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Machine Learning-Aided Design Optimisation (MLADO) in Vortex Shedding-Based Engineering Applications

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OVERVIEW

- Introduction
- CFD simulation of vortex shedding-based problem
- Prediction of vortex shedding
- Machine Learning-Aided Design (MLADO) workflow
- Conclusions

- INTRODUCTION

INTRODUCTION

- Vortex shedding is a common phenomenon in many engineering situations, such as civil engineering, aviation or wind energy.

- In certain applications, vortex shedding may be a desirable feature, as in heat and mass transfer, or undesired, as in many civil engineering applications.

- Performance of certain engineering devices often involve a passive element from which vortex shedding is observed.

INTRODUCTION

- If optimisation of the performance is sought, vortex shedding must be in our planification.

- Machine Learning-Aided Design Optimisation (MLADO) framework allows to optimise system performance by speeding-up the process of creating surrogates by saving computations/runs.

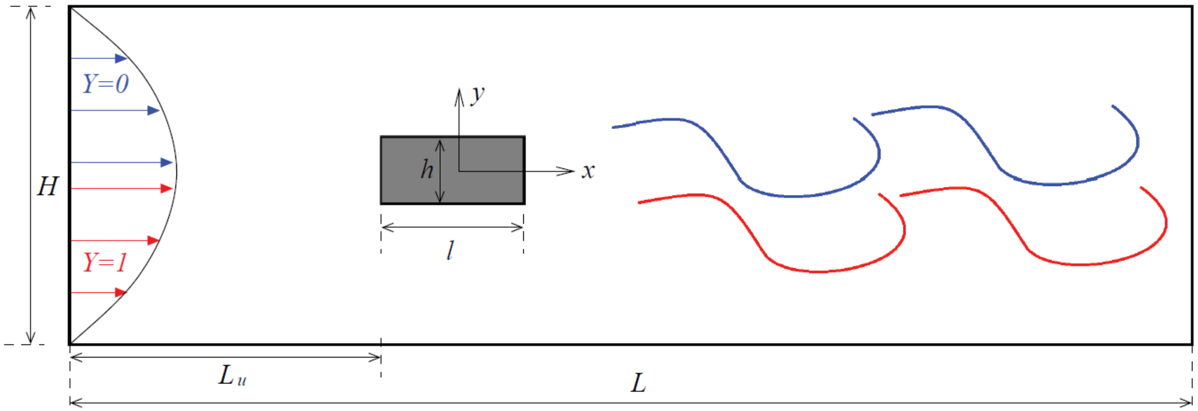
- **Example of application:** Design of an efficient vortex shedding-based mixer using a single object in a channel.

- CFD SIMULATION

CFD SIMULATION

Granados-Ortiz, F. J., & Ortega-Casanova, J. (2020). Mechanical Characterisation and Analysis of a Passive Micro Heat Exchanger. Micromachines, 11(7), 668.

- 2D Micromixer considered in this work:



Reynolds number: $Re = \frac{HU}{\nu}$; (U: Mean velocity; ν: kinematic viscosity)

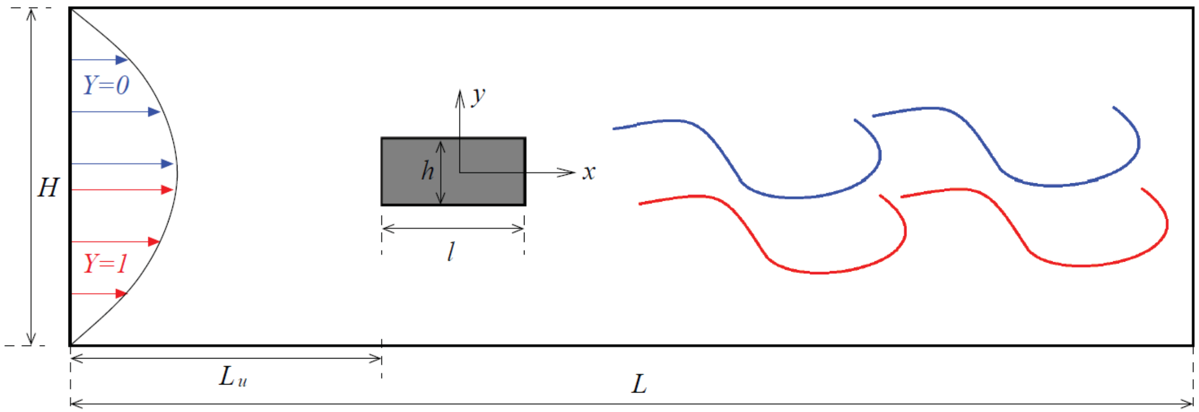
Blockage ratio: $BR = \frac{h}{H}$

Longitudinal aspect ratio: $AR = l/h$

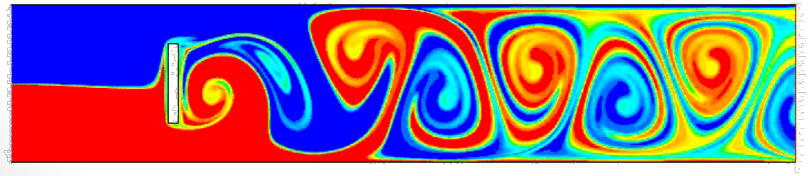
$$\boxed{Performance = f(Re, BR, AR)}$$

CFD SIMULATION

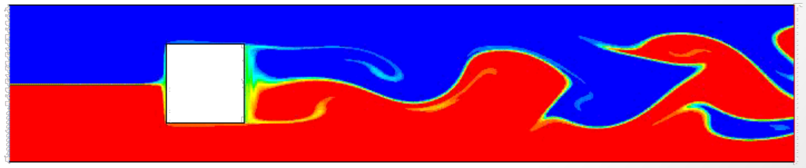
- 2D Micromixer considered in this work:



$Re = 200, BR = 0.2\ , AR = 1$



$Re = 200, BR = 0.5, AR = 0.125$

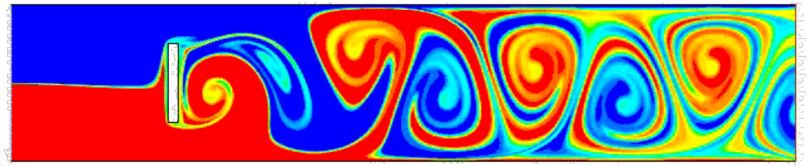


$Re = 200, BR = 0.5, AR = 1$

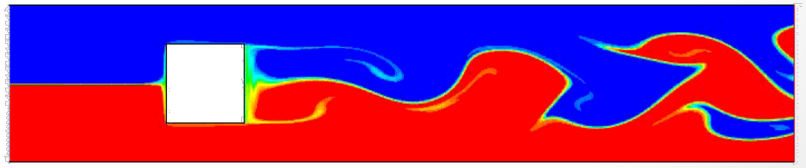
CFD SIMULATION

- Application of MLADO:
  - Optimisation: Efficient vortex shedding-based mixing at microscale.
    - Maximise mixing efficiency, η.
    - Minimise time-averaged pressure drop, $\langle \Pi \rangle$.
  - Method: surrogate modelling -> Can be accelerated by predicting vortex shedding configurations!

$Re = 200, BR = 0.2\,, AR = 1$



$Re = 200, BR = 0.5, AR = 0.125$



$Re = 200, BR = 0.5, AR = 1$

- PREDICTION OF VORTEX SHEDDING

VORTEX SHED. PREDICTOR

- Random Forest (RF) predictor
  - Classification problem: prediction of configurations with vortex shedding (VS=1) and without vortex shedding (VS=0).
  - Full dataset balanced enough (VS= 0 in 33.75% cases). **80 simulations** from the combinations amongst:

$$Re = \{120, 140, 160, 180, 200\}$$
$$BR = \{0.2, 0.3, 0.4, 0.5\}$$
$$AR = \{0.125, 0.25, 0.5, 1\}$$

  - RF: Bootstrap randomised sampling on the training dataset in order to train several decision trees that will be ensembled:

$$C^{RF}_{D_t,\Theta_1,\Theta_2,\ldots,\Theta_M} = arg\ max \sum_{m=1}^{M} (h(\mathbf{X}, \Theta_m) = c)$$

  - This bootstrap method with replacement (samples can be re-utilised to train the trees).

VORTEX SHED. PREDICTOR

- Random Forest (RF) predictor
  - Performance:

		Reference data	
		0	1
Predicted value	0	27	0
	1	0	53

  - However, nested training is interesting to find or recommend a minimum of samples N_p to train the predictive model. We can start from:

Initial ($N_p = 36$):
$Re = \{120, 160, 200\}$
$BR = \{0.2, 0.3, 0.4, 0.5\}$
$AR = \{0.125, 0.5, 1\}$

VORTEX SHED. PREDICTOR

- Random Forest (RF) predictor

		Reference data	
		0	**1**
Predicted value	**0**	21	2
	1	0	25

a)

		Reference data	
		0	**1**
Predicted value	**0**	22	0
	1	2	40

b)

		Reference data	
		0	**1**
Predicted value	**0**	27	2
	1	0	51

c)

		Reference data	
		0	**1**
Predicted value	**0**	41	0
	1	0	59

d)

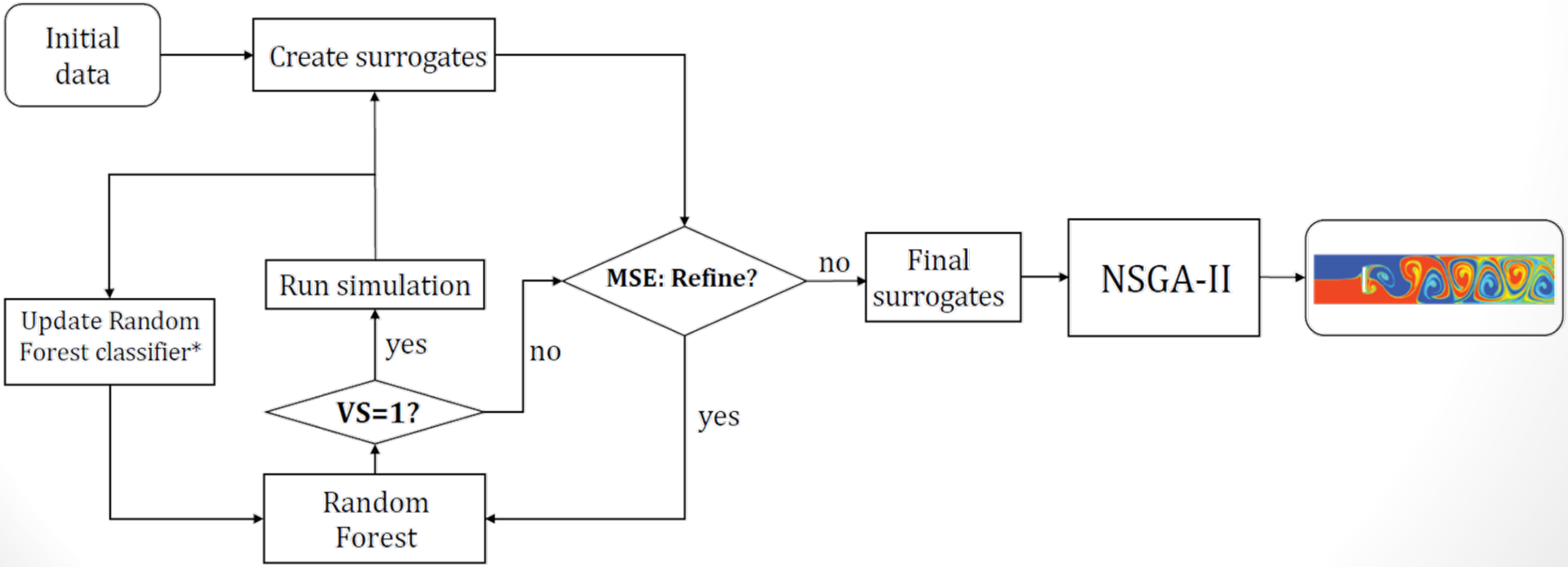
Evolution of the accuracy of the RF algorithm in the prediction of the next level of refinement as test samples. a) Confusion matrix in the classification of 48 samples (RF trained with $N_p = 36$, named RF1). b) Confusion matrix in the classification of 64 samples (RF trained with $N_p = 48$, named RF2). c) Confusion matrix in the classification of 80 samples (RF trained with $N_p = 64$, named RF3). d) Confusion matrix in the classification of 100 samples (RF trained with $N_p = 80$, named RF4).

- MACHINE LEARNING-AIDED DESIGN OPTIMIZATION (MLADO) WORKFLOW

MLADO WORKFLOW

Granados-Ortiz, F. J., & Ortega-Casanova, J. (2021). Machine Learning-Aided Design Optimisation of a Mechanical Micromixer. Physics of Fluids, 33(6), 063604
EDITOR'S PICK

- Machine Learning-Aided Optimisation (MLADO): Predictive models can be input in a framework in the following way to speed-up optimisation:



MLADO WORKFLOW

- Genetic Algorithms are applied onto the surrogates to find the optimal solutions:

Reference ($N_s = 80$)*:*	*Initial* ($N_s = 36$)*:*
$Re = \{120, 140, 160, 180, 200\}$	$Re = \{120, 160, 200\}$
$BR = \{0.2, 0.3, 0.4, 0.5\}$	$BR = \{0.2, 0.3, 0.4, 0.5\}$
$AR = \{0.125, 0.25, 0.5, 1\}$	$AR = \{0.125, 0.5, 1\}$

$Re = 140 \,\&\, VS = 1$ $AR = 0.25 \,\&\, VS = 1$ $Re = 180 \,\&\, VS = 1$

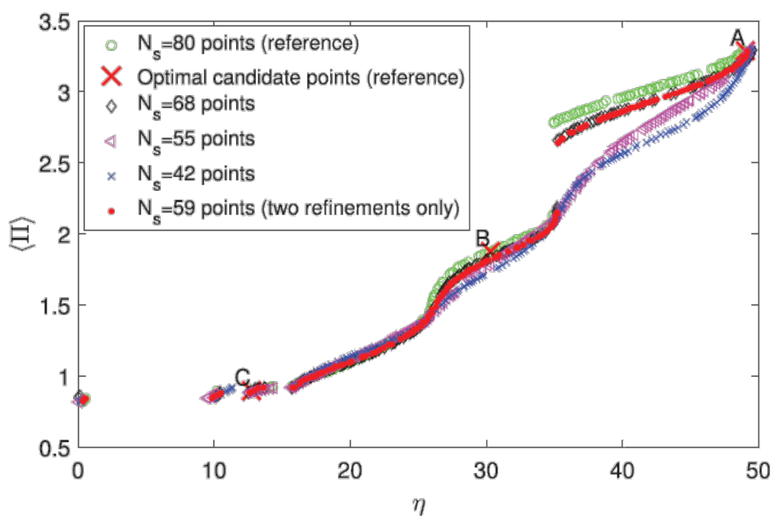
$N_s = 36$ ------------------> $N_s = 42$ ----------------------> $N_s =$

55 ------------> $N_s = 68$

$AR = 0.25 \,\&\, VS = 1$ $Re = 180 \,\&\, VS = 1$

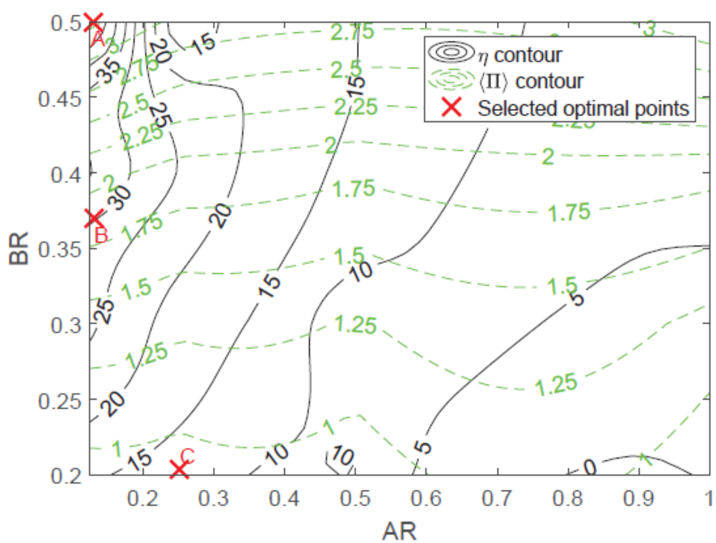
$= 36$ --> N_s

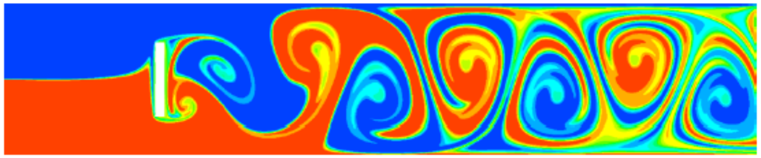
9



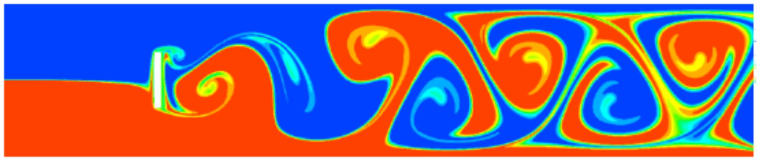
MLADO WORKFLOW

- Genetic Algorithms are applied onto the surrogates to find the optimal solutions:

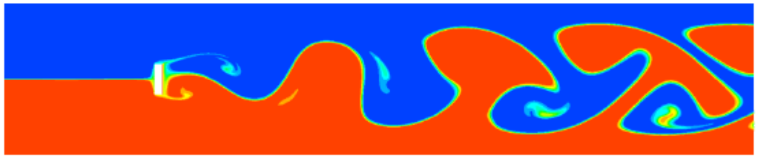




Config. A



Config. B



Config. C

- CONCLUSIONS

CONCLUSIONS

- The Machine Learning-Aided Design Optimisation (MLADO) method has been introduced.
- MLADO has been presented as a method to speed-up optimisation in vortex shedding-based engineering applications.
- An example of application of MLADO has been presented, to optimize the performance of a vortex shedding-based micromixer.
- Computational costs have been saved in comparison to a classic optimization approach.

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ευχαριστώ!

(Thank you!)