UNIVERSITÉ DE SHERBROOKE

Airfoil trailing-edge optimization for noise reduction

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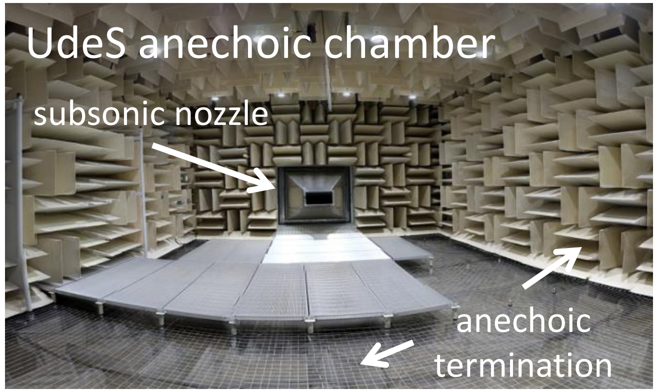
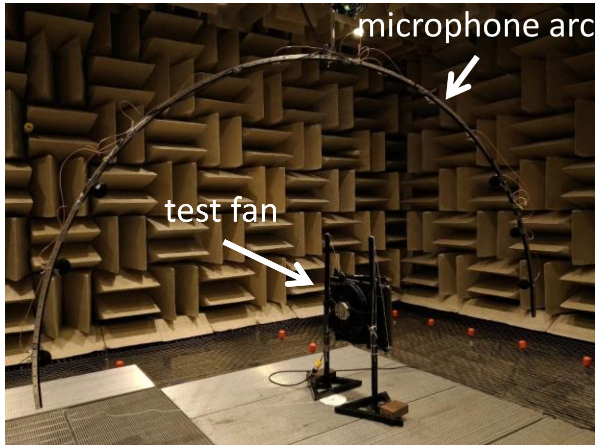
Profile: Aeroacoustic Group at UdeS

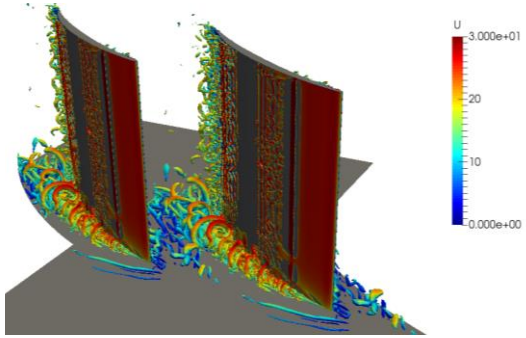
Aerodynamic noise prediction and minimization:

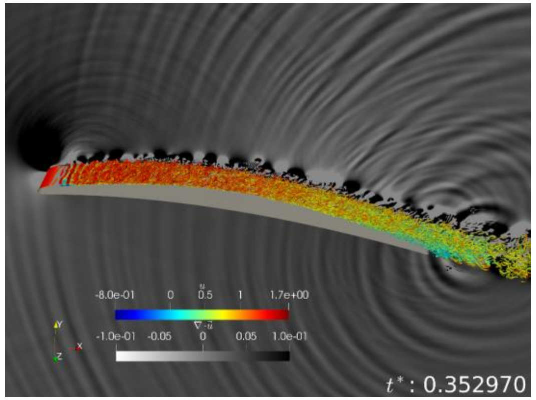
Experimental

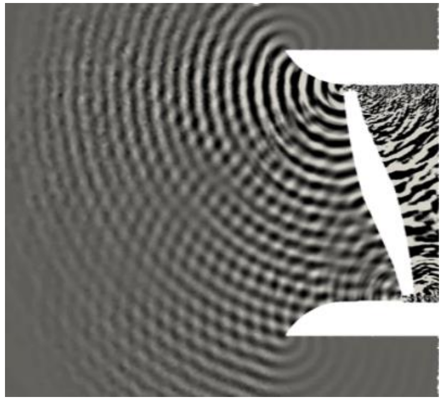




Computational



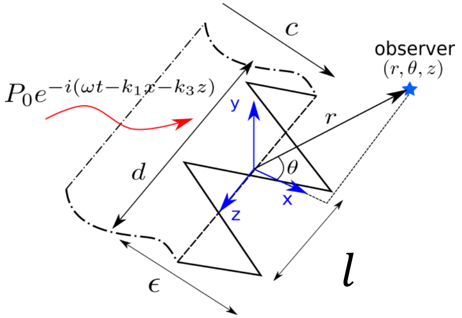




Analytical

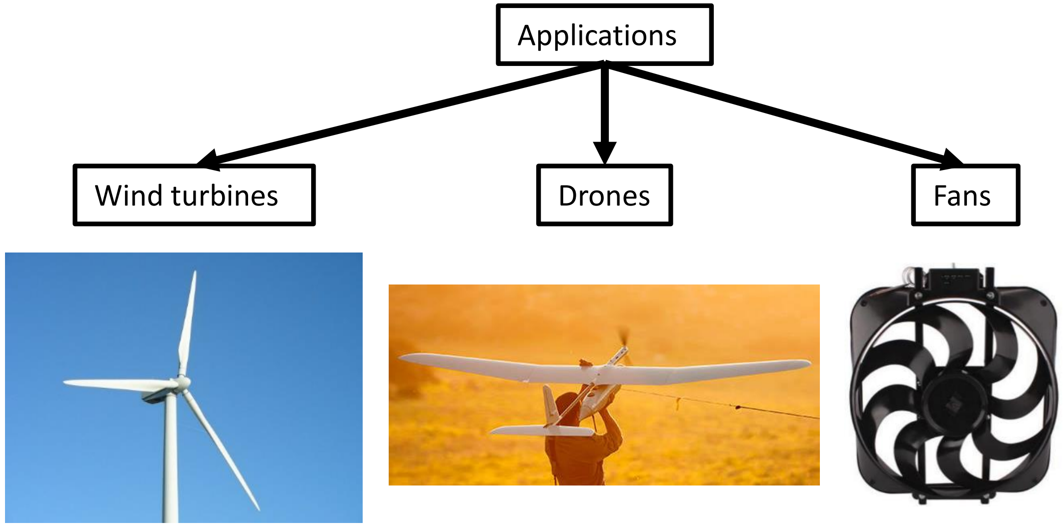
$$S_{pp}(\vec{x},\omega) \sim \frac{\bar{k}}{2\pi r}\sin^2\frac{\theta}{2}\frac{\delta+\bar{k}}{2(\delta-\bar{k}\cos\theta)^2}\sum_{-\infty}^{+\infty}\Pi_0(\omega,k_3)\left|E_n\left(\frac{(\tilde{k}_1-w_n\cos\theta)\epsilon}{4},\zeta\right)\right|^2$$

$$\Pi_0(k_3,\omega)=\frac{1}{\pi}\Phi_{pp}(\omega)\,l_y(\omega,k_3)$$



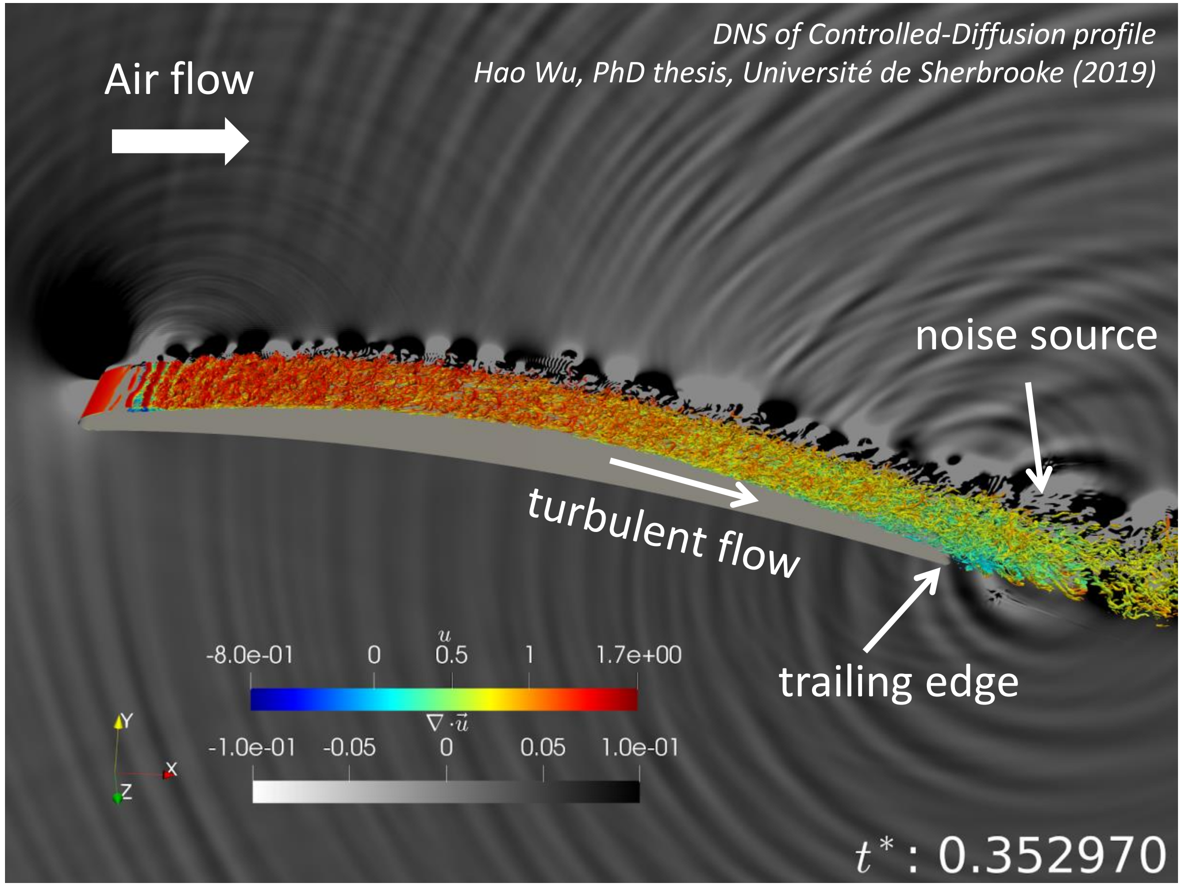
Motivation: airfoil trailing-edge noise (1/2)

- Why important?



Defines minimum level of noise

- How generates?



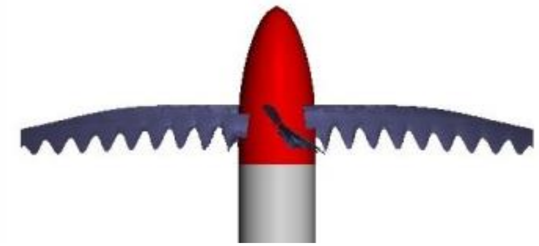
Motivation: airfoil trailing-edge noise (2/2)

- How to reduce?

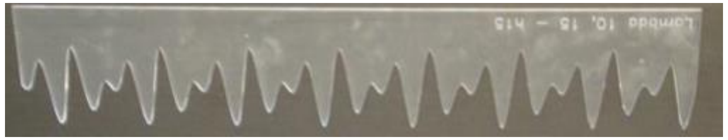
✖ Don't fly/rotate/move (speed ↓)

☺ Modify geometry (*serrations*) →

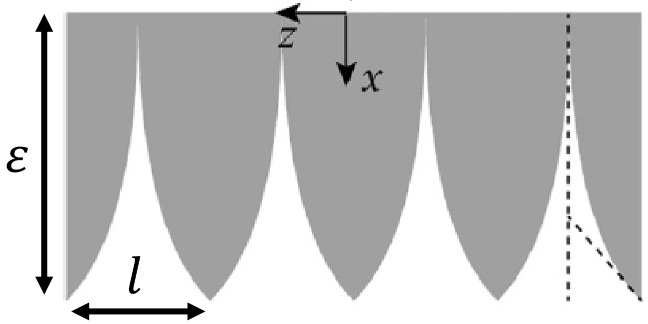
Halimi et. al., AIAA 2018



Chaitanya et al., AIAA 2016



Avallone et al., JSV 2018



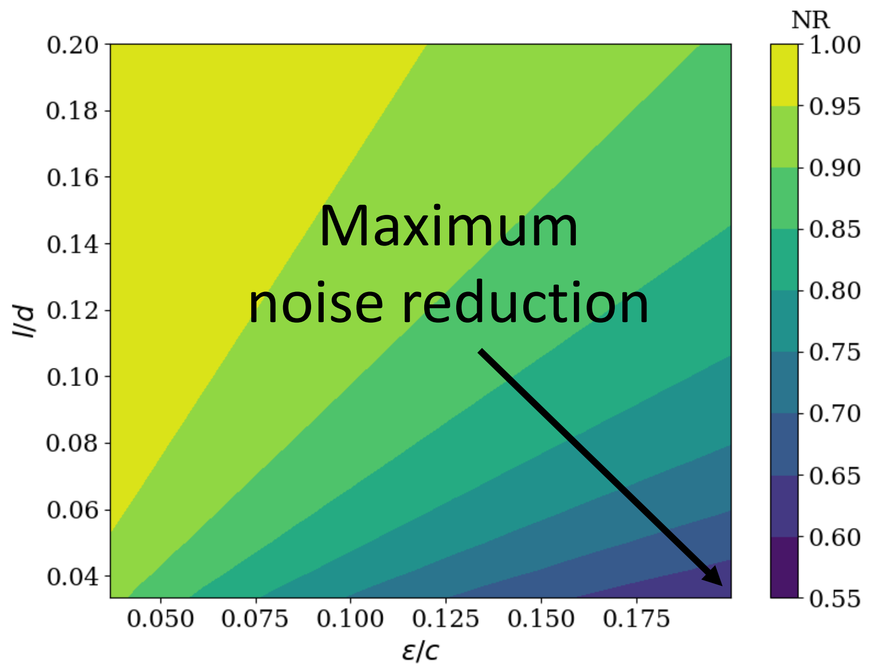
Many shapes, but no one seems the best

Goal of the study:

Find the optimal shape of the trailing-edge

Motivation: practical problems

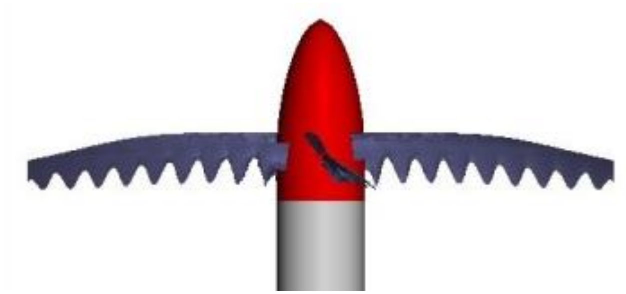
Noise-only optimization:



max ε + min l

and no practical limit… → **Cannot produce!**

Aerodynamic effect:



Too large serrations

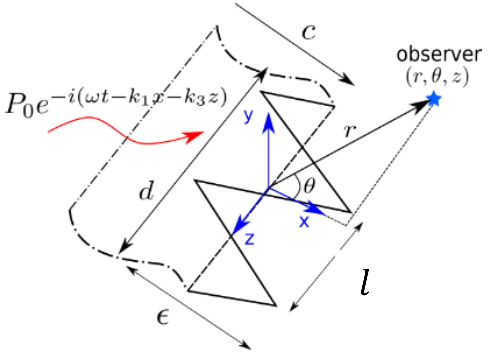
drop in [aerodynamic] performance…

Cannot fly/rotate/move!

Motivation: constrained optimization

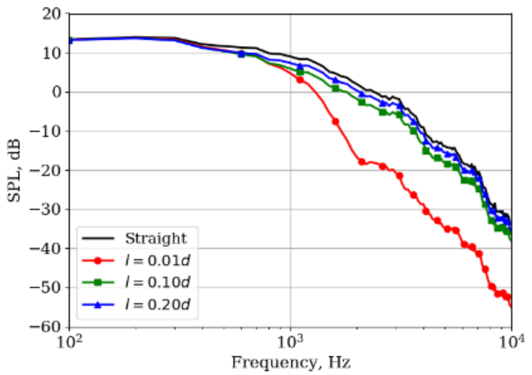
Combine the acoustical and aerodynamical optimum

Acoustics: analytical model

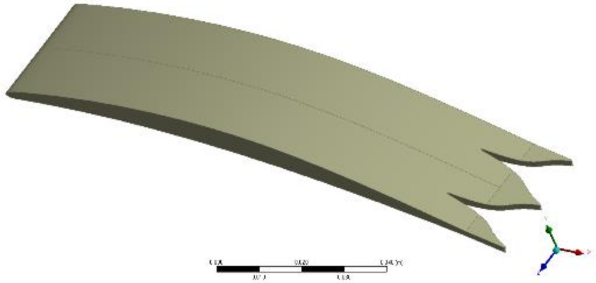


Noise reduction

$$NR = \frac{\int_{f_{min}}^{f_{max}} SPL^{serr}\, df}{\int_{f_{min}}^{f_{max}} SPL^{clean}\, df}$$



Aerodynamics: 3D CFD model

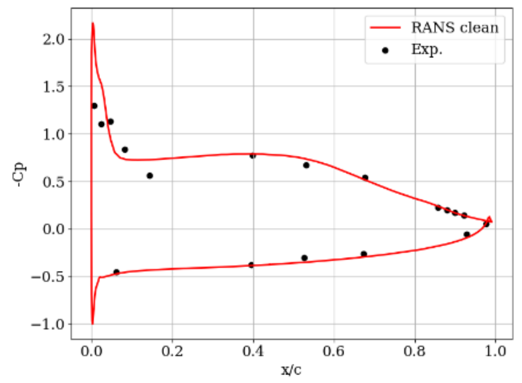


Lift/Drag ratio

$$LDR = \frac{\left(C_l/C_d\right)^{serr}}{\left(C_l/C_d\right)^{clean}}$$

Moment

$$\overline{C_m} = \frac{C_m^{\ serr}}{C_m^{\ clean}}$$



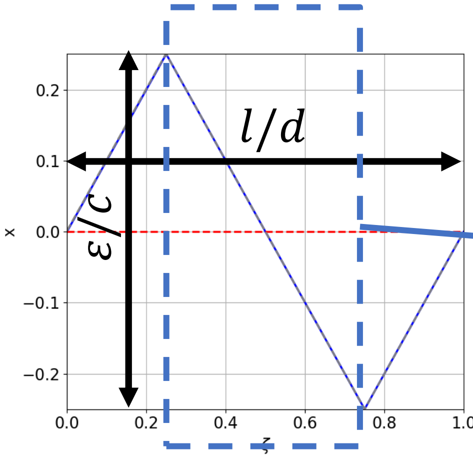
Problem statement and parameterization

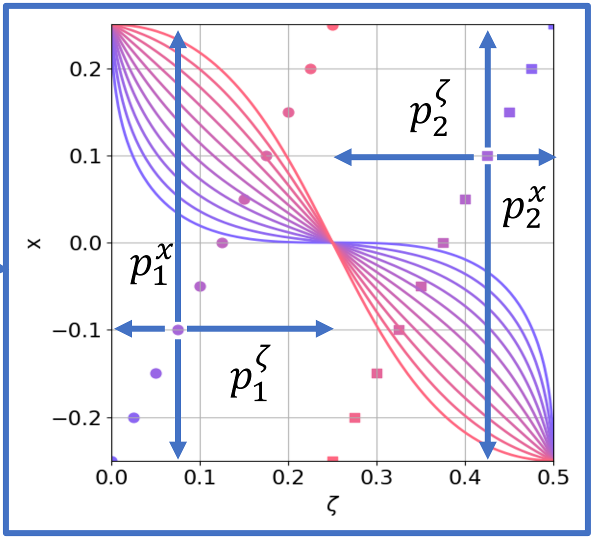
Local shape: B-spline with 2 knot points (4 parameters)

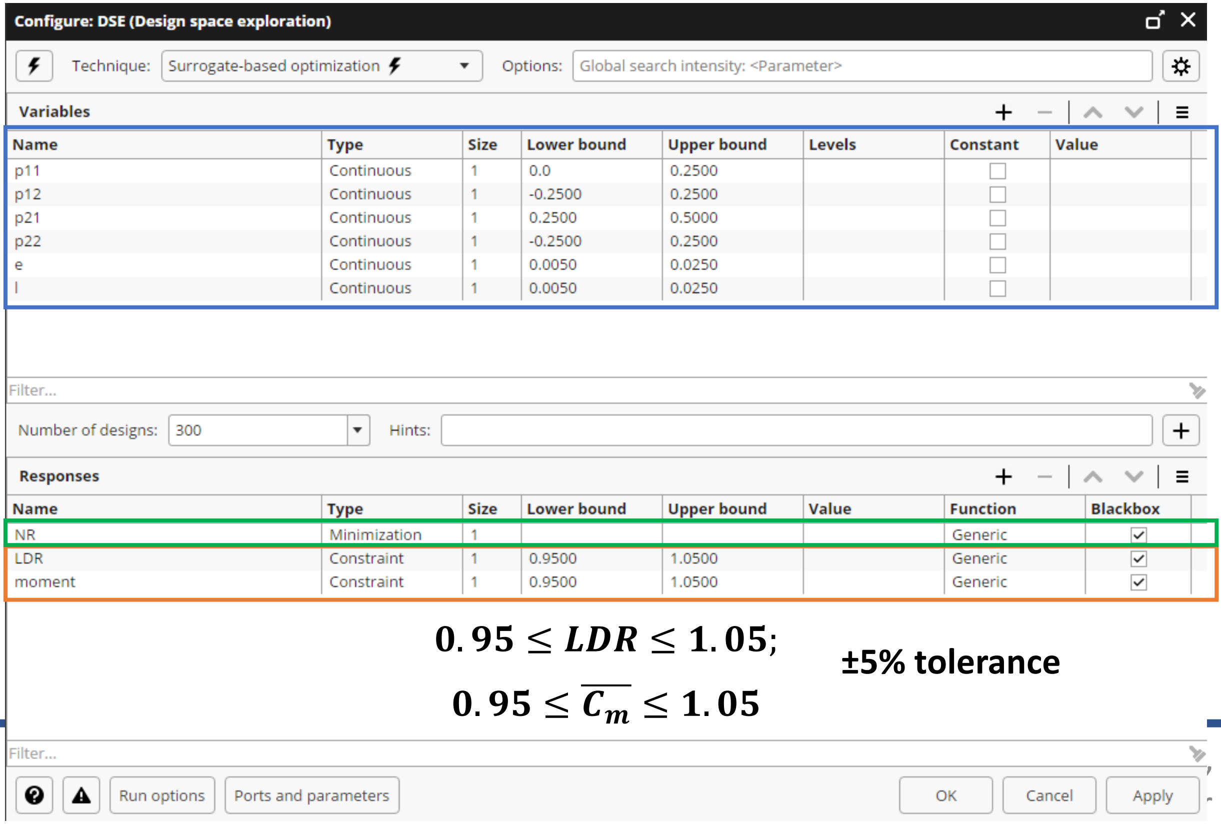
Global size: depth & wavelength (+2 parameters)

Aerodynamics: 2 constraints (lift/drag ratio, moment)

Objective function: Noise reduction







Name	Type	Size	Lower bound	Upper bound	Levels	Constant	Value
p11	Continuous	1	0.0	0.2500		☐	
p12	Continuous	1	-0.2500	0.2500		☐	
p21	Continuous	1	0.2500	0.5000		☐	
p22	Continuous	1	-0.2500	0.2500		☐	
e	Continuous	1	0.0050	0.0250		☐	
l	Continuous	1	0.0050	0.0250		☐	

Name	Type	Size	Lower bound	Upper bound	Value	Function	Blackbox
NR	Minimization	1				Generic	☑
LDR	Constraint	1	0.9500	1.0500		Generic	☑
moment	Constraint	1	0.9500	1.0500		Generic	☑

$\mathbf{0.95 \leq LDR \leq 1.05;}$

$\mathbf{0.95 \leq \overline{C_m} \leq 1.05}$

±5% tolerance

Find $\vec{x} = \{p_1, p_2, \varepsilon, l\}^T$ such that

minimizes noise reduction (NR)

subject to constraints:

$$\{0.0, -0.25\}^T \leq p_1 \leq \{0.25, 0.25\}^T$$

$$\{0.0, -0.25\}^T \leq p_2 \leq \{0.25, 0.25\}^T$$

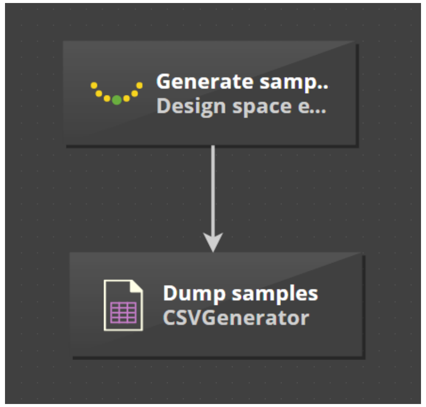
$$0.01 \leq \varepsilon/c \leq 0.2$$

$$0.01 \leq l/d \leq 0.1$$

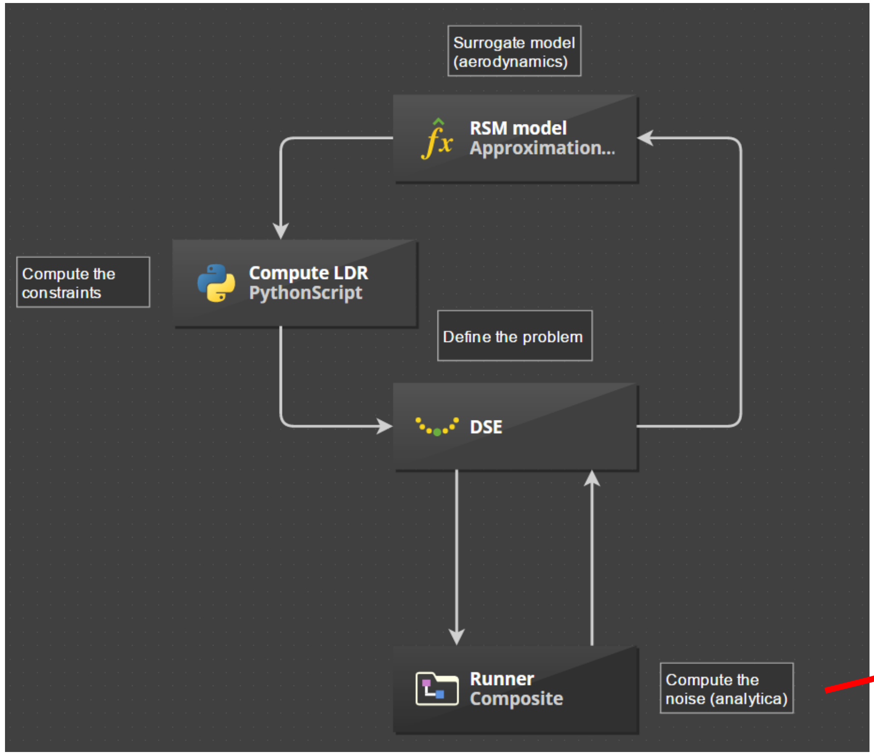
workflow

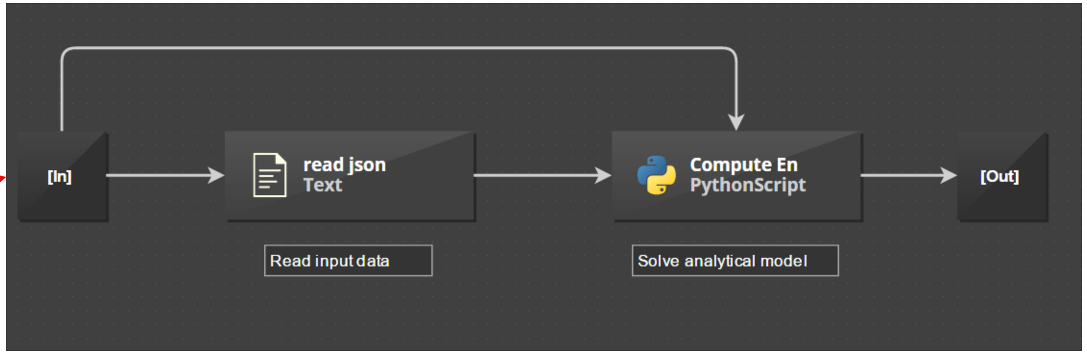
- Acoustics: cheap (<1 s / point) → direct evaluations
- Aerodynamics: expensive (~2 h / point) → needs a surrogate model

Pre-generate all DoE samples (118 pts)
& solve on a cluster



Construct a surrogate model





DoE for aerodynamics

Lift/Drag ratio

Correlation: Pearson

Rows: DoE_p11; DoE_p12; DoE_p21; DoE_p22; DoE_e; DoE_l

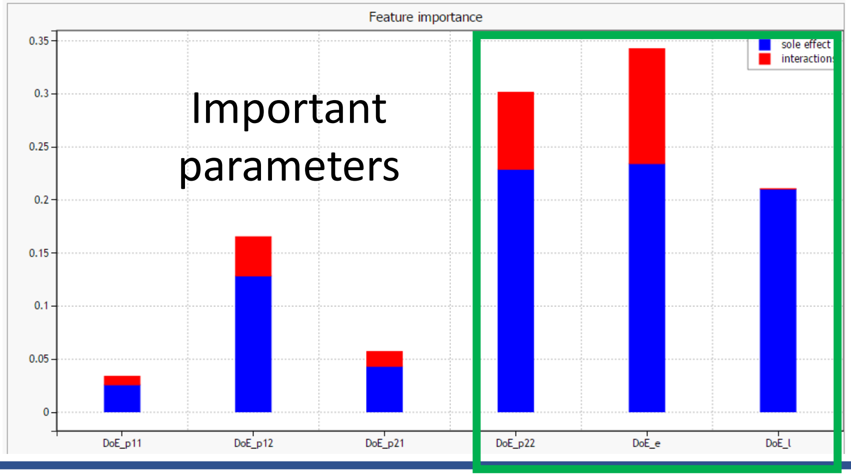
Columns: DoE_Lift-to-drag

Term pair	Top coefficients	p-value
DoE_p22 ⇌ DoE_Lift-to-drag	-0.52	4.69e-10
DoE_l ⇌ DoE_Lift-to-drag	-0.45	2.86e-7
DoE_e ⇌ DoE_Lift-to-drag	0.42	0.00000193
DoE_p12 ⇌ DoE_Lift-to-drag	-0.34	0.000174
DoE_p11 ⇌ DoE_Lift-to-drag	-0.18	0.0449
DoE_p21 ⇌ DoE_Lift-to-drag	-0.15	0.103

Model statistics

- Effective sample size: 118
- Duplicate points: 0
- Ambiguous points: 0

Errors	Train accuracy	Internal validation
RRMS	0.14	0.20
Max	0.15	0.21
Q99	0.07	0.11
Q95	0.07	0.09
Median	0.02	0.03
Mean	0.02	0.03
RMS	0.03	0.04
R^2	0.98	0.96



← Quadratic dependency →

Moment

Correlation: Pearson

Rows: DoE_p11; DoE_p12; DoE_p21; DoE_p22; DoE_e; DoE_l

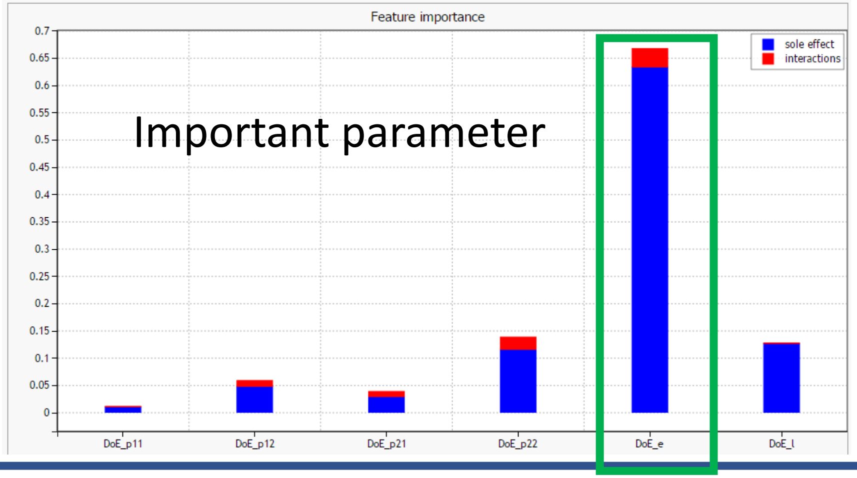
Columns: DoE_moment

Term pair	Top coefficients	p-value
DoE_e ⇌ DoE_moment	-0.77	1.21e-27
DoE_p22 ⇌ DoE_moment	0.41	0.00000274
DoE_l ⇌ DoE_moment	0.29	0.00147
DoE_p12 ⇌ DoE_moment	0.18	0.0536
DoE_p21 ⇌ DoE_moment	0.14	0.143
DoE_p11 ⇌ DoE_moment	0.081	0.382

Model statistics

- Effective sample size: 118
- Duplicate points: 0
- Ambiguous points: 0

Errors	Train accuracy	Internal validation
RRMS	0.05	0.07
Max	0.00	0.00
Q99	0.00	0.00
Q95	0.00	0.00
Median	0.00	0.00
Mean	0.00	0.00
RMS	0.00	0.00
R^2	1.00	0.99

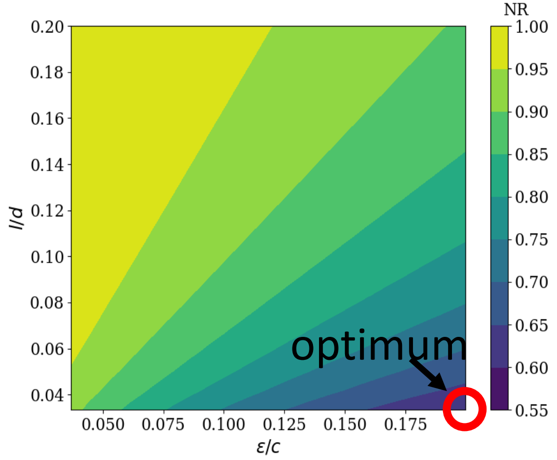


DoE

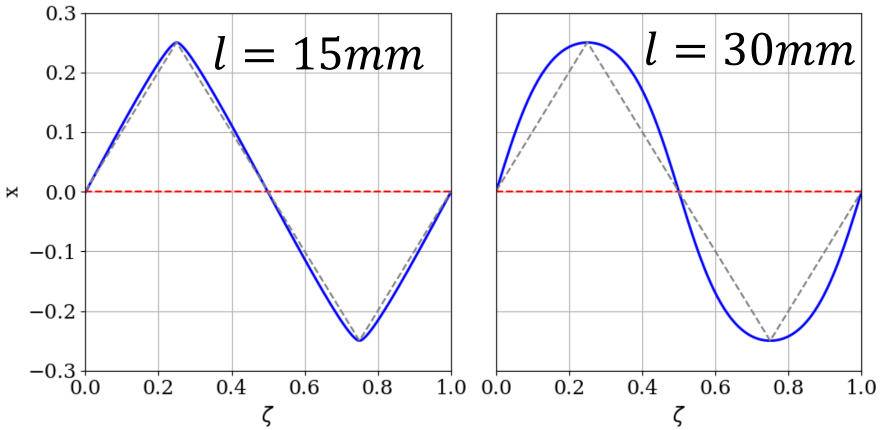
Surrogate model: Gaussian Process (GP)

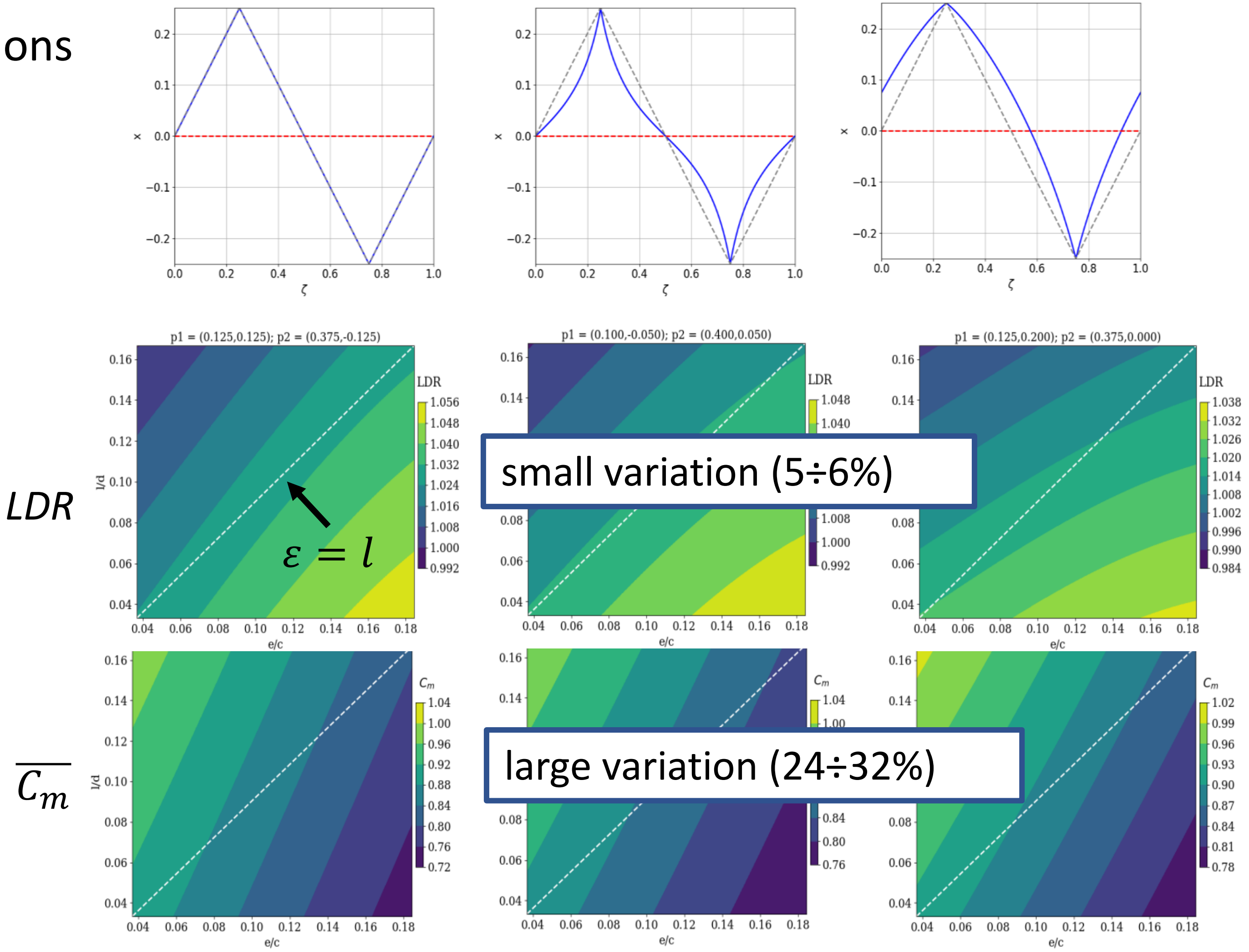
Acoustics:

Fixed local shape: tends to deep and sharp serrations



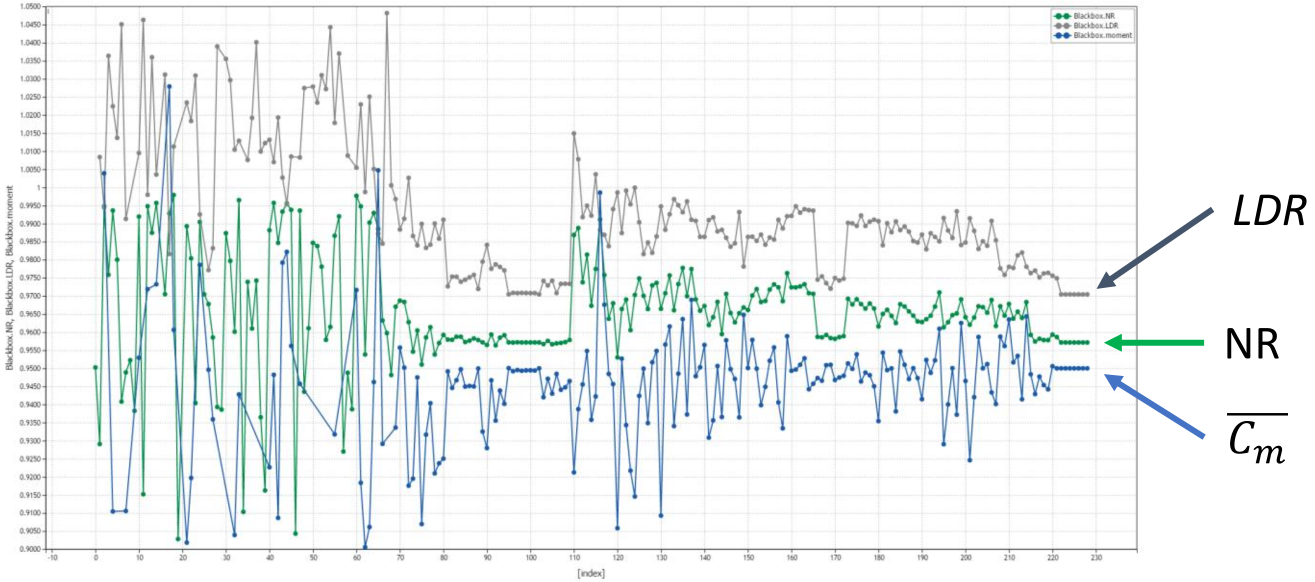
Fixed global size: optimal shape for each size

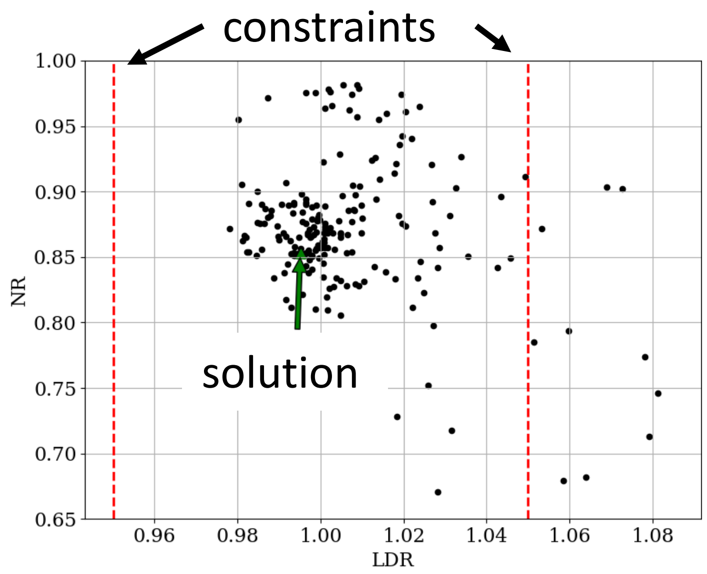


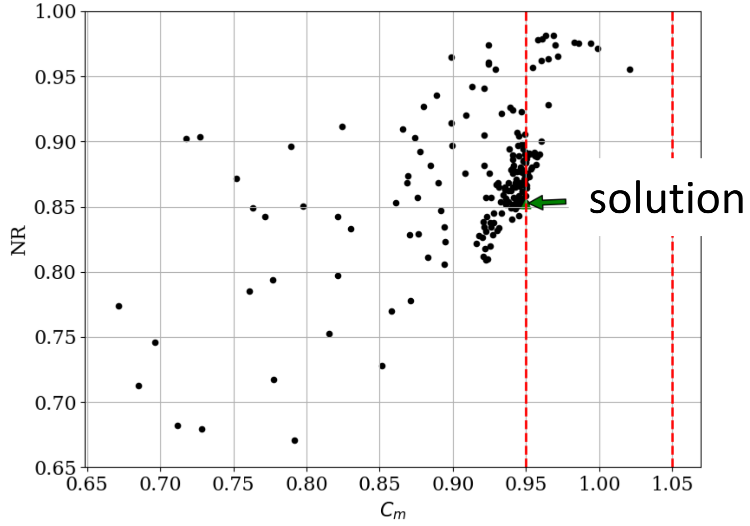


Optimization (1/3)

- Surrogate-based optimization
- 228 evaluation steps
- GPI = 50 (25,75 tested)





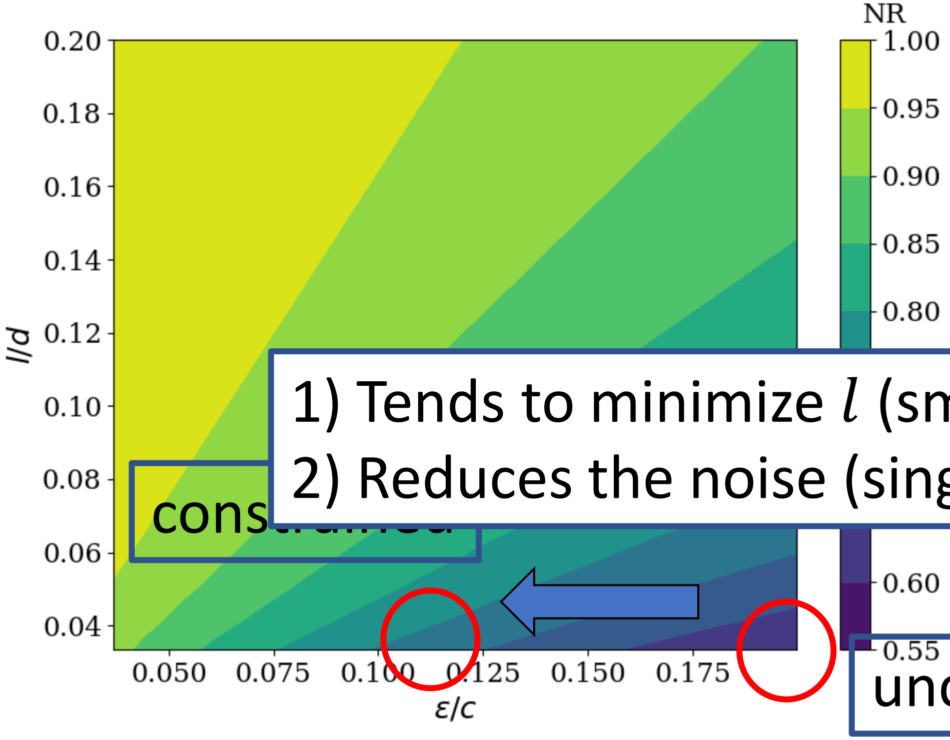


Constraint on moment is harder to respect

Optimization (2/3)

Global Optimization: Optimal values

p_1^{ζ}	p_1^x	p_2^{ζ}	p_2^x	ϵ/c	l/d'	NR	LDR	C_m
0.152	0.25	0.5	0.25	0.12	0.03	0.85	0.995	0.95



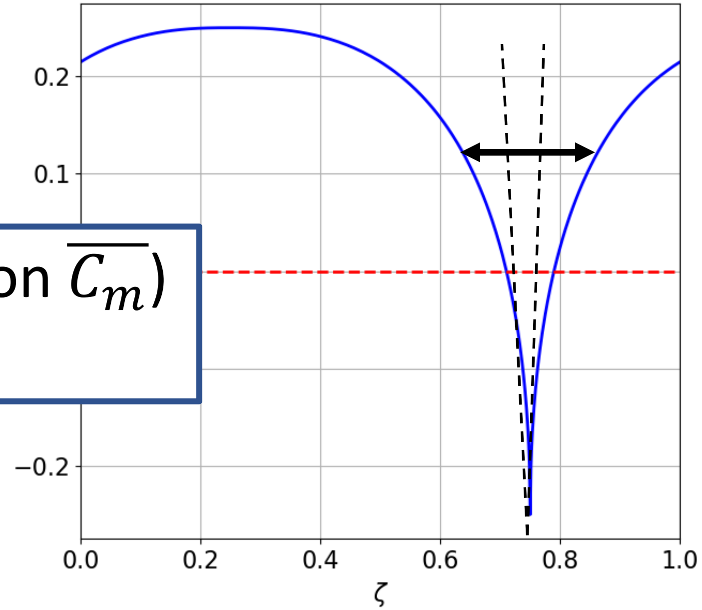
constrained

unconstrained

1) Tends to minimize l (smaller impact on $\overline{C_m}$)

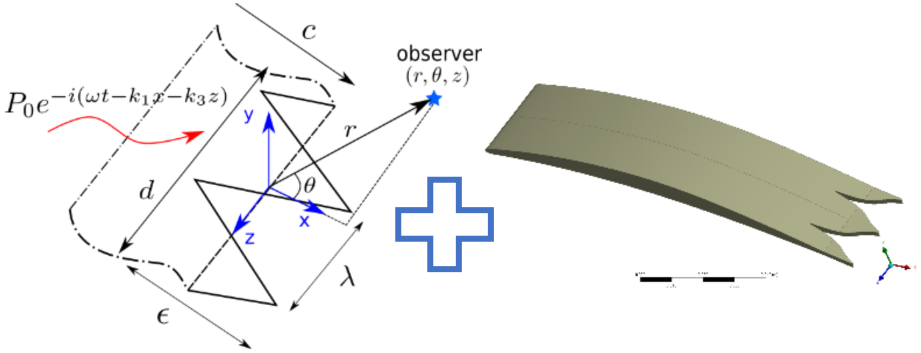
2) Reduces the noise (singular point)

Optimal shape



Conclusions

acoustical & aerodynamical optimization

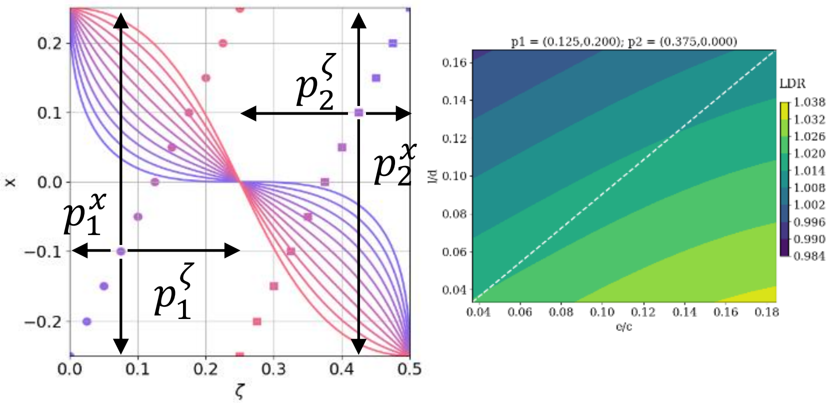


reduce the noise

&

preserve the performance

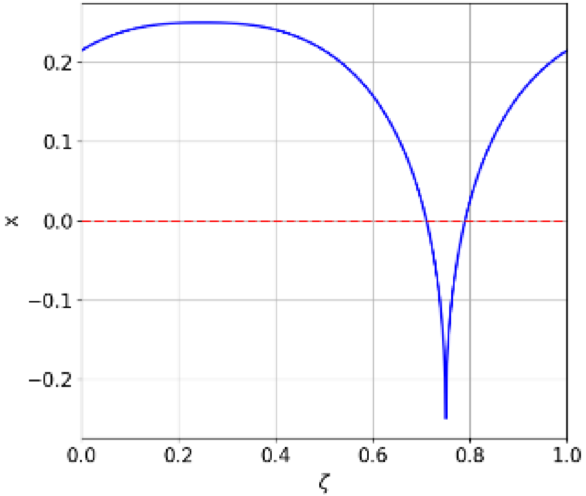
Design of Experiments



Serration depth is the most important

LDR change is smaller than $\overline{C_m}$

Optimization



iron shape wins

Moment constraint limits the noise reduction

More information: Pavel.Kholodov@usherbrooke.ca

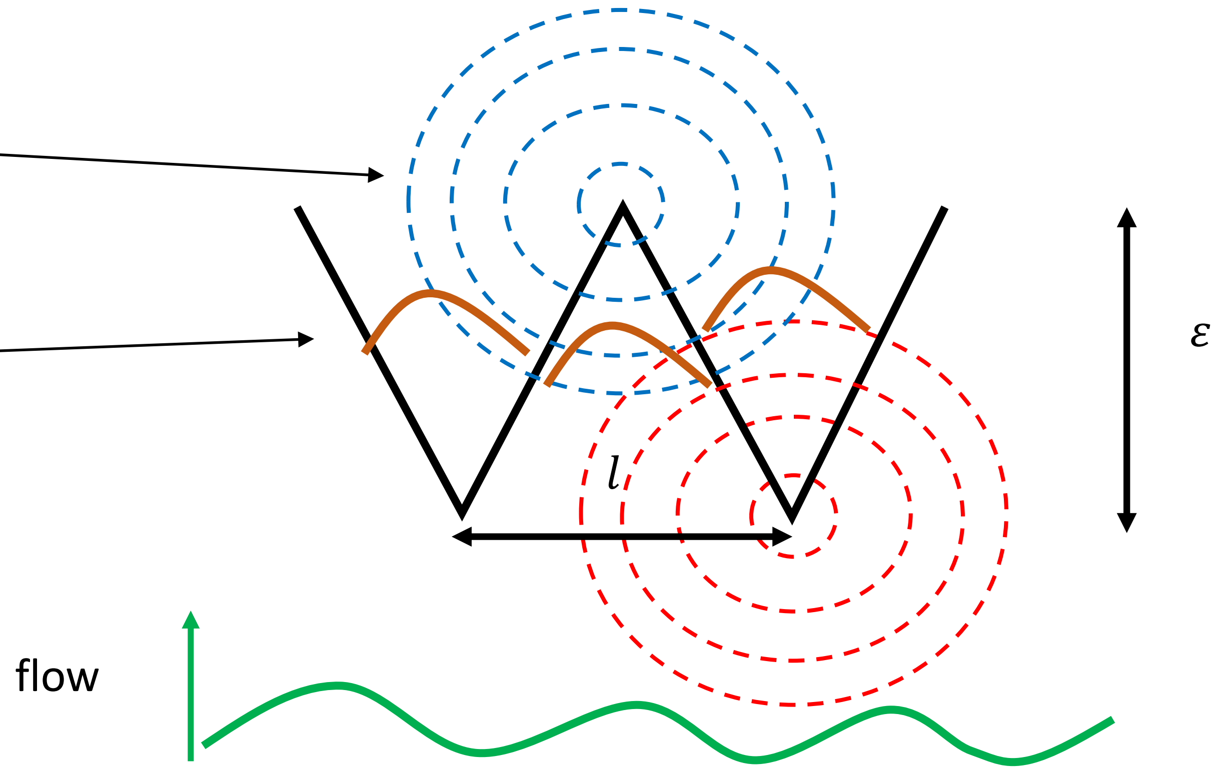
- P. Kholodov, S. Moreau. Optimization of serrations for broadband trailing-edge noise reduction using an analytical model. *25th AIAA/CEAS Aeroacoustics Conference. Delft, The Netherlands, 2020. AIAA2019-2655.* https://doi.org/10.2514/6.2019-2655
- P. Kholodov, S. Moreau. Numerical study of optimized airfoil trailing-edge serrations for broadband noise reduction. *AIAA AVIATION Forum, 2020. AIAA2020-2541.* https://doi.org/10.2514/6.2020-2541
- P. Kholodov, S. Moreau. Optimization of trailing-edge serrations with and without slits for broadband noise reduction. *Journal of Sound and Vibration, 115736, 2020.* https://doi.org/10.1016/j.jsv.2020.115736

Backup

Noise reduction due to serrations

1) "breaking coherence"
- *Reduces the scale of interactions*

2) "destructive interference"
- *Tips and roots emit their own wavelengths that destruct each other*

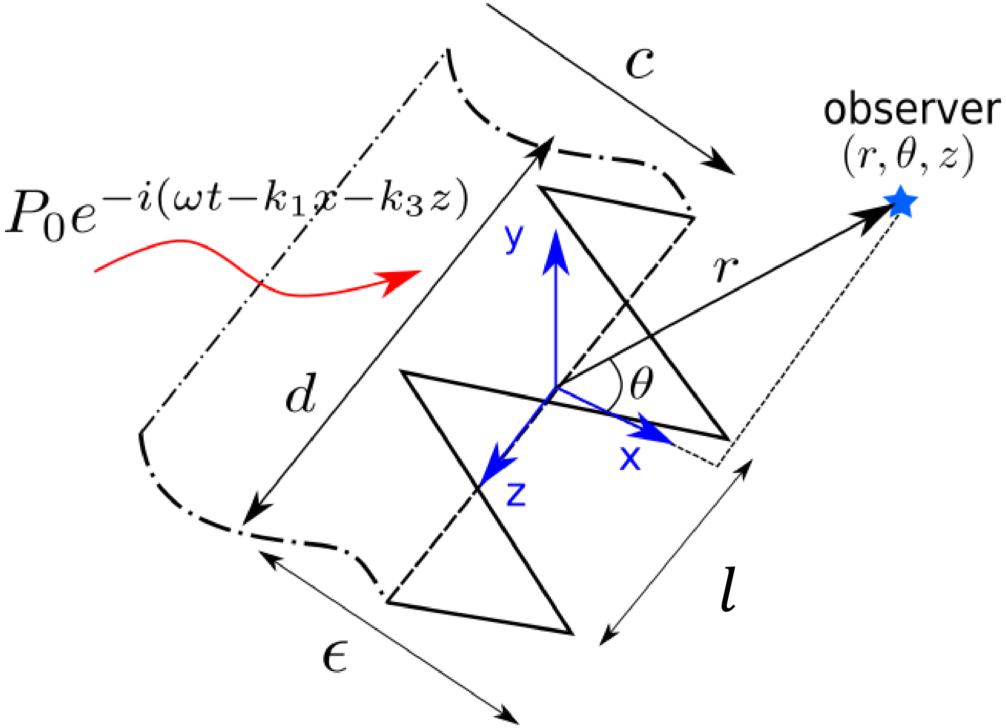


Acoustics: Analytical model

Trailing-edge noise model for serrated airfoil

Ayton, JFM 2018
Lyu & Ayton, AIAA2019-2674
Sanjosé et al., AIAA2019-2450

- Zero-thickness flat plate at 0° AoA
- Semi-infinite in *x*
- Spanwise-periodic
- Frozen turbulence



Acoustics: Analytical model

Trailing-edge noise model for serrated airfoil

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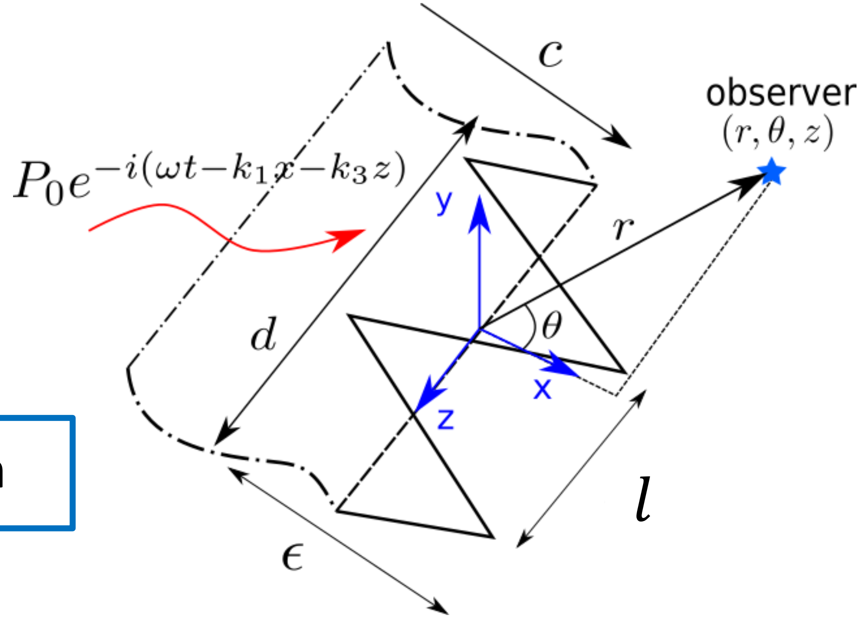
$$S_{pp}(\vec{x},\omega) \sim \frac{\bar{k}}{2\pi r}\sin^2\frac{\theta}{2}\,\frac{\delta+\bar{k}}{2(\delta+\bar{k}\cos\theta)^2}\sum_{-\infty}^{+\infty}\Pi_0(\omega,k_3)\left|E_n\left(\frac{(\tilde{k}_1-w_n\cos\theta)\epsilon}{4},\zeta\right)\right|^2$$

acoustic wavenumber — directivity — wall-pressure spectral density — radiation integral



- $\Pi_0(\omega,k_3)$: wall-pressure spectrum + spanwise correlation length

(Sanjosé et al., AIAA 2019-2450)

$$\Pi_0(k_3,\omega) = \frac{1}{\pi}\Phi_{pp}(\omega)\,l_y(\omega,k_3)$$

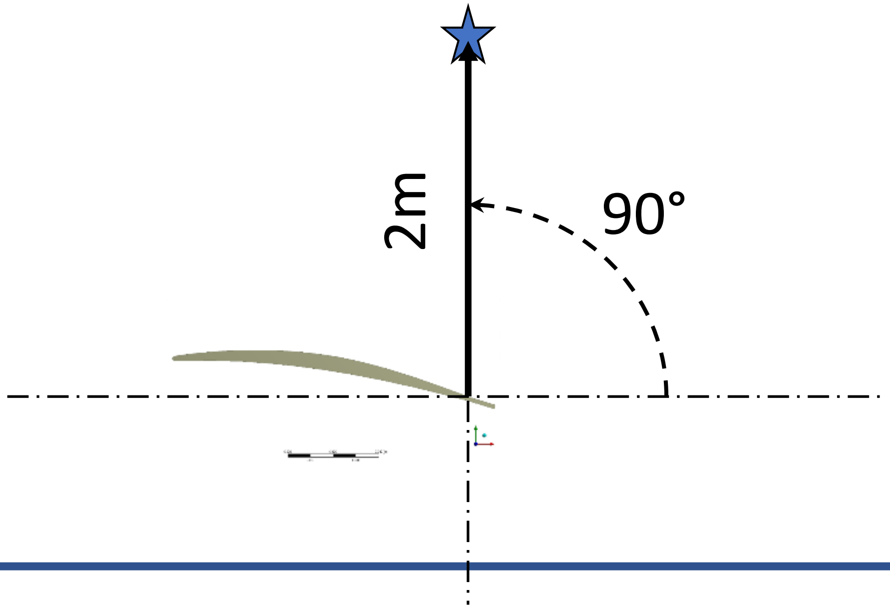
Wall pressure: Controlled-Diffusion airfoil, 8°
(Ecole Centrale de Lyon, France)

Acoustics: Analytical model

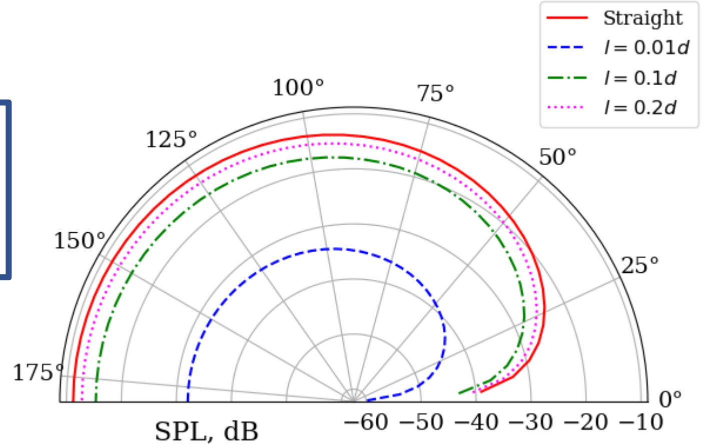
Noise reduction

$$SPL = 10\log_{10} \frac{S_{pp}}{P_{ref}^2}$$

$$NR = \frac{\int_{f_{min}}^{f_{max}} SPL^{serr}\, df}{\int_{f_{min}}^{f_{max}} SPL^{clean}\, df} \quad NR \sim 1$$



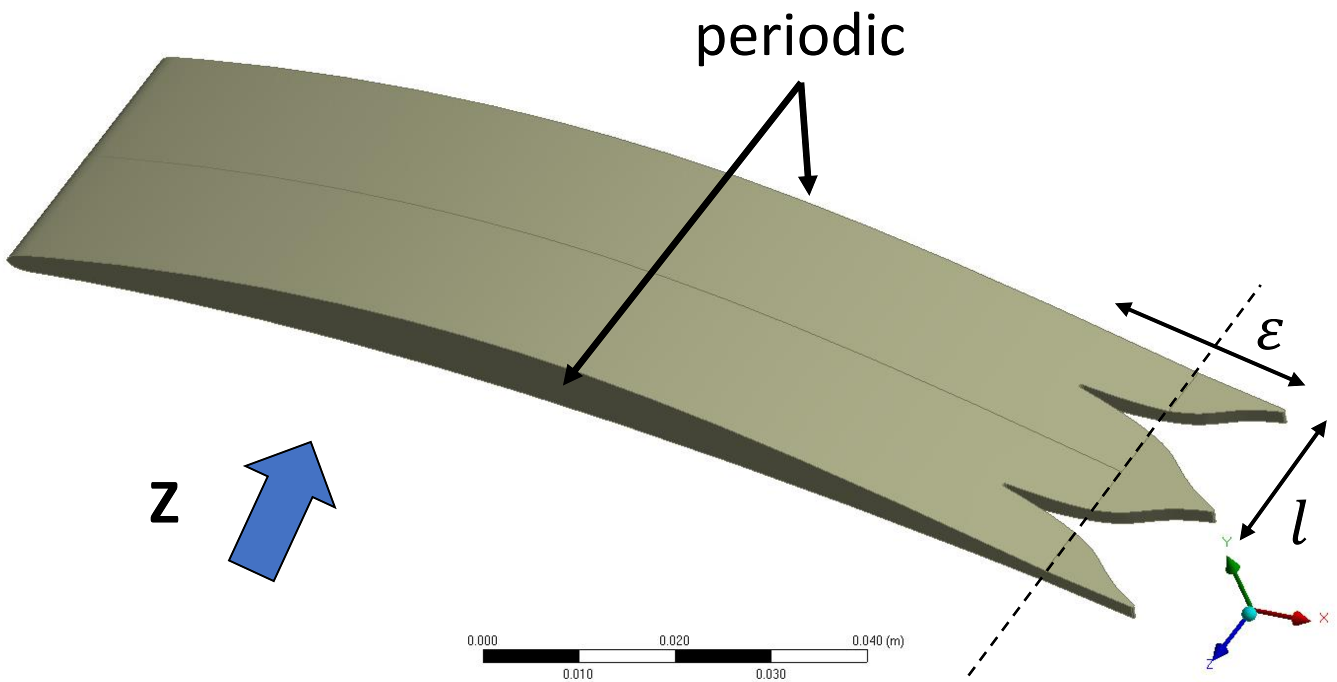
the noise gain is omnidirectional

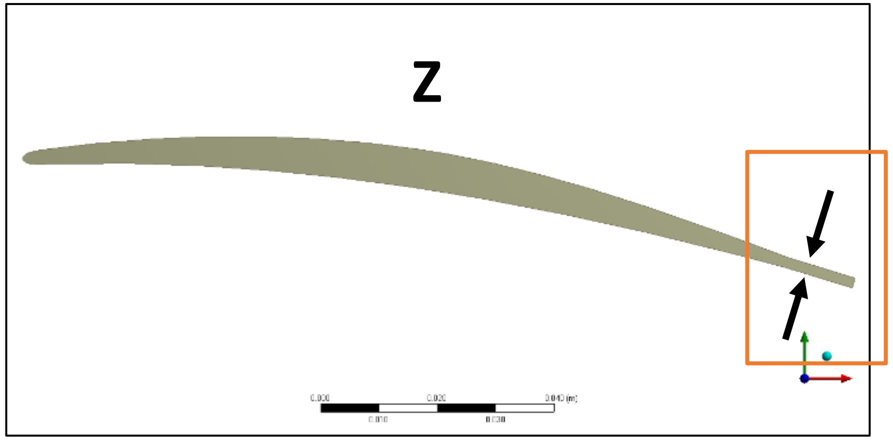


Aerodynamics: CFD RANS model

- 3D periodic model
- 2 wavelengths
- constant width at the trailing edge

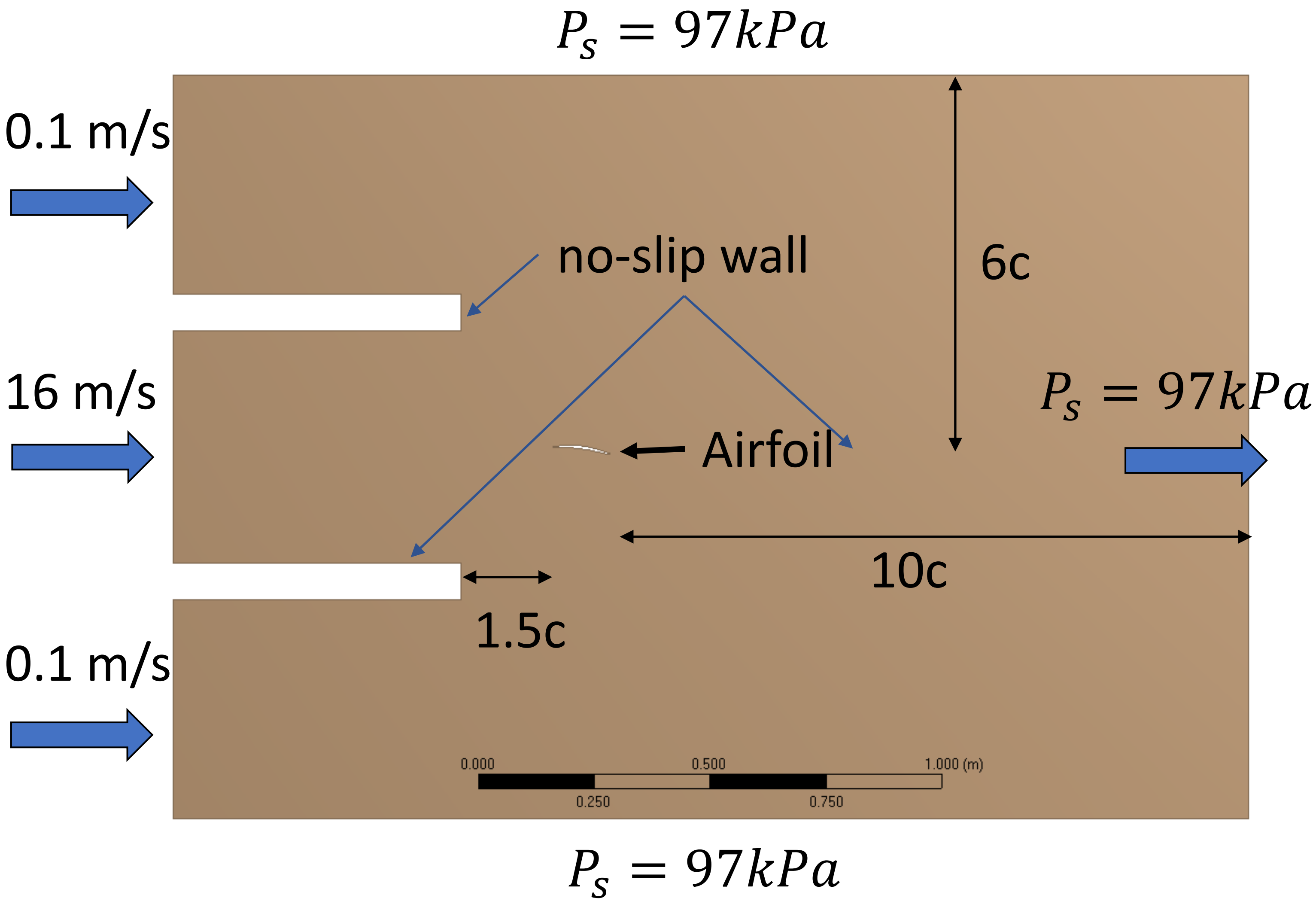
- no roundings included (except the roots)





Aerodynamics: CFD RANS model

- ANSYS Fluent 2019R2
- Incompressible
- Steady-state
- $k - \omega$ SST model
- 2^{nd} order scheme



DoE for aerodynamics

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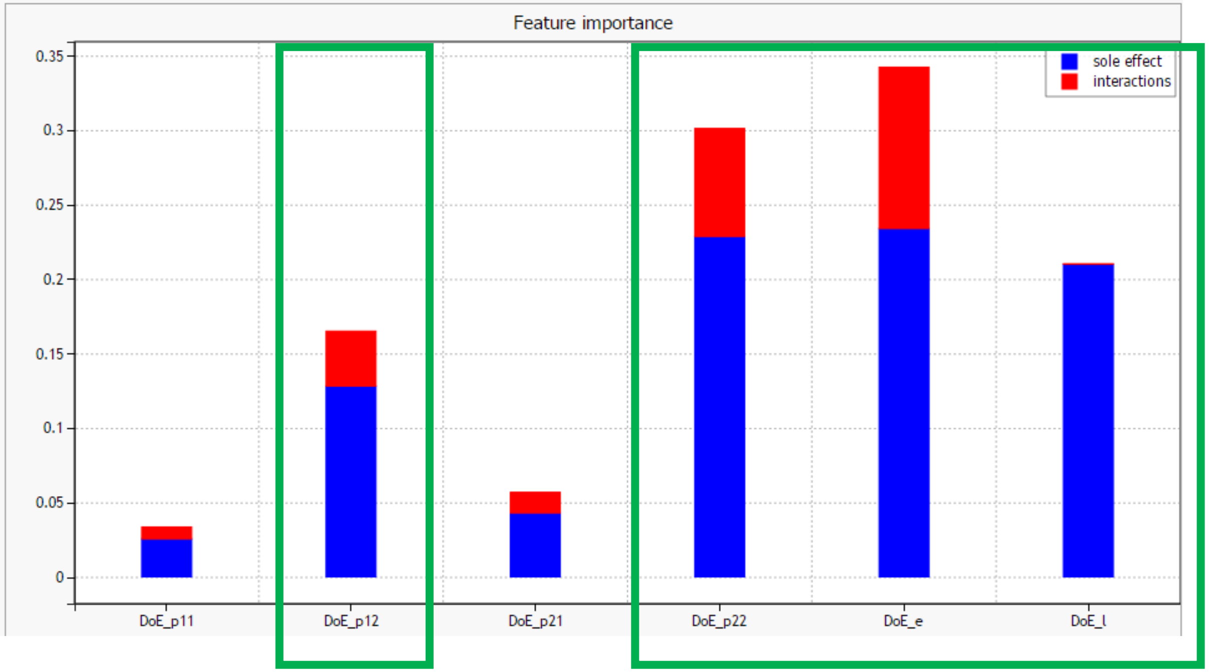

Surrogate model: Gaussian Process (GP)

Model statistics:

	R^2	RMS (rel.), %	Max error (rel.), %
6 inputs	0.9742	0.33	0.69
4 inputs	0.7980	0.89	1.74

Accuracy statistics of the surrogate models for the prediction of the lift-to-drag ratio.

~17% of precision loss

	R^2	RMS (rel.), %	Max error (rel.), %
6 inputs	0.9975	0.42	0.92
4 inputs	0.9776	1.33	2.16

Accuracy statistics of the surrogate models for the prediction of the moment coefficient.

x3 larger error with 4 variables

Use 6-input model for the optimization