Static and Dynamic Aeroelastic Scaling of the CRM Wing via Multidisciplinary Optimization

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from PhD work of Joan Mas Colomer
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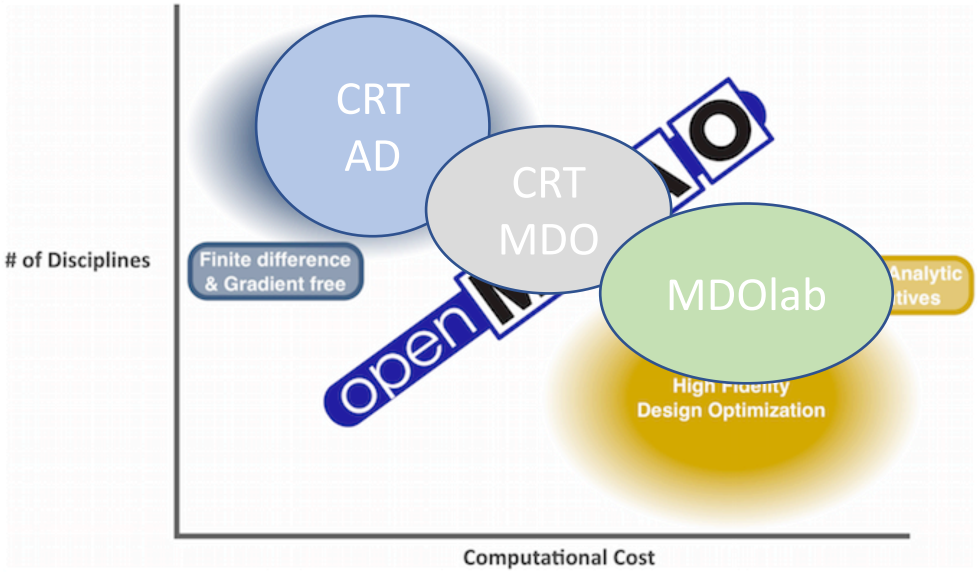
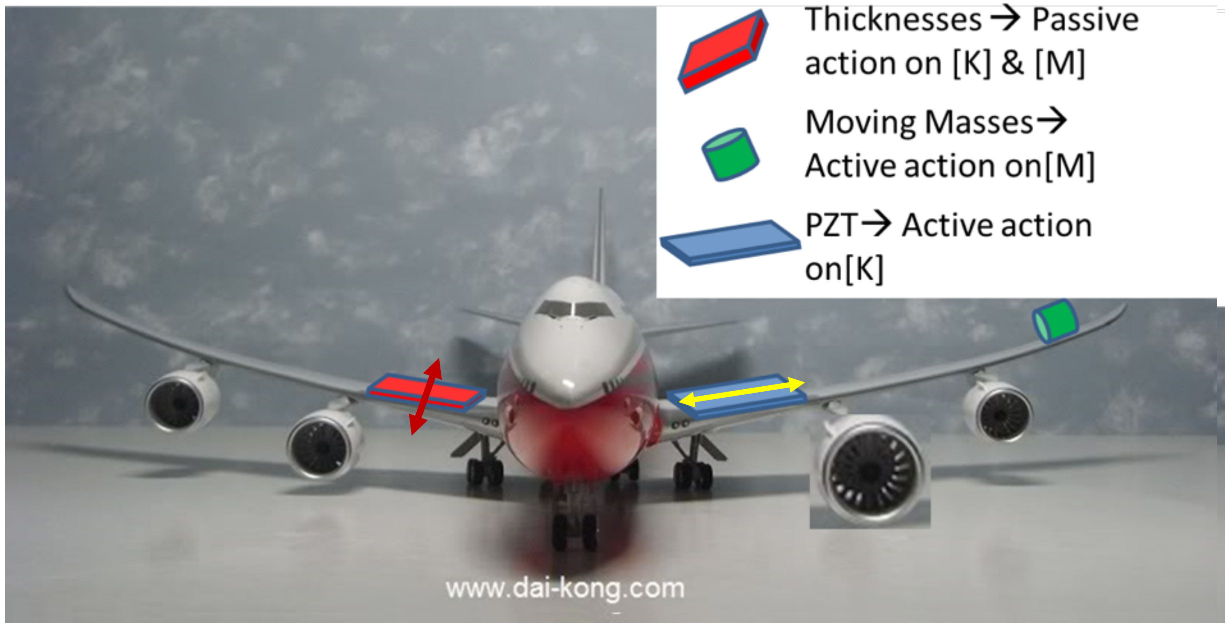
Joaquim Martins (University of Michigan)

Common Research Team (ONERA-SUPAERO) : CRT



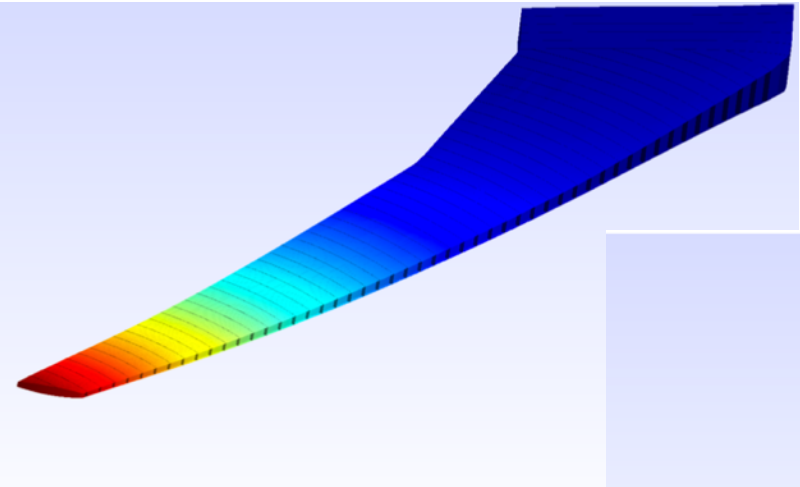
The Big Picture of Joan's thesis

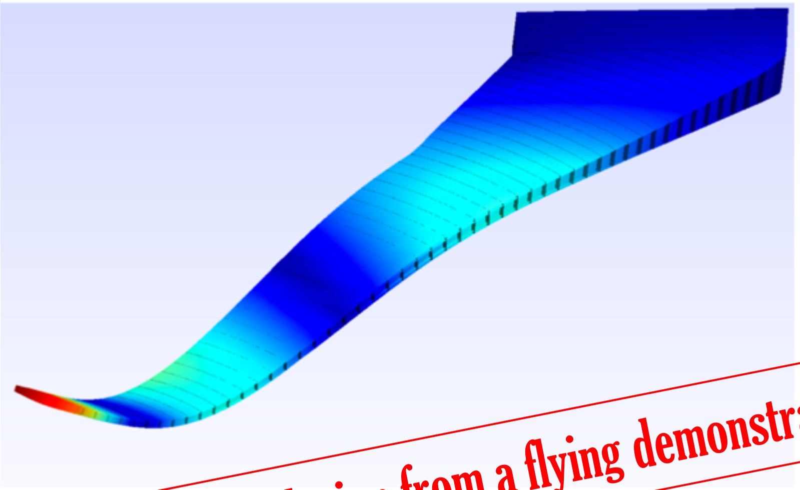
- Dynamic Aeroelastic Similarity between a reference aircraft and a scaled model
- Design variables (passive+active)
- New objective function (aeroelasticity-based) to ensure the similarity



What if our methodology could help to : Test/validate new (or derived) concepts on a flight demonstrator?

Aircraft DNA: Modal basis





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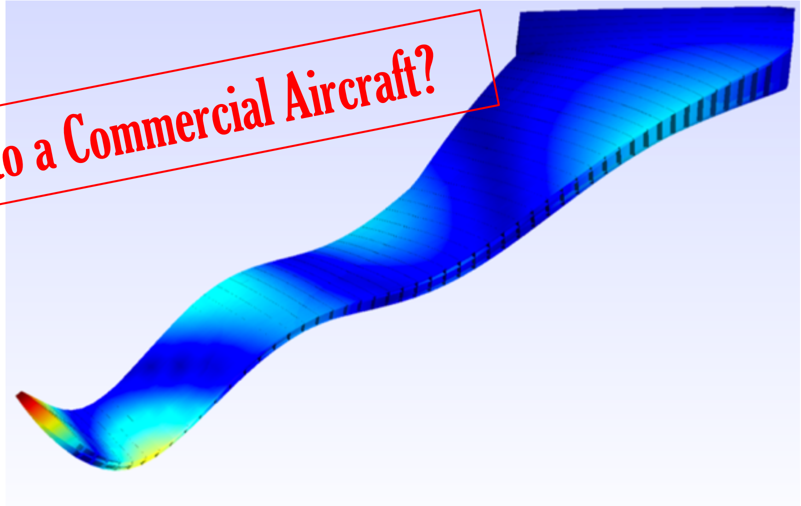


Can we easily traduct original design from a flying demonstrator to a Commercial Aircraft?

Computational Tools for CFD/CSM

- Nastran 95*: Normal Modes and Flutter Analysis (DLM)
- Panair/a502†: Static aerodynamics
- OpenMDAO‡ Framework

*[github.com/nasa/NASTRAN-95]

†[pdas.com/panair.html]

‡[Gray et al., AIAA/ISSMO, 2014]

Allemang, R. J. (2003). The modal assurance criterion–twenty years of use and abuse. *Sound and vibration*, *37*(8), 14-23.

- Optimizer: SLSQP (Gradient-based, from Scipy library) and SEGOMOE (Surrogate-based)

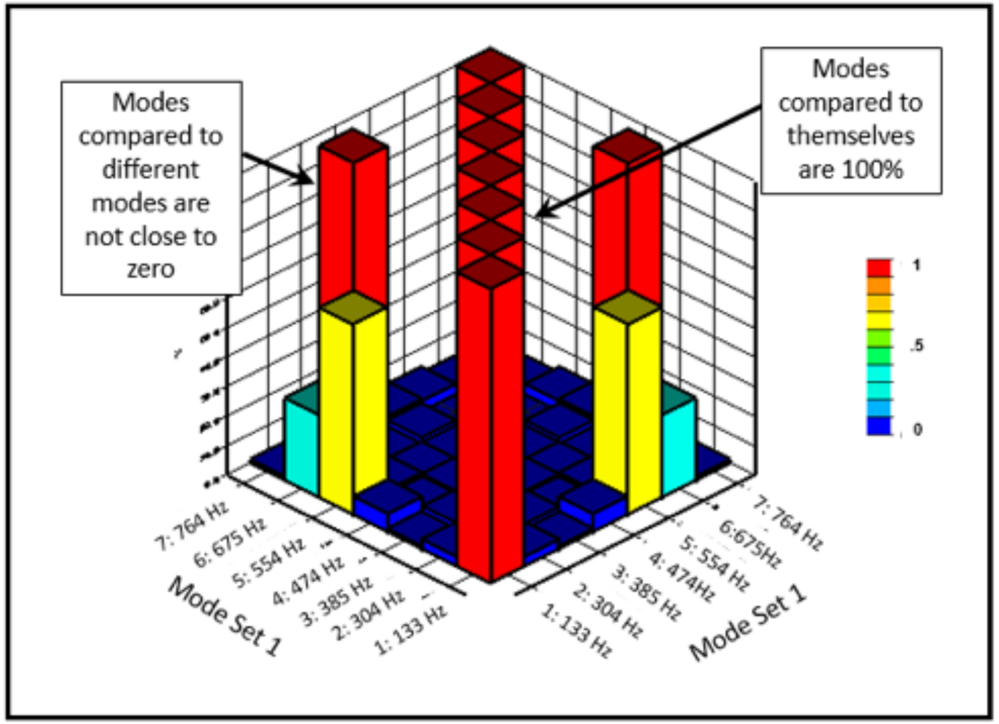
Method for Modal Analysis

- MAC (Modal Assurance Criterion) usualy used for Experimental/Numerical correlation (late 70s)

→Adapted here for Reference/Scaled aircraft

Common framework / results with Postdoc of Claudia Bruni (next presentation)

Mode pairing

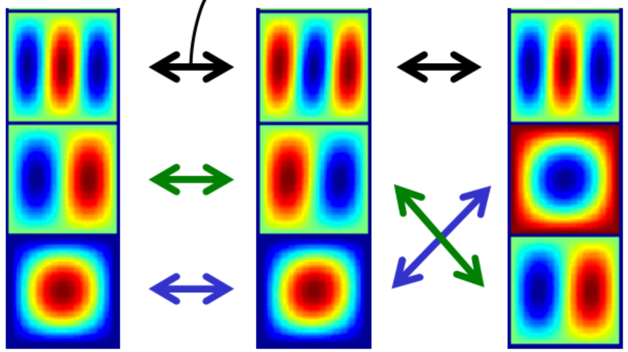


$$\mathbf{K} \cdot V = \lambda \cdot \mathbf{M} \cdot V$$

$$MAC(V_1, V_2) = \frac{\left(V_1^T\, V_2\right)^2}{\left(V_1^T\, V_1\right)\left(V_2^T\, V_2\right)}$$

pairing

MAC > 0.9



Reference aircraft: r

Scaled model: m

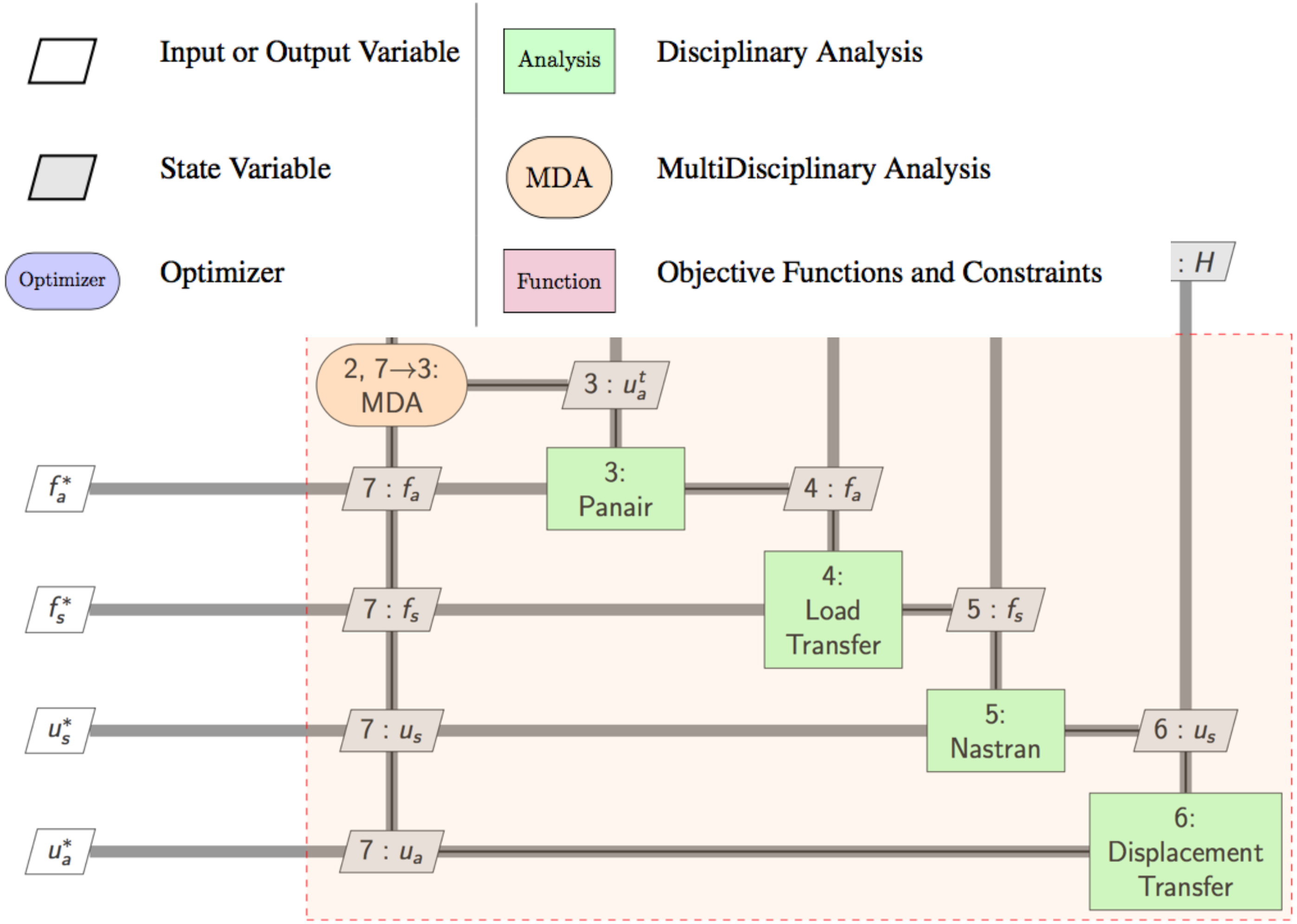
Outlines

1. OpenMDAO strategy
2. First application: Modes tracking strategy
3. Second application: Wing planform optimization for flutter similarity

The part 1 will be introduced in details by the next presentation…
we focus here more on the results

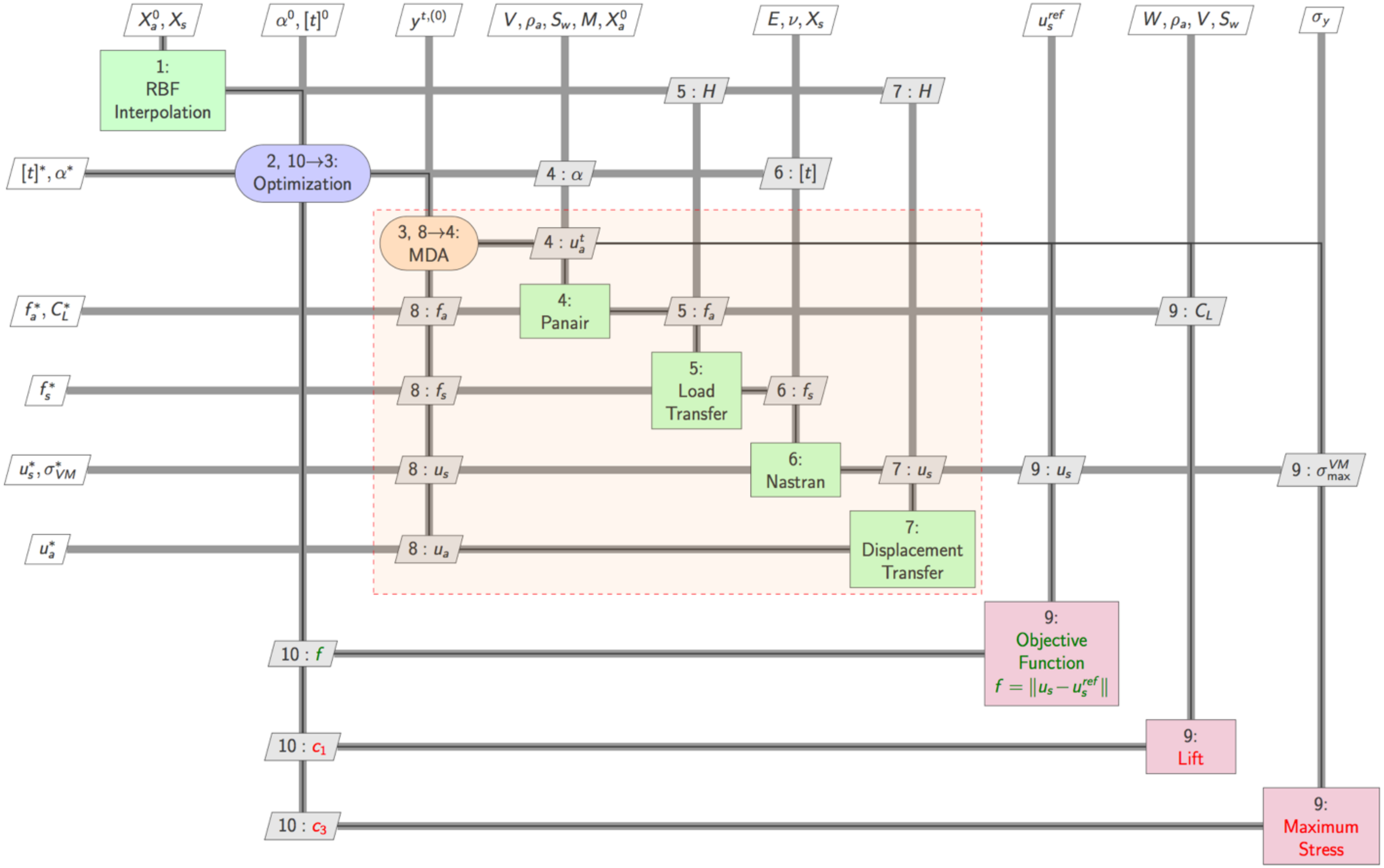
1. OpenMDAO strategy

Preliminary works MDA: Static Aeroelasticity XDSM

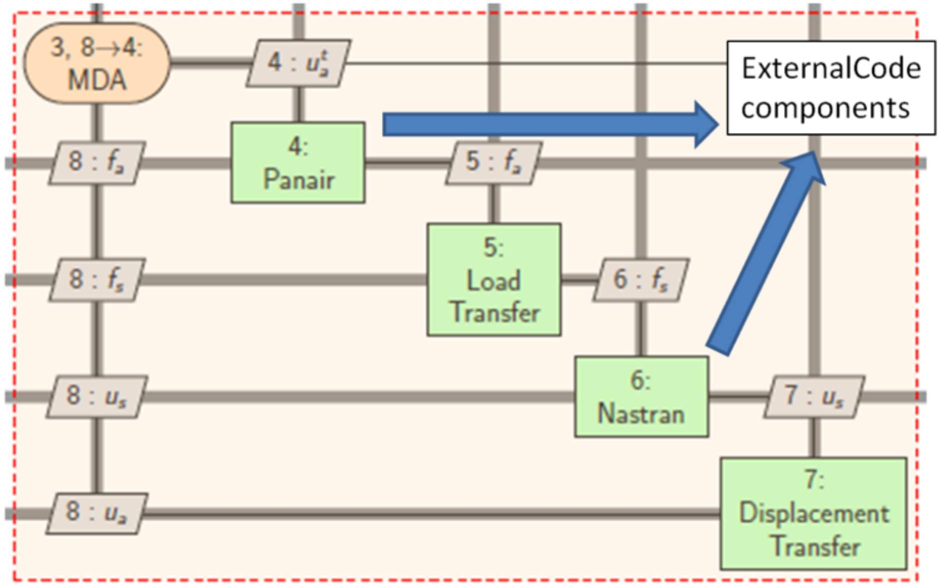


[Lambe and Martins, Structural and Multidisciplinary Optimization, 2012]

Static aeroelasticity Optimization

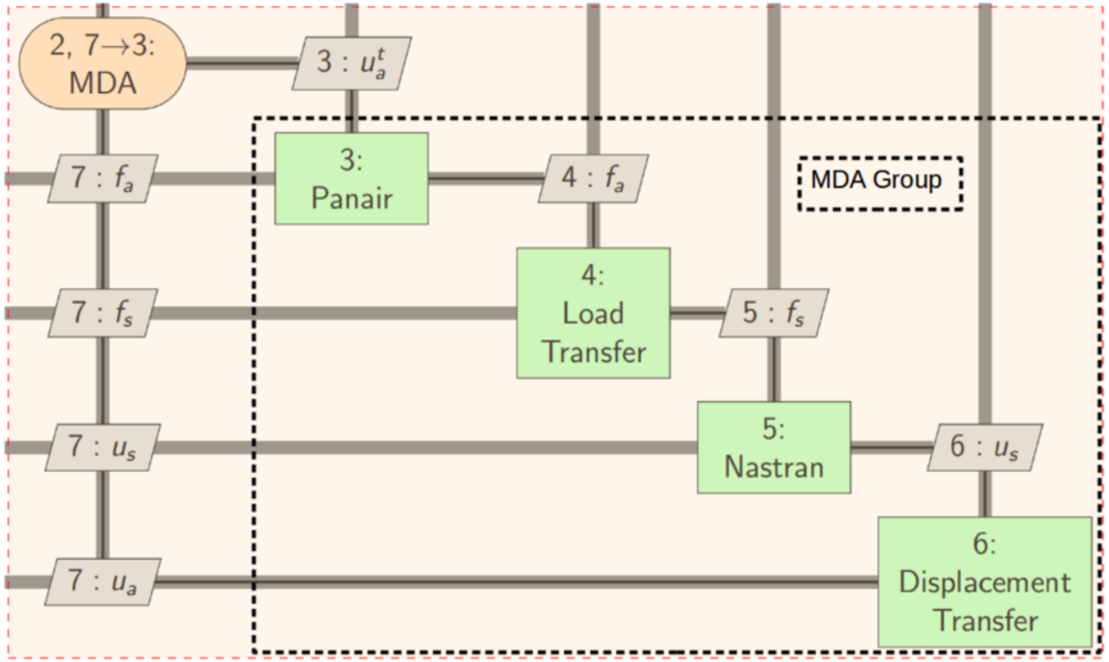


Implementation in OpenMDAO (1)



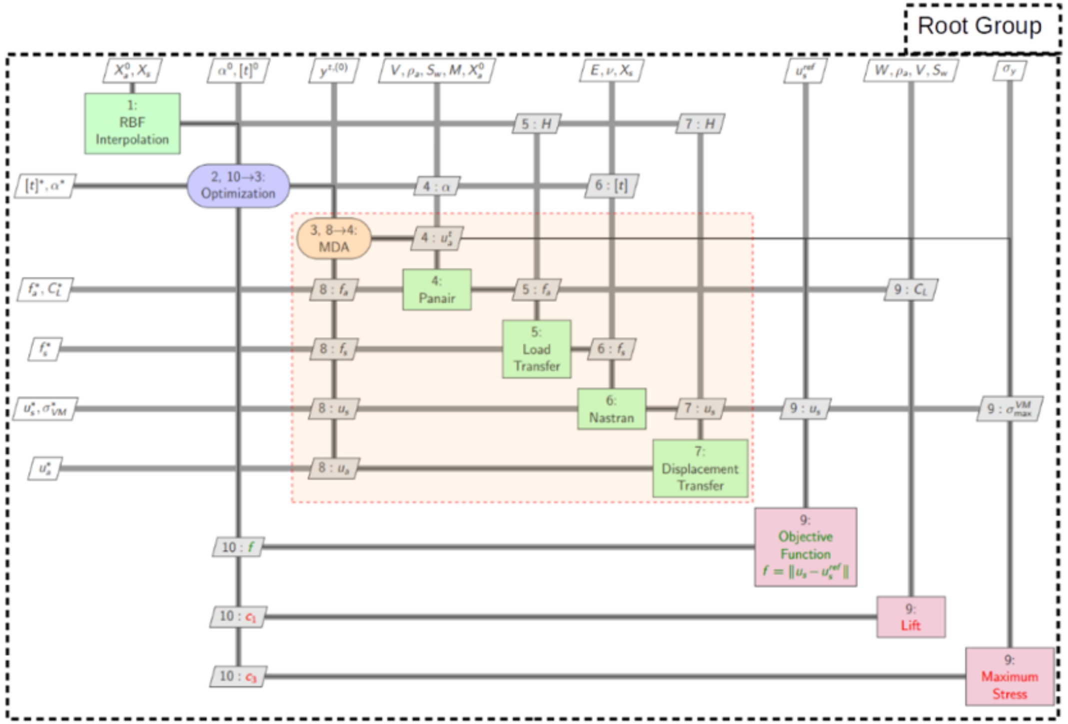
- ExternalCode type of component
- From the inputs of the component, the input file of the external analysis code is written
- Analysis is run
- Output files are read and the outputs are set accordingly

Implementation in OpenMDAO (2)



- All components are added into a group
- The nonlinear solver of the group is defined as Gauss–Seidel

Implementation in OpenMDAO (3)



- The optimizer is defined as the problem's driver
- MDF architecture

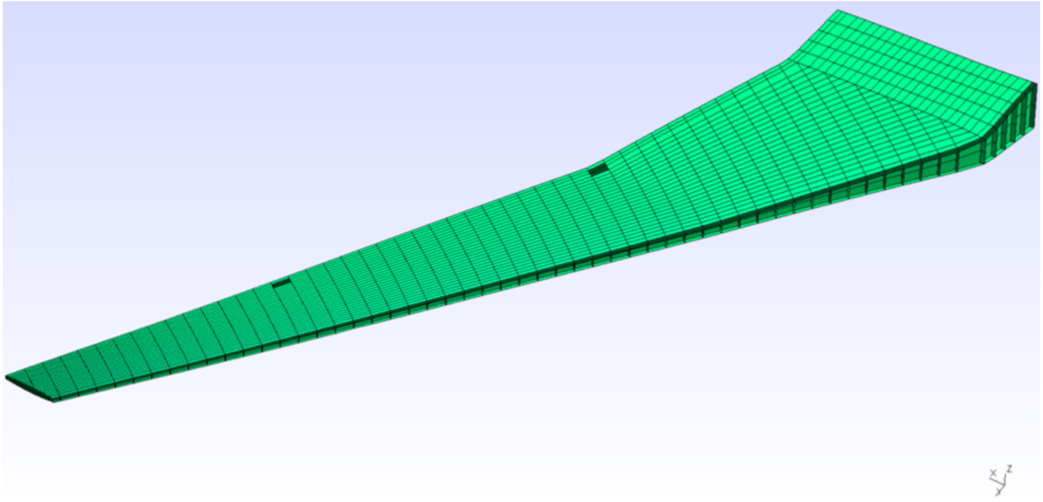
- The rest of components and MDA group are added larger group

2. First application: Mode tracking strategy

- Blind identification
- From ONERA Chatillon's optimized CRM (thanks to C. Blondeau)

FROM A GIVEN MODAL BASIS AND GEOMETRY, CAN WE UPDATE A FEM ?

Reference Design* (jig shape): For all elements $t_r = 8.89mm$



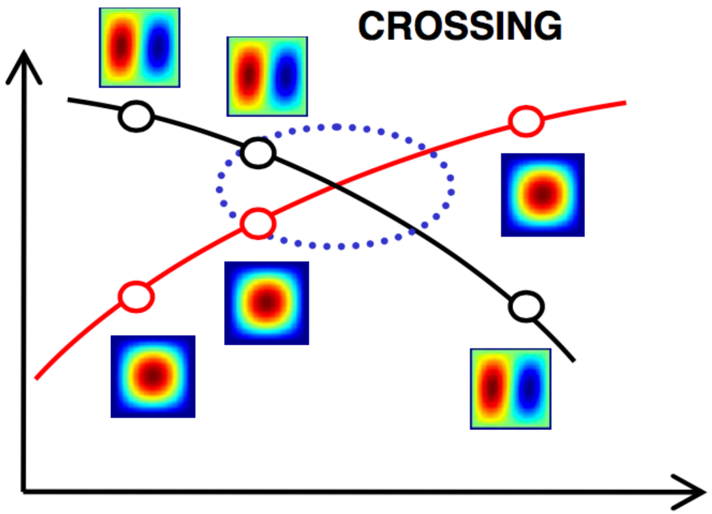
Model provided by T. Achard and C. Blondeau*

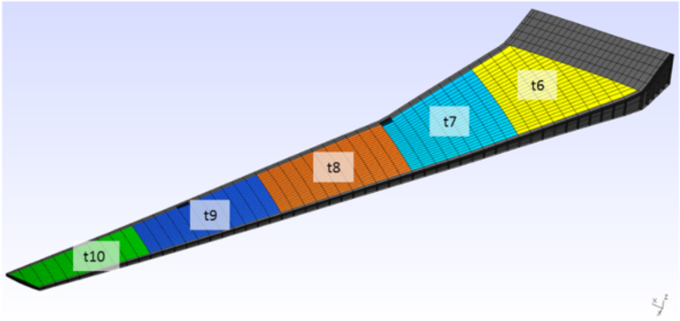
Modes pairing/tracking: Problem definition

Thickness initialization :Vector of size 10 t1-t10 (meter):

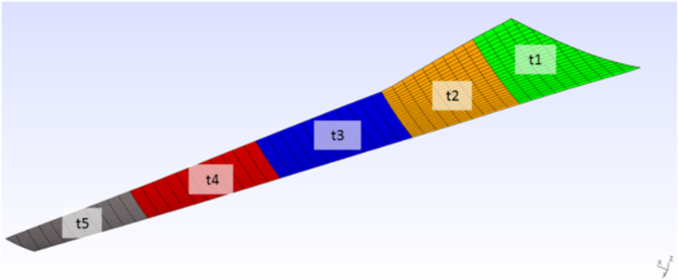
array([
0.01863388, 0.01661411, 0.01273371, 0.01495363, 0.00847329, 0.01743593, 0.02332176, 0.02023447, 0.02068164, 0.0213995])

Objective Function		**Dimension**	**Bounds**
Mode shape difference minimization	$\min(N - \mathrm{trace}(\mathrm{MAC}([\Phi_r], [\Phi_m])))$	$\mathbb{R}$	
Design Variables			
Skin thicknesses vector	$[t]$	$\mathbb{R}^{10}$	$[0.0889, 26.67]$ mm
Constraints			
Reduced frequency matching	$\lVert\omega_r - \omega_m\rVert = 0$	$\mathbb{R}$	
Mass matching	$M_r - M_m = 0$	$\mathbb{R}$	
Generalized masses matching	$\lVert m_r - m_m\rVert = 0$	$\mathbb{R}$	



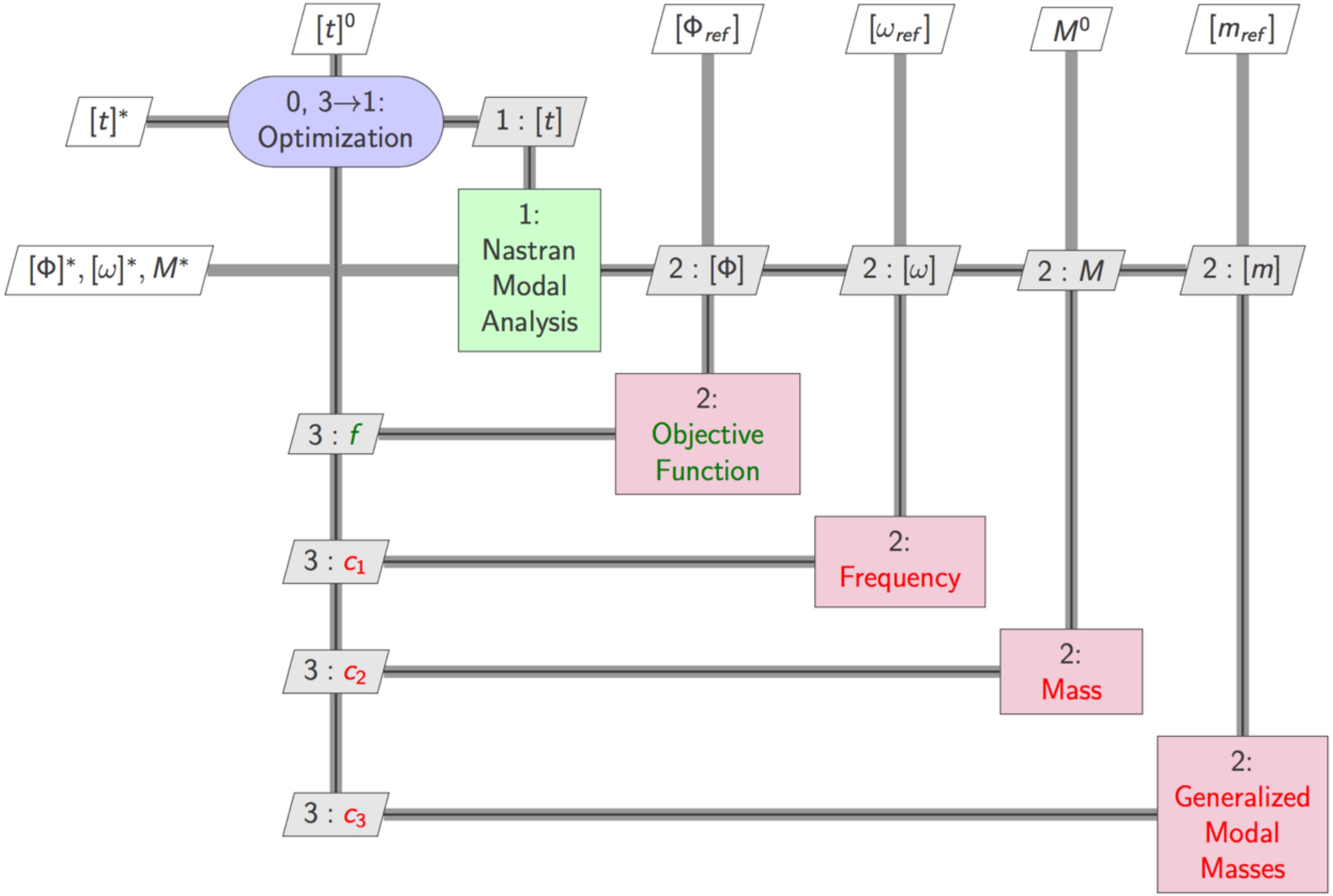


→ Upper skin panels

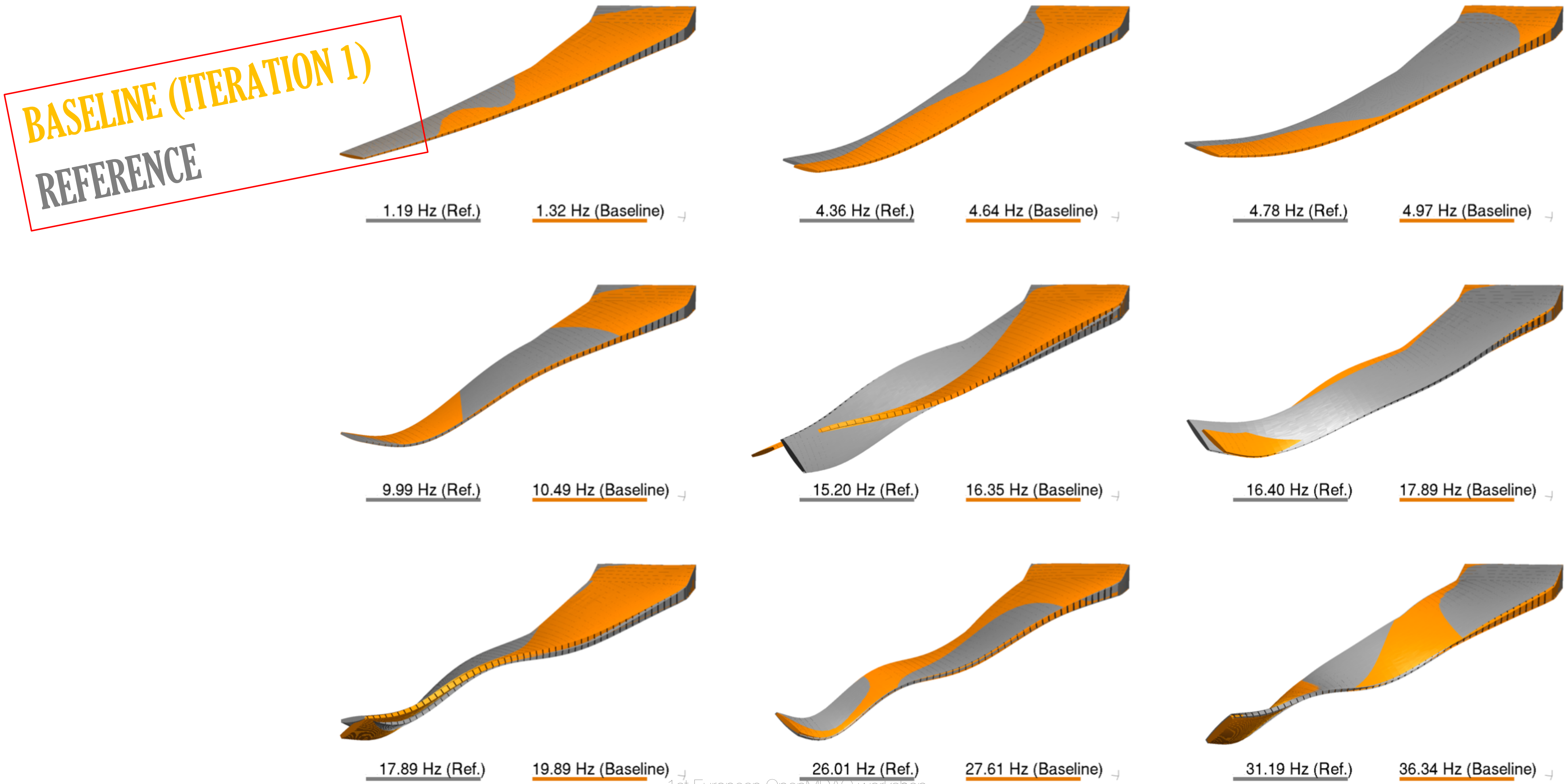


Lower skin panels ←

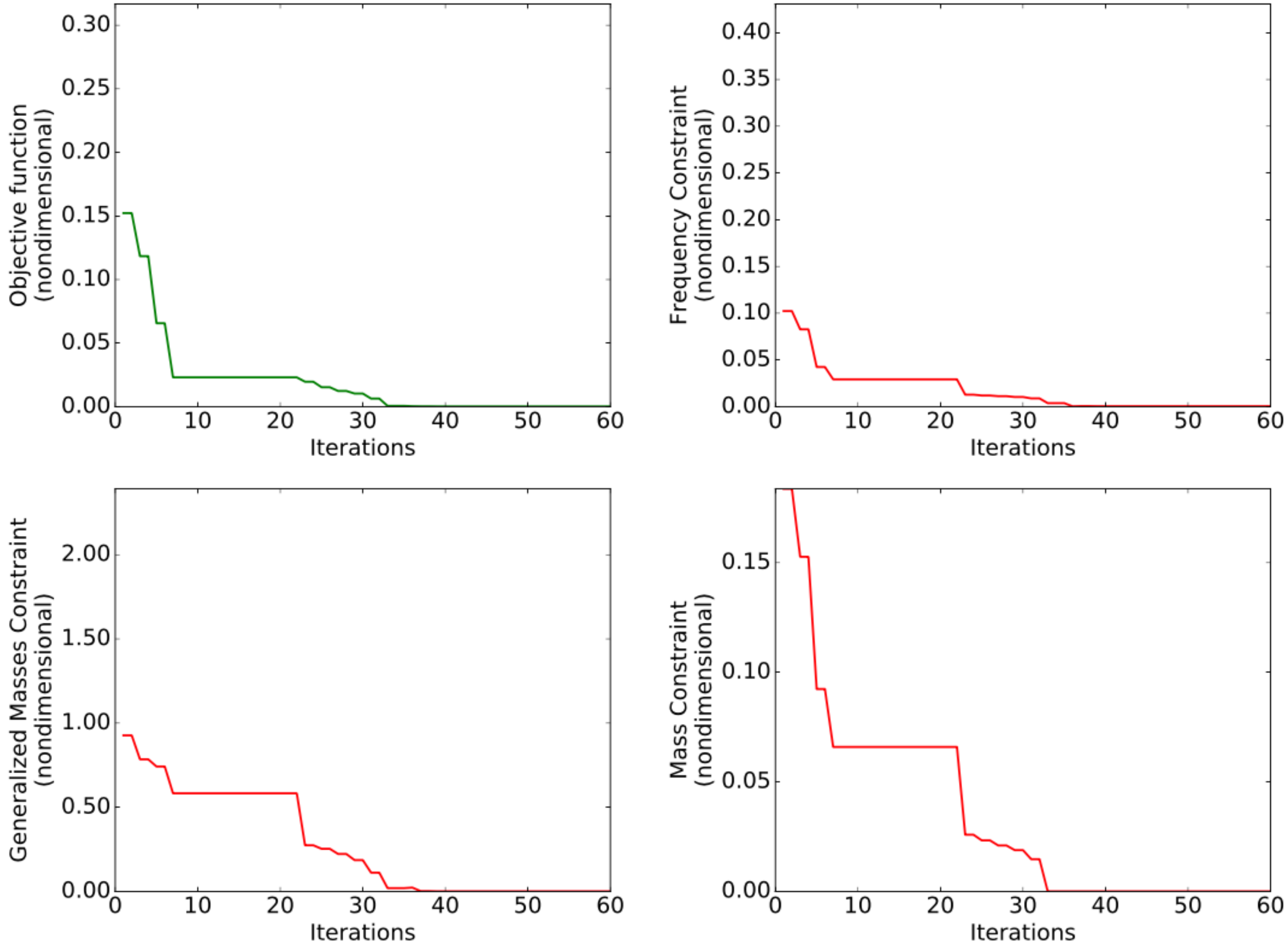
Modal Optimization



1st Validation CRM Blind Updating



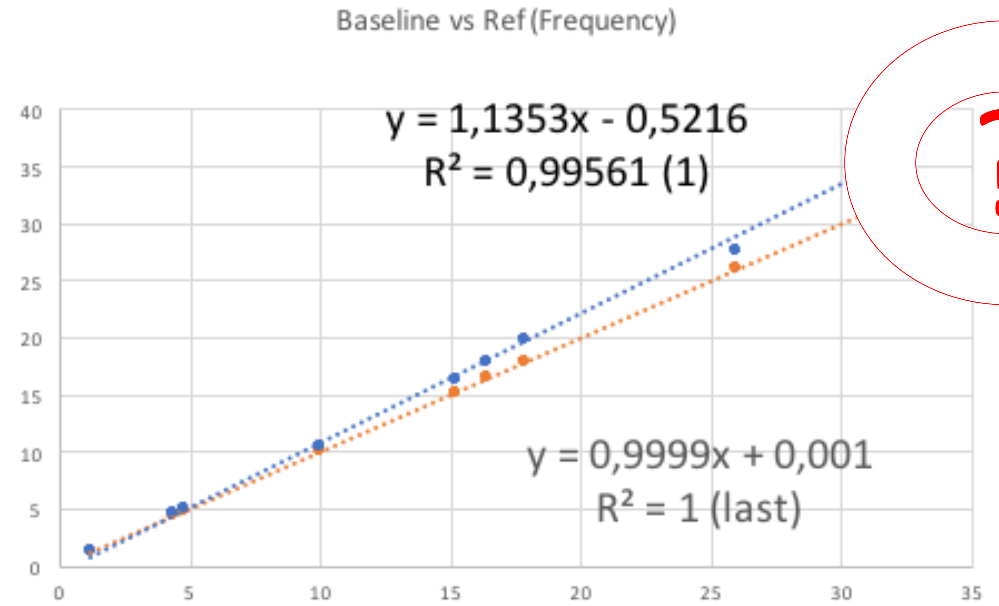
Results of the Optimization (SLSQP)

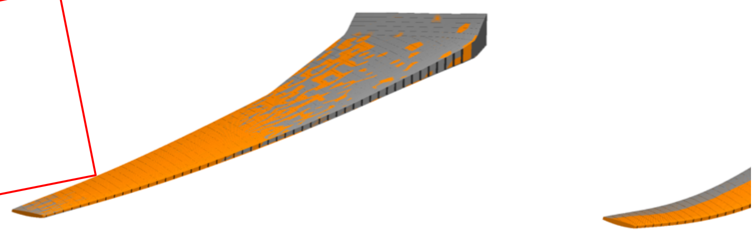


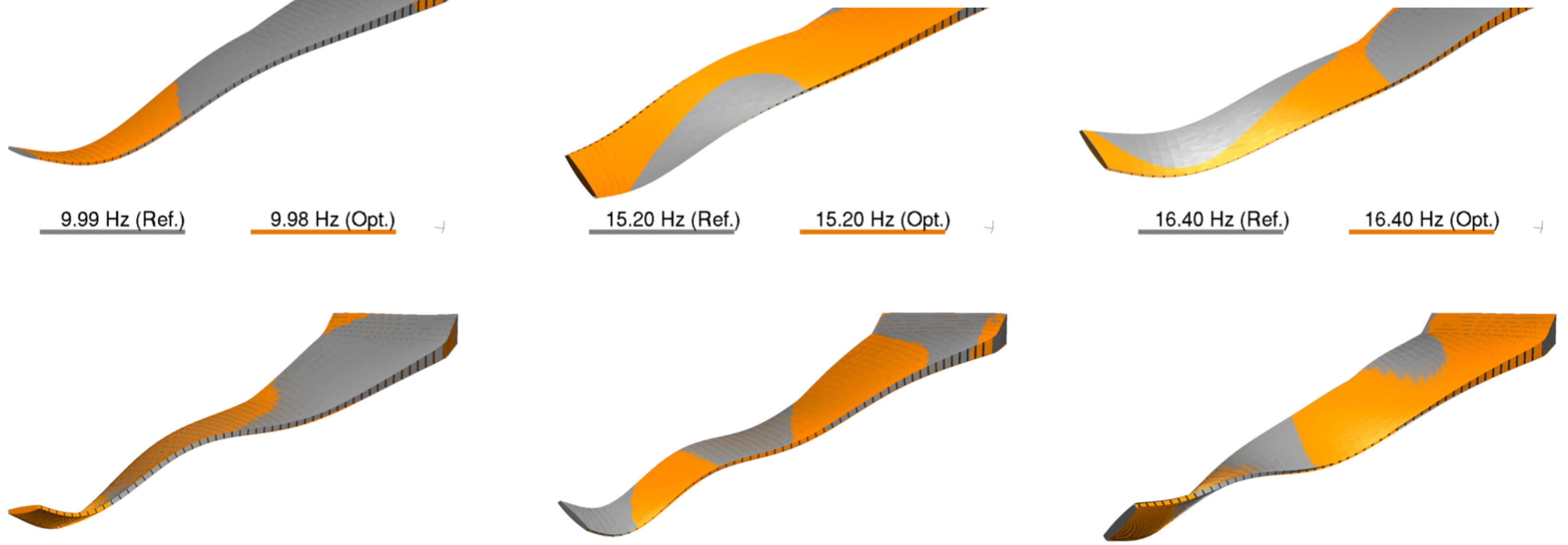
Graphicaly AT CONVERGENCE…

BASELINE (ITERATION Last)

REFERENCE







3. Second application: Flutter similarity

- Wing planform optimization using Nastran DLM

Can we easily find the optimal planform for the scaled model that ensure Flutter similarity with a reference aircraft? We are

Theoretical Background

Aeroelastic scaling theory and similarity criteria

With the purpose of determining the parameters that must be respected for the design of an aeroelastically scaled flight demonstrator, we will adimensionalize the dynamic aeroelastic equation of motion,

$$[\mathbf{M}]\{\ddot{x}\} + [\mathbf{K}]\{x\} = [\mathbf{A_k}]\{x\} + [\mathbf{A_c}]\{\dot{x}\} + [\mathbf{A_m}]\{\ddot{x}\} + [\mathbf{M}]\{a_g\},$$

where $[\mathbf{M}]$ is a vector of elastic and rigid body degrees of freedom, $[\mathbf{K}]$ is the stifness matrix, $[\mathbf{A_k}]$, $[\mathbf{A_c}]$, and $[\mathbf{A_m}]$ are the aerodynamic matrices, which relate the aerodynamic forces to the displacements, speeds, and accelerations respectively, and $\{a_g\}$ is the vector of gravitational acceleration for each degree of freedom.

Final normalized equation… and list of the conditions

$$\langle \bar{\mathbf{m}} \rangle \{\overset{\star\star}{\eta}\} + \left\langle \bar{\mathbf{m}}\bar{\omega}^{\mathbf{2}} \right\rangle \{\eta\} = \frac{1}{2}\frac{\mu_1}{\kappa_1^2}\left([\bar{\mathbf{a}}_{\mathbf{k}}]\{\eta\} + \kappa_1[\bar{\mathbf{a}}_{\mathbf{c}}]\{\overset{\star}{\eta}\} + \kappa_1^2[\bar{\mathbf{a}}_{\mathbf{m}}]\{\overset{\star\star}{\eta}\}\right) + \frac{1}{\kappa_1^2 Fr^2}\langle \bar{\mathbf{m}}\rangle [\mathbf{\Phi}]^{-1}\{\bar{a}_g\}.$$

implies that the solution of two models which have different scales is the same (in terms of the nondimensional variables) as long as the nondimensional parameters are respected. This translates into satisfying the following conditions:

1. reduced frequency of the first mode κ_1,
2. inertia ratio μ_1,
3. Froude number Fr,
4. nondimensional modal masses $\langle \bar{\mathbf{m}} \rangle$,
5. nondimensional modal frequencies $\langle \bar{\omega} \rangle$,
6. nondimensional mode shapes $[\mathbf{\Phi}]$,
7. aerodynamic shape,
8. Mach number if compressibility effects are important, and
9. Reynolds number if viscous effects are important.

Nonlinear aeroelastic **scaling** of a joined-wing **aircraft**
AP **Ricciardi**, RA Canfield, MJ Patil… - Proceedings of the 53rd …, 2012 - arc.aiaa.org
This paper develops and demonstrates a nonlinear aeroelastic scaling procedure. Previous work showed that matching scaled structural frequencies and mode shapes as well as a buckling eigenvalue produced a scaled model that did not have adequately consistent
Cité 8 fois Autres articles Les 2 versions

[HTML] Nonlinear aeroelastic-**scaled**-model optimization using equivalent static loads
AP **Ricciardi**, CAG Eger, RA Canfield, MJ Patil - Journal of **Aircraft**, 2014 - arc.aiaa.org
Copyright© 2014 by Anthony P. Ricciardi., Charles AG Eger, Robert A. Canfield, and Mayuresh J. Patil. Published by the American Institute of Aeronautics and Astronautics, Inc., with permission. Copies of this paper may be made for personal or internal use, on condition
Cité 8 fois Autres articles Les 6 versions Web of Science: 5

[HTML] aiaa.org

Problem description

Reference aircraft: r
Scaled model: m

This complex aerodynamic matrix is computed for each frequency ω and depends on the flow conditions (M). Taking this into consideration, and considering that we have a reference aircraft (r) and the model we want to optimize to have the same aeroelastic behavior (r), we can write Eq. for each aircraft as

$$\langle \bar{\mathbf{m}}_\mathbf{r} \rangle \{\overset{\star\star}{\eta}\} + \left\langle \bar{\mathbf{m}}_\mathbf{r} \bar{\omega}_\mathbf{r}^2 \right\rangle \{\eta\} = \frac{1}{2} \frac{\mu_{1r}}{\kappa_{1r}^2} [\bar{\mathbf{a}}_\mathbf{hr}(\mathbf{X}_\mathbf{ar}, \kappa, \mathbf{M}_\mathbf{r})] \{\eta\},$$

$$\overbrace{\langle \bar{\mathbf{m}}_\mathbf{m} \rangle \{\overset{\star\star}{\eta}\} + \left\langle \bar{\mathbf{m}}_\mathbf{m} \bar{\omega}_\mathbf{m}^2 \right\rangle}^{\text{Match } [\mathbf{\Phi}],\ \langle\bar{\omega}\rangle,\ \langle\bar{\mathbf{m}}\rangle \text{ (from the problem } K-\omega^2[\mathbf{M}]\{\phi\}=0) \text{ through optimization}} \{\eta\} = \frac{1}{2} \frac{\mu_{1m}}{\kappa_{1m}^2} \overbrace{[\bar{\mathbf{a}}_\mathbf{hm}(\mathbf{X}_\mathbf{am}, \kappa, \mathbf{M}_\mathbf{m})]}^{\text{Equal if same aerodynamic shape and flow similarity}} \{\eta\}$$

What if the flow is not similar?

Reference aircraft: r

Scaled model: m

$$\underbrace{\langle \bar{\mathbf{m}}_{\mathbf{r}} \rangle \{\overset{\star\star}{\eta}\} + \langle \bar{\mathbf{m}}_{\mathbf{r}} \bar{\omega}_{\mathbf{r}}^{2} \rangle}\{\eta\} = \frac{1}{2}\frac{\mu_{1r}}{\kappa_{1r}^{2}} \underbrace{[\bar{\mathbf{a}}_{\mathbf{hr}}(\mathrm{X}_{\mathbf{ar}}, \kappa, \mathrm{M}_{\mathbf{r}})]}\{\eta\}$$

$$\overbrace{\langle \bar{\mathbf{m}}_{\mathbf{m}} \rangle \{\overset{\star\star}{\eta}\} + \langle \bar{\mathbf{m}}_{\mathbf{m}} \bar{\omega}_{\mathbf{m}}^{2} \rangle}^{\text{matched through modal optimization}} \{\eta\} = \frac{1}{2}\frac{\mu_{1m}}{\kappa_{1m}^{2}} \overbrace{[\bar{\mathbf{a}}_{\mathbf{hm}}(\mathrm{X}_{\mathbf{am}}, \kappa, \mathrm{M}_{\mathbf{m}})]}^{\text{optimize w.r.t. } \mathrm{X}_{am}}\{\eta\}$$

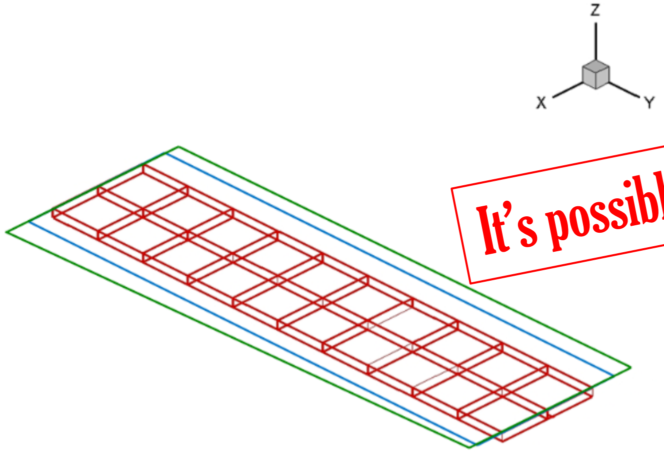
Objective function

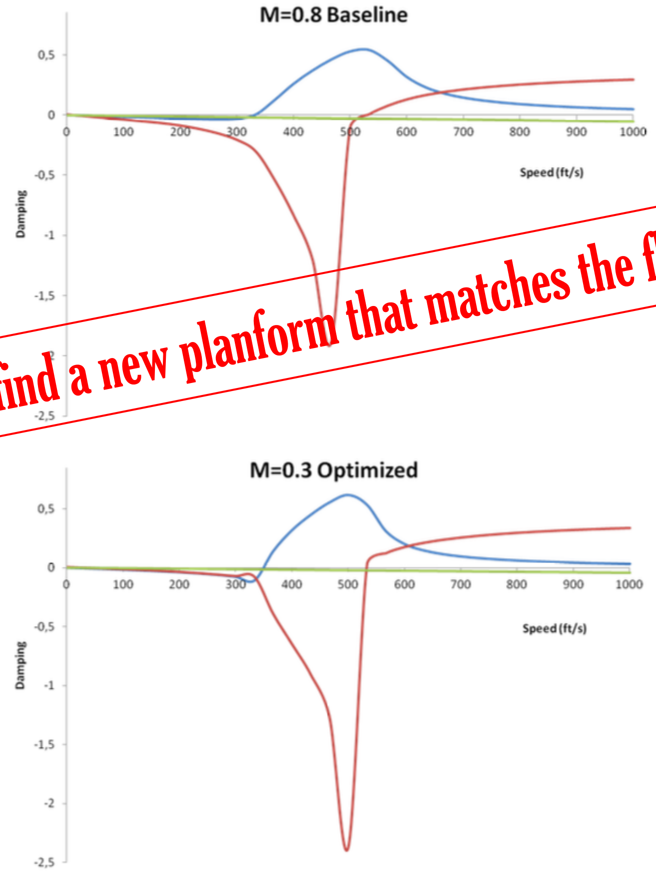
we can define an optimization problem that searches to optimize the design variables defining the planform of the model wing in order to minimize the difference between these two terms. Thus, we can an objective function

$$f = \sum_i (\|[\bar{\mathbf{a}}_{\mathbf{hr}}(\mathbf{X}_{\mathbf{ar}}, \kappa_{\mathbf{i}}, \mathbf{M}_{\mathbf{r}})] - [\bar{\mathbf{a}}_{\mathbf{hm}}(\mathbf{X}_{\mathbf{am}}, \kappa_{\mathbf{i}}, \mathbf{M}_{\mathbf{m}})]\|)$$

that quantifies the difference between the two aerodynamic models through the L^2 sum of the norms of the difference of the aerodynamic matrices for a set of reduced frequencies.

Goland Wing results





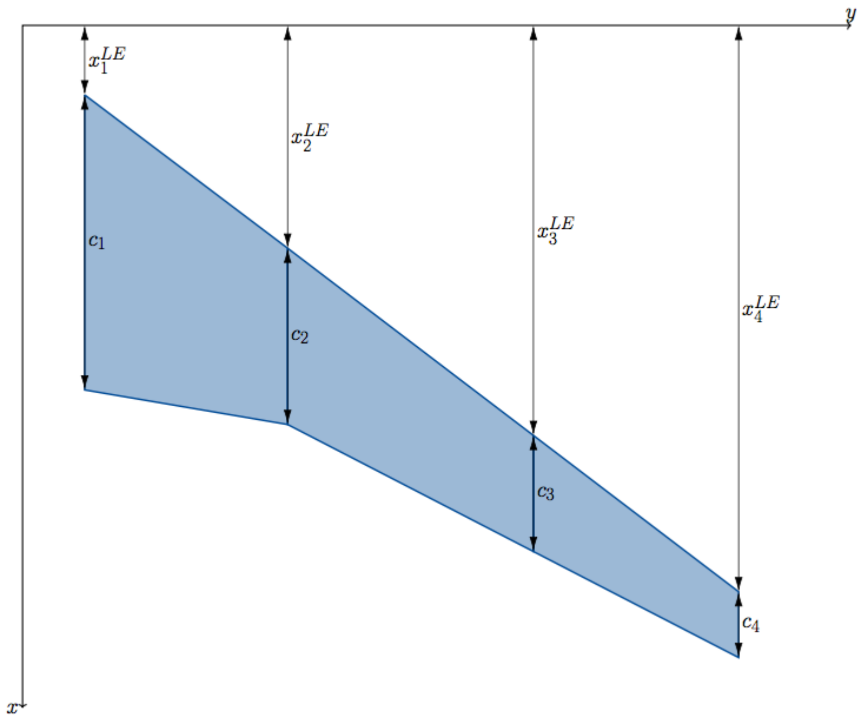
It's possible to find a new planform that matches the flutter map of the reference aircraft

Objective function & Design Variables

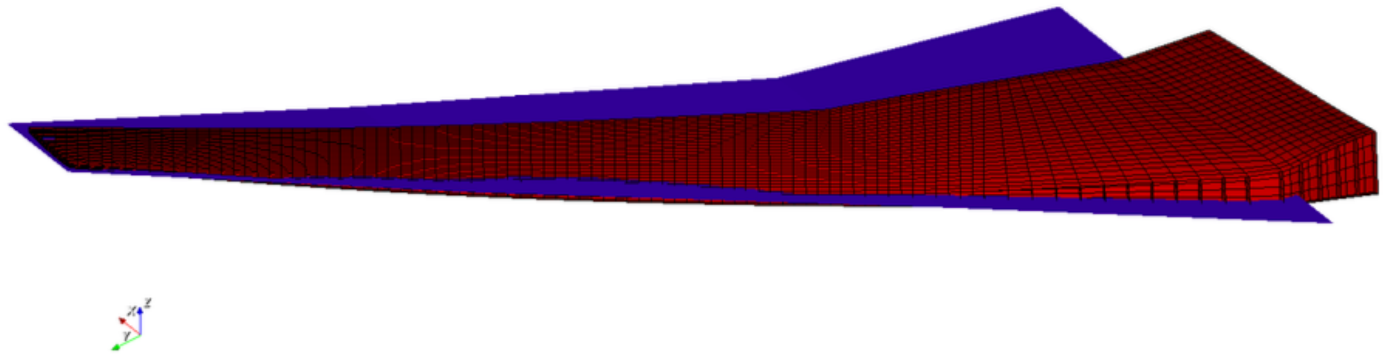
Objective Function		**Dimension**	**Bounds**
Aerodynamic matrix difference minimization	$\sum_i (\|\|[\bar{\mathbf{a}}_{\mathbf{hr}}(X_{\mathbf{ar}}, \kappa_{\mathbf{i}}, M_{\mathbf{r}})] - [\bar{\mathbf{a}}_{\mathbf{hm}}(X_{\mathbf{am}}, \kappa_{\mathbf{i}}, M_{\mathbf{m}})]\|\|)$	$\mathbb{R}$	
Design Variables			
Chord lengths	$[c]$	$\mathbb{R}^4$	$[0.5c_{baseline}, 2.5c_{baseline}]$
Leading edge positions	$[x_{le}]$	$\mathbb{R}^4$	$[0.5x^{le}_{baseline}, 1.5x^{le}_{baseline}]$

Mr=0.85

Mm=0.3

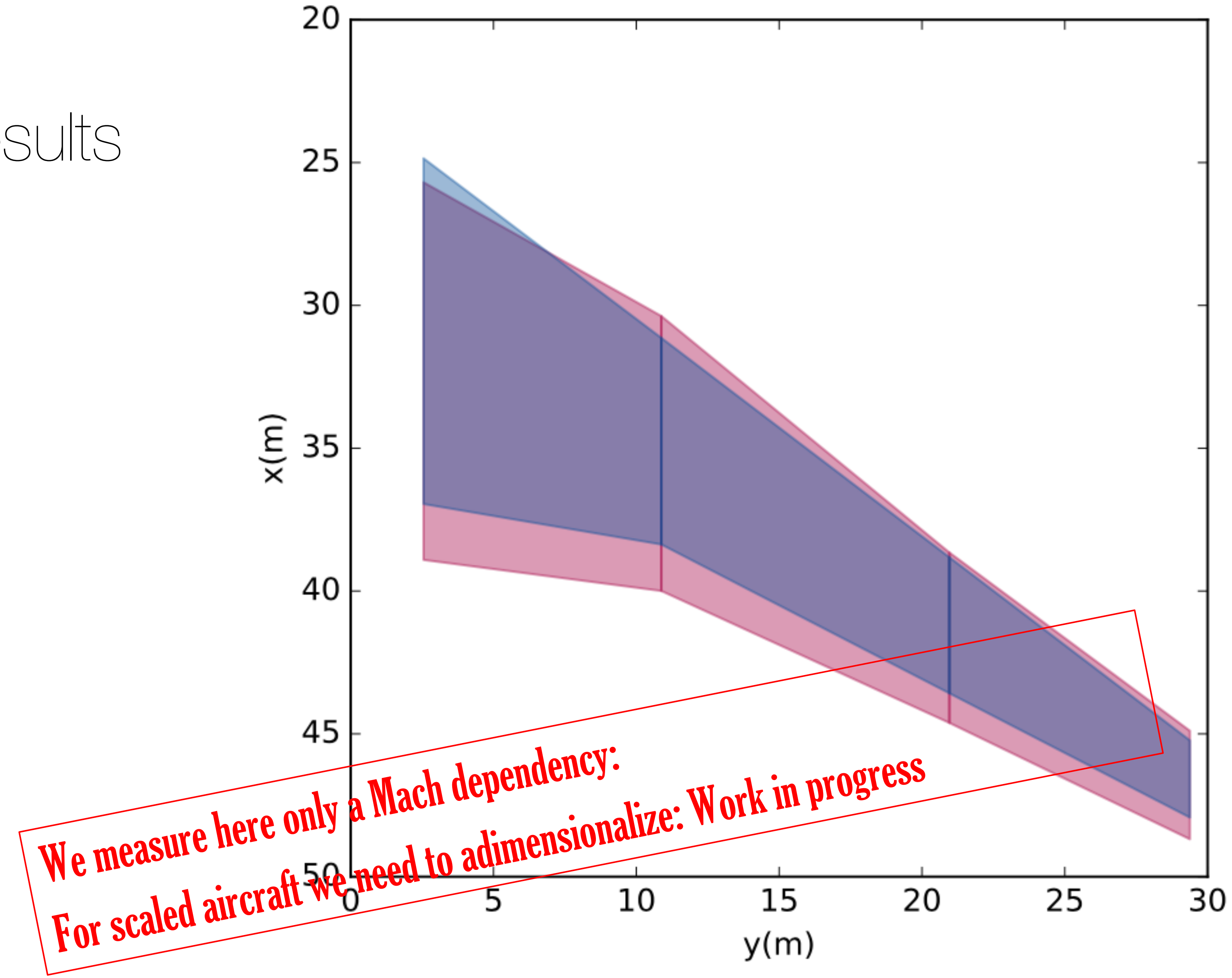


Design variables of the wing planform.



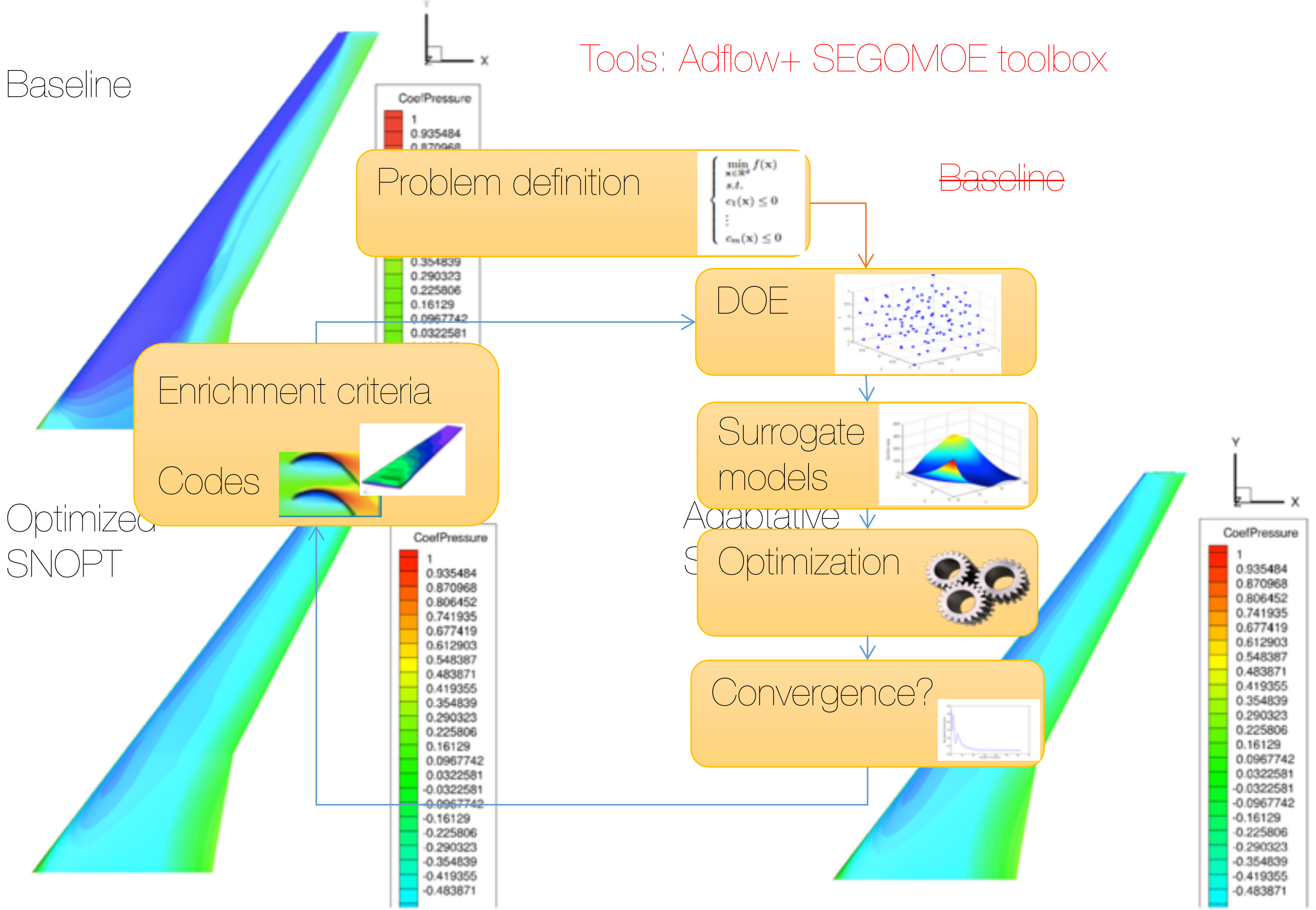
Aerodynamic surface of the doublet lattice method along with the FEM model.

Results



Optimized planform (red) and baseline (blue).

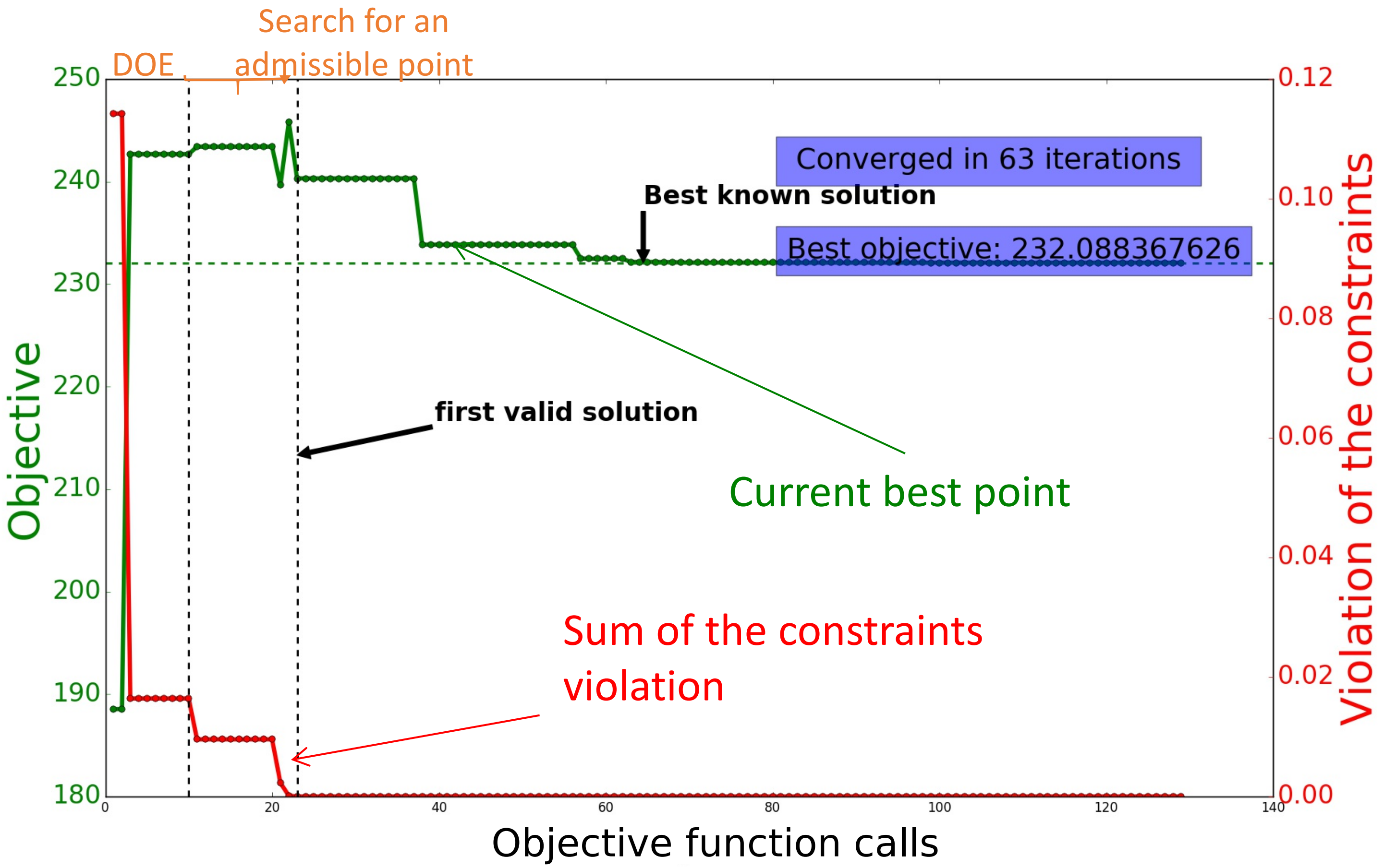
SEGOMOE (A surrogate based optimizer with adaptative sampling)



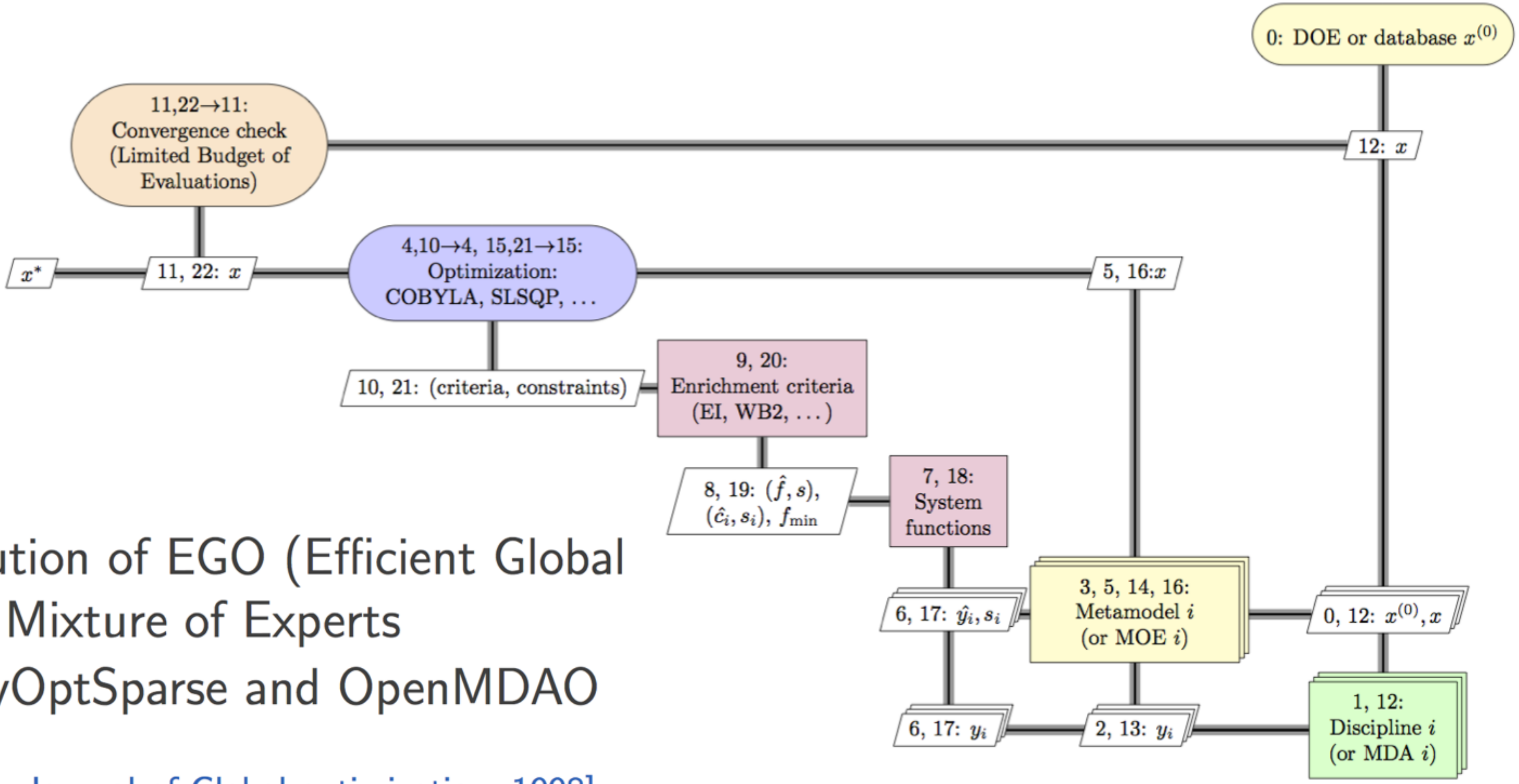
N. Bartoli, T. Lefevbre, N. Bons, M. Bouhlel, S. Dubreuil, R. Olivanti, J.R.R. Martins and J. Morlier. An adaptive optimization strategy based on mixture of experts for wing aerodynamic design optimization. Proceedings of AIAA AVIATION Forum 5-9 June 2017, Denver, Colorado 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference 2017

SEGOMOE results: objective function

Initial 9-points DOE
First steps to find an admissible point (constraints satisfied)
Then iterative process to reduce the objective function



SEGOMOE (A surrogate based optimizer with adaptative sampling)



- SEGOMOE: a evolution of EGO (Efficient Global Optimization) with Mixture of Experts
- Wrapper done to pyOptSparse and OpenMDAO

[Jones, Schonlau and Welch, Journal of Global optimization, 1998]
[Sasena, Ph.D. thesis, University of Michigan, 2002]
[Bartoli et al., AIAA-2016-2301 and AIAA-2017-4433]

Conclusions

- Original contribution on scaled aircraft
- Two elementary bricks have been established to ensure the aeroelastic similiraity
  1. Blind modal identification tested with different initial design (robust updating)
  2. Aeroelastic simillarity between a demonstrator and a reference aircraft was ensured using an MDO formulation
- Good performance of the Surrogate-based optimization methods versus Gradient-based (SLSQP versus SEGOMOE)
- Strong interaction with UoM (PhD of Joan Mas Colomer) : use of High Fidelity CFD code ADflow in our optimization loop
- Last year of Joan's PhD dedicated to mission-based optimization
- Opensource tools for aeroelastic sizing constraints (related to the next presentation on BWB)

Short list of publications

Aeroelastic scaling

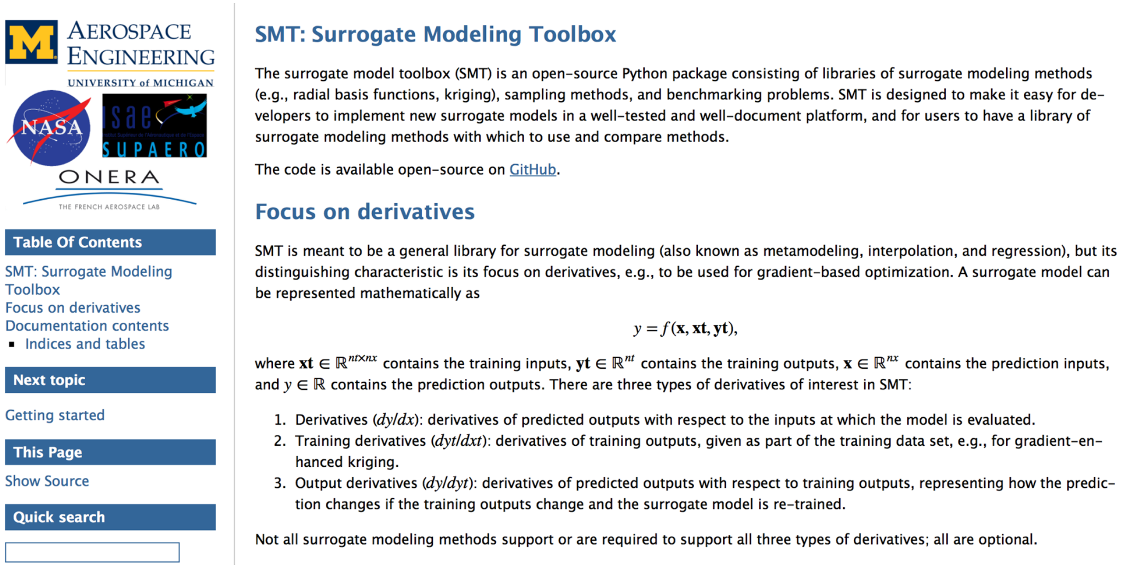
- J. Mas Colomer, N. Bartoli, T. Lefebvre, S. Dubreuil, J.R.R. Martins, E. Benard and J. Morlier. Similarity Maximization of a Scaled Aeroelastic Flight Demonstrator via Multidisciplinary Optimization. Proceedings of 58th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference Grapevine, Texas 2017
- J. Mas Colomer, N. Bartoli, T. Lefebvre, S. Dubreuil, P. Schmollgruber, J.R.R. Martins and J. Morlier. Static and Dynamic Aeroelastic Scaling of the CRM Wing via Multidisciplinary Optimization. WCSMO12 12th World Congress of Structural and Multidisciplinary Optimisation 5 - 9 June 2017, Braunschweig, Germany 2017

Mixture of experts

- N. Bartoli, T. Lefevbre, N. Bons, M. Bouhlel, S. Dubreuil, R. Olivanti, J.R.R. Martins and J. Morlier. An adaptive optimization strategy based on mixture of experts for wing aerodynamic design optimization. Proceedings of AIAA AVIATION Forum 5-9 June 2017, Denver, Colorado 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference 2017projet
- N. Bartoli, I. Kurek, R. Lafage, T. Lefebvre, R. Priem , M. Bouhlel, J. Morlier, V. Stilz and R. Regis. Improvement of efficient global optimization with application to aircraft wing design . Proceedings of 17th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference 2016
- D. Bettebghor, N. Bartoli, S. Grihon, J. Morlier and M. Samuelides. Surrogate modeling approximation using a mixture of experts based on EM joint estimation. Structural and Multidisciplinary Optimization. 43(2)243 - 259. 2011

Surrogate models

Visit :
https://github.com/SMTorg/SMT



SMT: Surrogate Modeling Toolbox

The surrogate model toolbox (SMT) is an open-source Python package consisting of libraries of surrogate modeling methods (e.g., radial basis functions, kriging), sampling methods, and benchmarking problems. SMT is designed to make it easy for developers to implement new surrogate models in a well-tested and well-document platform, and for users to have a library of surrogate modeling methods with which to use and compare methods.

The code is available open-source on GitHub.

Focus on derivatives

SMT is meant to be a general library for surrogate modeling (also known as metamodeling, interpolation, and regression), but its distinguishing characteristic is its focus on derivatives, e.g., to be used for gradient-based optimization. A surrogate model can be represented mathematically as

$$y = f(\mathbf{x}, \mathbf{xt}, \mathbf{yt}),$$

where $\mathbf{xt} \in \mathbb{R}^{nt \times nx}$ contains the training inputs, $\mathbf{yt} \in \mathbb{R}^{nt}$ contains the training outputs, $\mathbf{x} \in \mathbb{R}^{nx}$ contains the prediction inputs, and $y \in \mathbb{R}$ contains the prediction outputs. There are three types of derivatives of interest in SMT:

1. Derivatives (dy/dx): derivatives of predicted outputs with respect to the inputs at which the model is evaluated.
2. Training derivatives (dyt/dxt): derivatives of training outputs, given as part of the training data set, e.g., for gradient-enhanced kriging.
3. Output derivatives (dy/dyt): derivatives of predicted outputs with respect to training outputs, representing how the prediction changes if the training outputs change and the surrogate model is re-trained.

Not all surrogate modeling methods support or are required to support all three types of derivatives; all are optional.