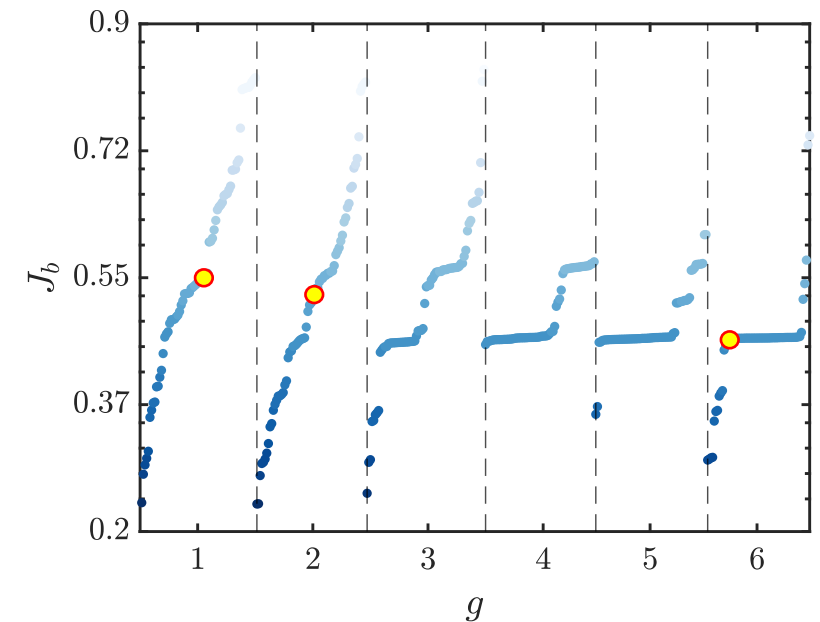
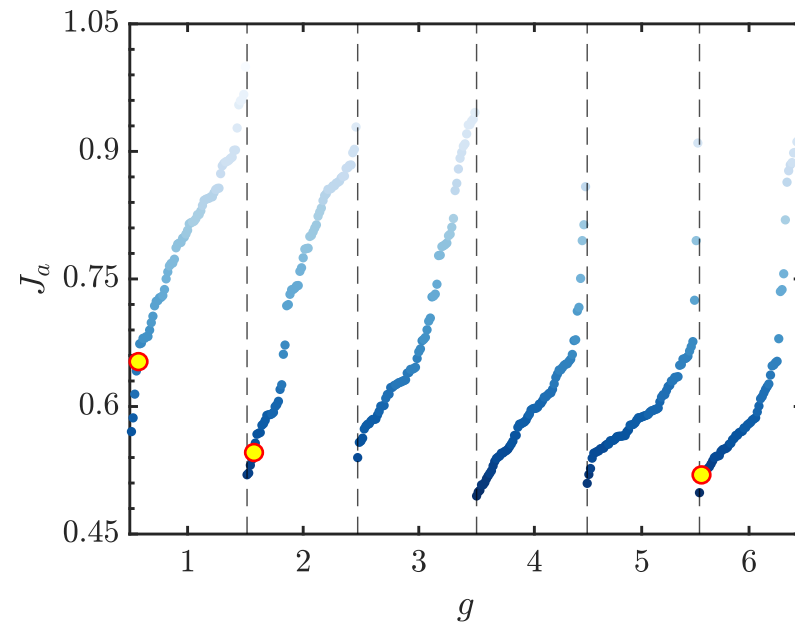
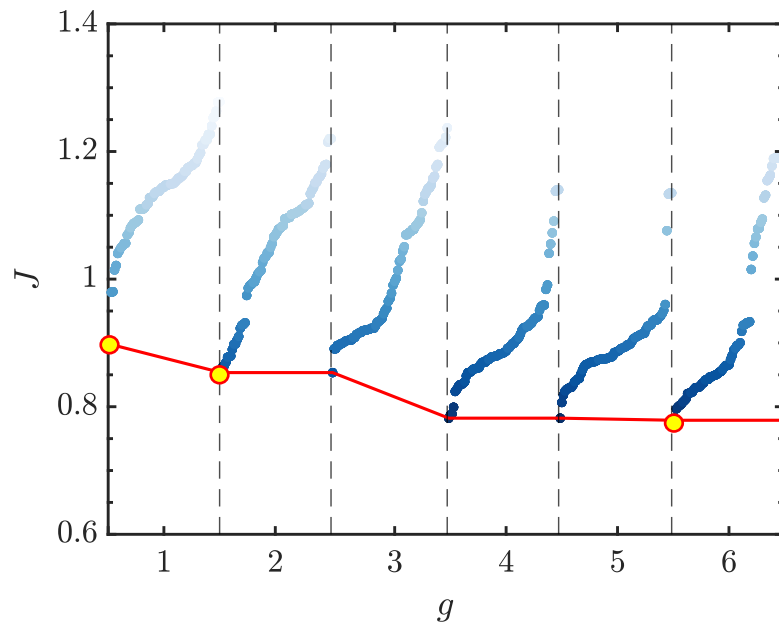
» Training main evolutions after generations 1, 2 and 6:

»  $\theta_1^* = [119.36\text{Hz}, 30\%, 255^\circ, 114^\circ, 56^\circ, 346^\circ, 238^\circ]$ .

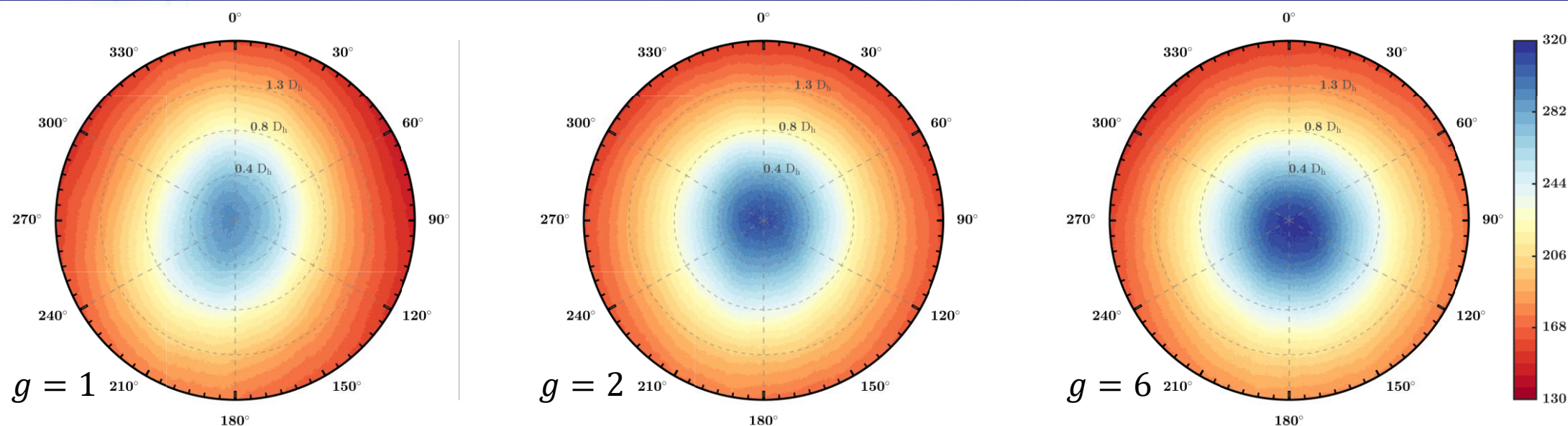
»  $\theta_2^* = [114.06\text{Hz}, 40\%, 263^\circ, 98^\circ, 48^\circ, 349^\circ, 202^\circ] \rightarrow$  Tune the frequency and  $\Phi_5$ .

»  $\theta_6^* = [115.39\text{Hz}, 30\%, 266^\circ, 114^\circ, 49^\circ, 339^\circ, 207^\circ] \rightarrow$  Final phase and DC tuning.

» By injecting 10% of the main jet mass-flow rate there is a heat transfer enhancement of 13% w.r.t the baseline.

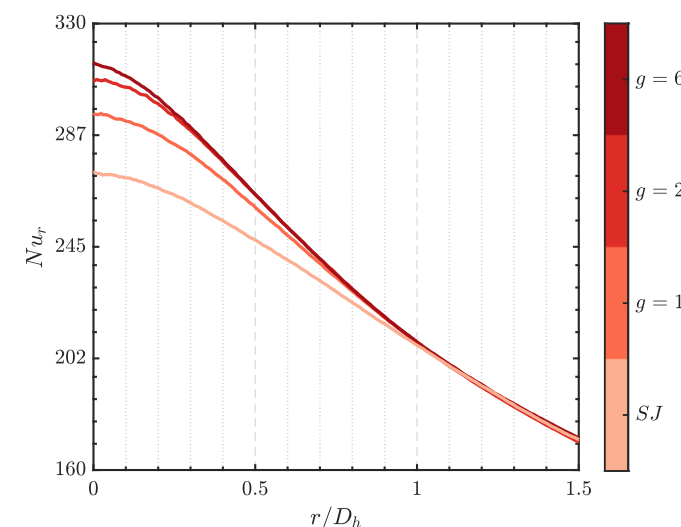


# Training evolution and results



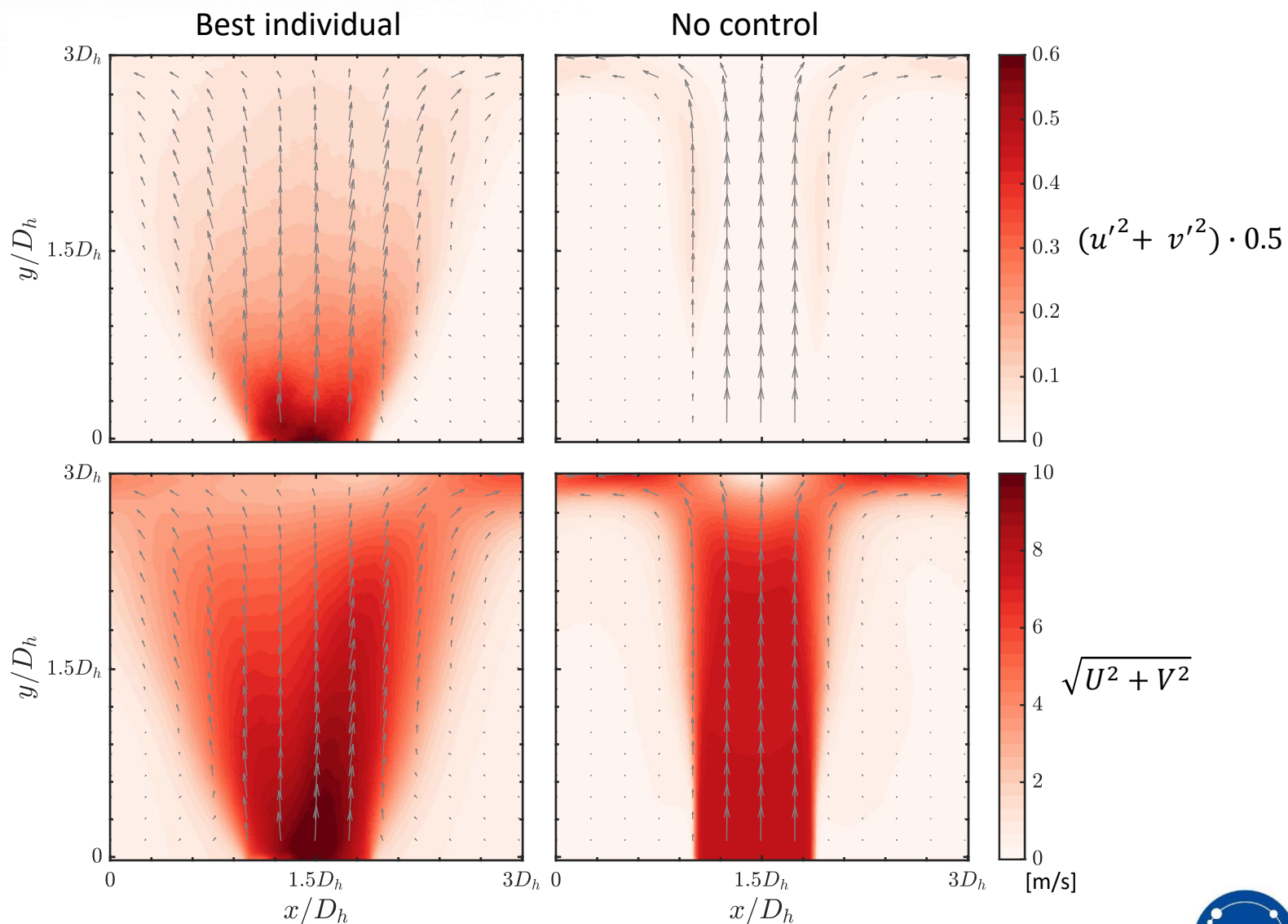
## » Nusselt shape evolution with generations:

- » Initial elliptical shape induced by mini-jet pulsation.
- » Frequency and  $\Phi_5$  tuning promote a circular pattern and  $Nu$  growth.
- » Final phase and DC changes maintain the shape and still increase  $Nu$ .
- » Influence domain radius  $\in [0 - 0.8 D_h]$ .



# Flow physics and future work

- » Jet analysis of PIV snapshots: **turbulent kinetic energy.**
- » No control
  - » Concentrated TKE in the shear layer and on the forming BL over the impact location.
- » Best individual
  - » Strong TKE at nozzle exit progressively decays towards the wall.
  - » High spread, increasing mixing.
- » High-accuracy IR thermography is critical for optimisation-based flow control, enabling small thermal differences between similar actuation states to be resolved reliably.
- » Python SDK integration supports fully automated experimental acquisition and evaluation.



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de Técnica  
Aeroespacial**

Víctor Duro, Juan Alfaro, Isaac Robledo, Rodrigo Castellanos, Andrea Ianaro & Carlos Sanmiguel Vila  
*Enhancing impinging-jet heat transfer with pulsed mini-jets: optimisation and low-dimensional analysis*  
Submitted to International Journal of Heat and Mass Transfer

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