MDO Workshop@DLR

Recent advances in structural and multidisciplinary optimization @SUPAERO

Prof. J. Morlier

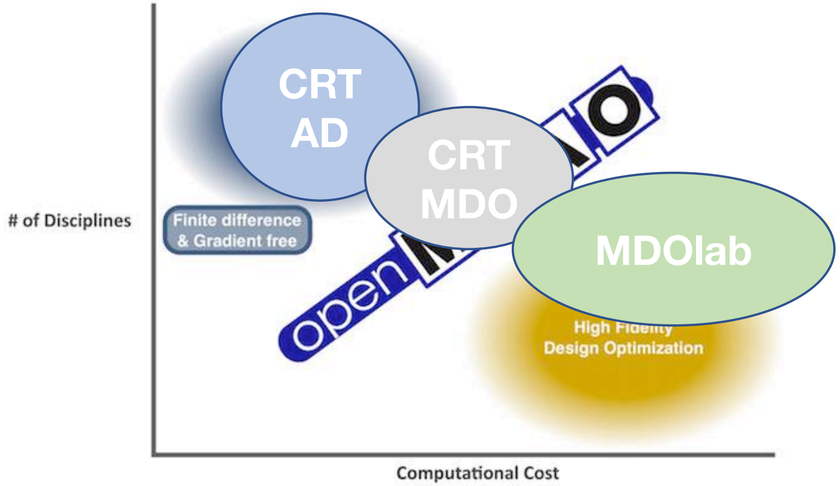
Currently I'm working on the fields:

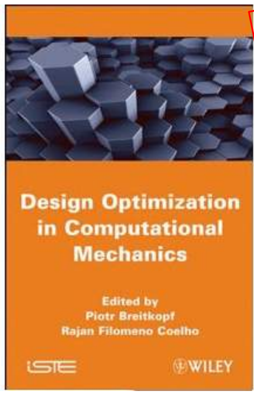
- MDO, Topology optimization, surrogate modeling, machine learning,

But in the past

- SHM, composites structures, system identification, Neural networks

Common Research Team (ONERA-SUPAERO) : New in 2015





Started in 2007 with
Manuel Samuelides&
Nathalie Bartoli

Our Goals

- Reduce in a « smart way » the computation time of optimization for coupled simulations
- Global Optimization using surrogate modeling → fixed budget (enriching process)
- Specialized surrogates for HD (engineering) problems and UQ
- Taking into account different levels of fidelity

N. Bartoli et al, Improvement of efficient global optimization with mixture of experts: methodology developments and preliminary results in aircraft wing design, Proceedings of AIAA 2016

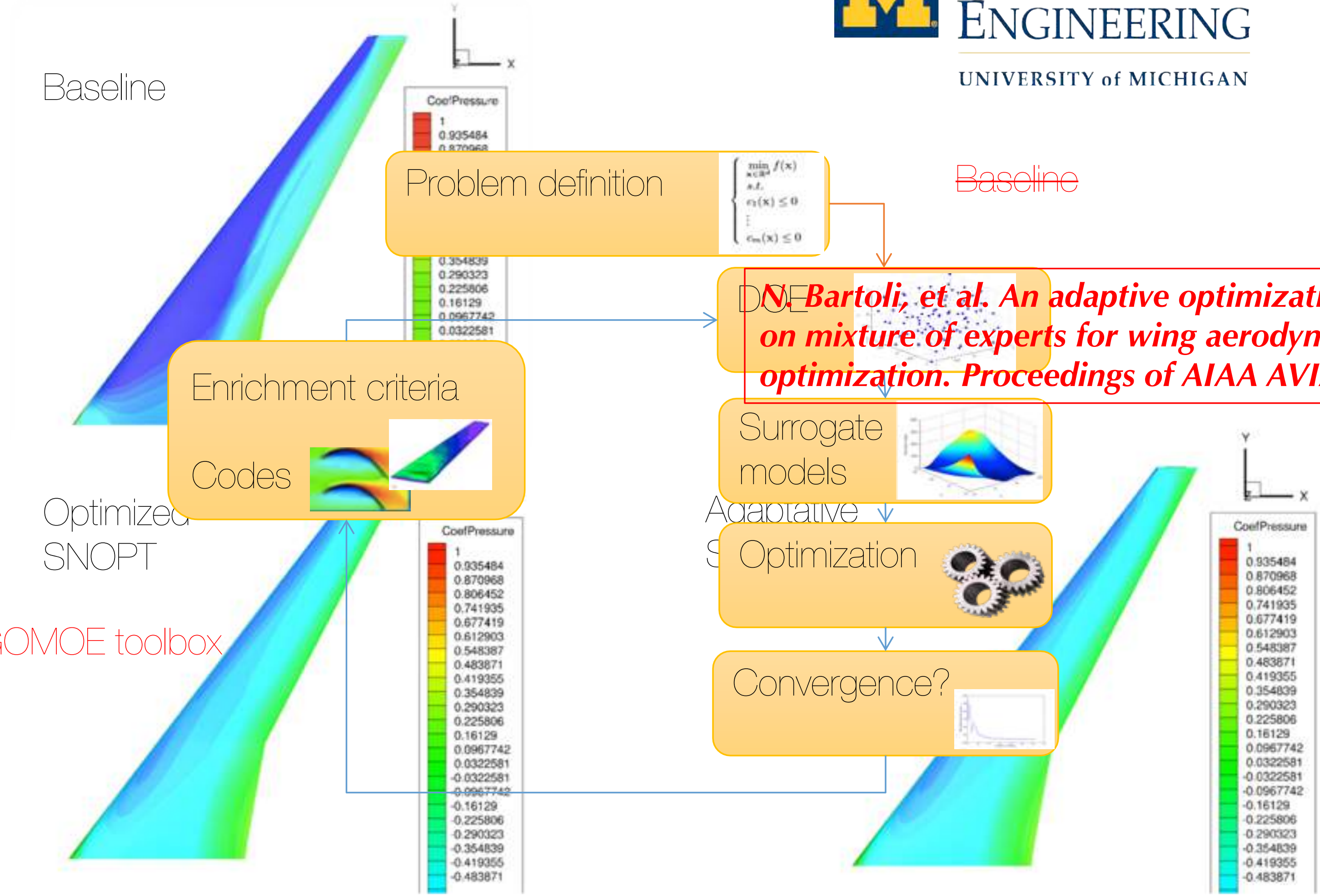
→ Methods applied to AD Aircraft Design,: Put the aircraft structure / aeroelasticity in the loop at the early stage of MDO process

→ compatible with

openMDAO

AIAA Aviation 2017, Collaboration with MDOlab

AEROSPACE ENGINEERING
UNIVERSITY of MICHIGAN



Tools: Adflow+ SEGOMOE toolbox

N. Bartoli, et al. An adaptive optimization strategy based on mixture of experts for wing aerodynamic design optimization. Proceedings of AIAA AVIATION 2017

Outlines

1. Overview of actual PhDs
2. OpenMDAO+ OpenNastran, but why?
3. Discrete Continuous Optimization in CSM

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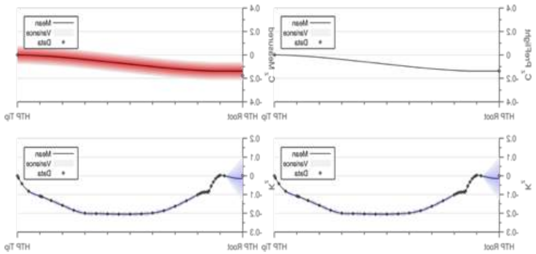
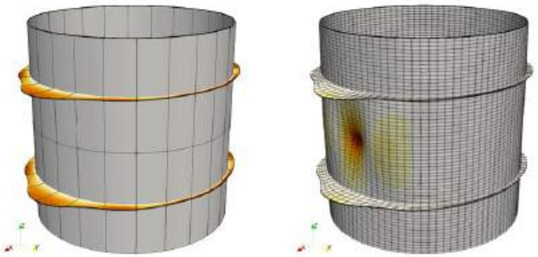
1. Overview of actual PhDs
2. OpenMDAO+ OpenNastran, but why?
3. Discrete Continuous Optimization in CSM

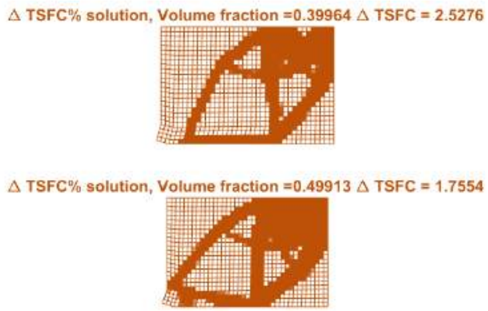
My Group

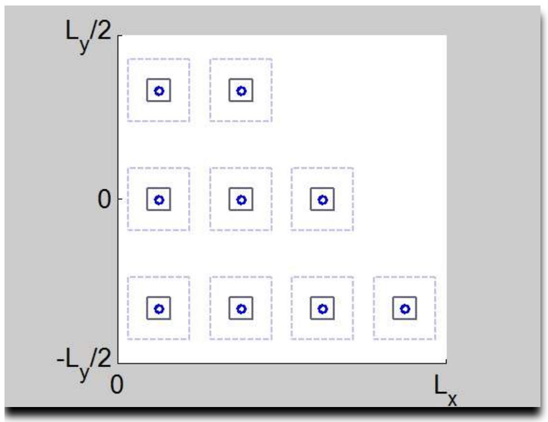
http://www.institut-clement-ader.org/pageperso.php?id=jmorlier

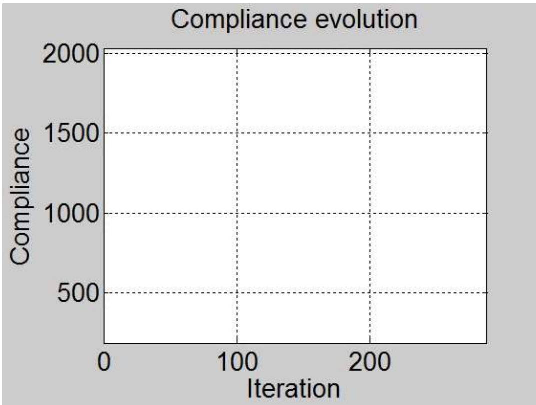
- 5 PhDs, 1 postdoc

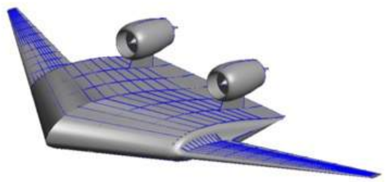








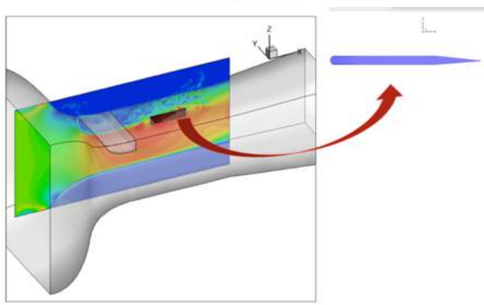




$$\min_{\substack{(\boldsymbol{t},\boldsymbol{A}) \in \mathbb{R}^{2N} \\ \boldsymbol{c} \in \Gamma^N}} W(\boldsymbol{c},\boldsymbol{t},\boldsymbol{A})$$

Subjected to:

$$\boldsymbol{RF}(\boldsymbol{c},\boldsymbol{t},\boldsymbol{A},IL(\boldsymbol{c},\boldsymbol{t},\boldsymbol{A})) \geq 1$$
$$G(\boldsymbol{c},\boldsymbol{t},\boldsymbol{A}) \leq 0$$
$$\underline{t}(\boldsymbol{c}) \leq \boldsymbol{t} \leq \overline{t}(\boldsymbol{c})$$
$$\underline{\alpha}(\boldsymbol{c}) \leq \frac{\boldsymbol{A}}{\boldsymbol{bt}} \leq \overline{\alpha}(\boldsymbol{c})$$



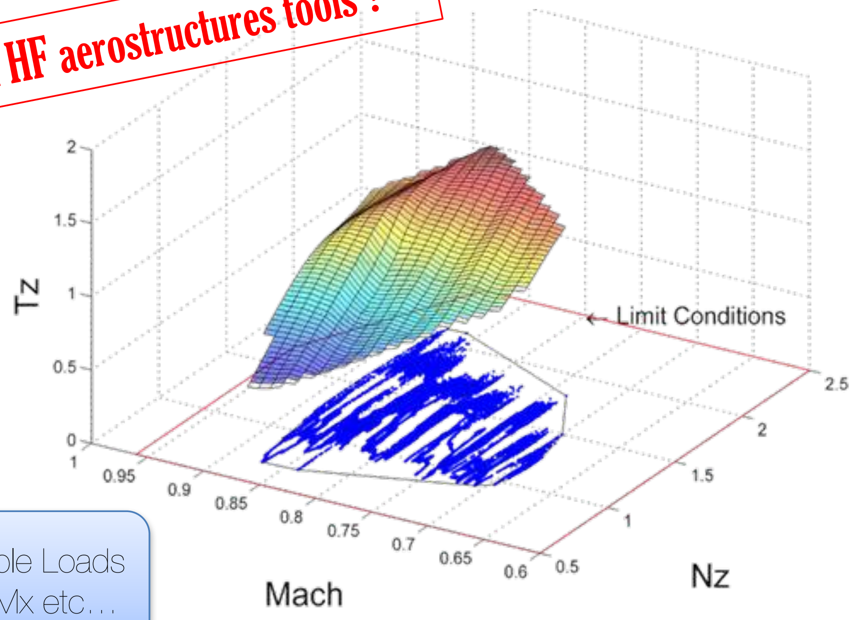
Machine learning for load estimation (Ankit Chiplunkar, AIRBUS FUND)

Kriging	Gaussian Processes
Developed by Daniel Krige – 1951; formalized by Georges Mathéron	Neural network with infinite neurons tend to Gaussian Process 1994
Evaluation: minimize error variance	Evaluation: Marginal Likelihood

Loads identification

First flight ready → Flight test of Maneuvers → Capture aero/ structural data → Extract loads → Certification of limit loads

Can we extrapolate limit loads using both measurements and HF aerostructures tools ?

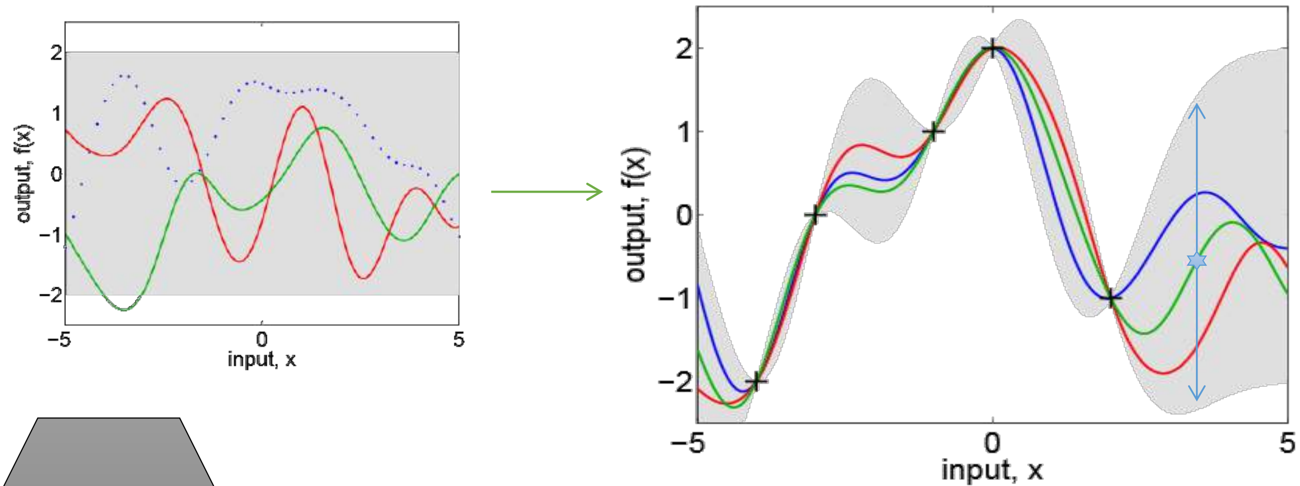


Can we automate the process?

Statistical step

A/C states α, β, M, δ's → Distributed Gaussian Process → Flexible Loads Tz, Mx etc…

Gaussian Process Regression



Prior
f|x
$GP(0, K)$

X
Y

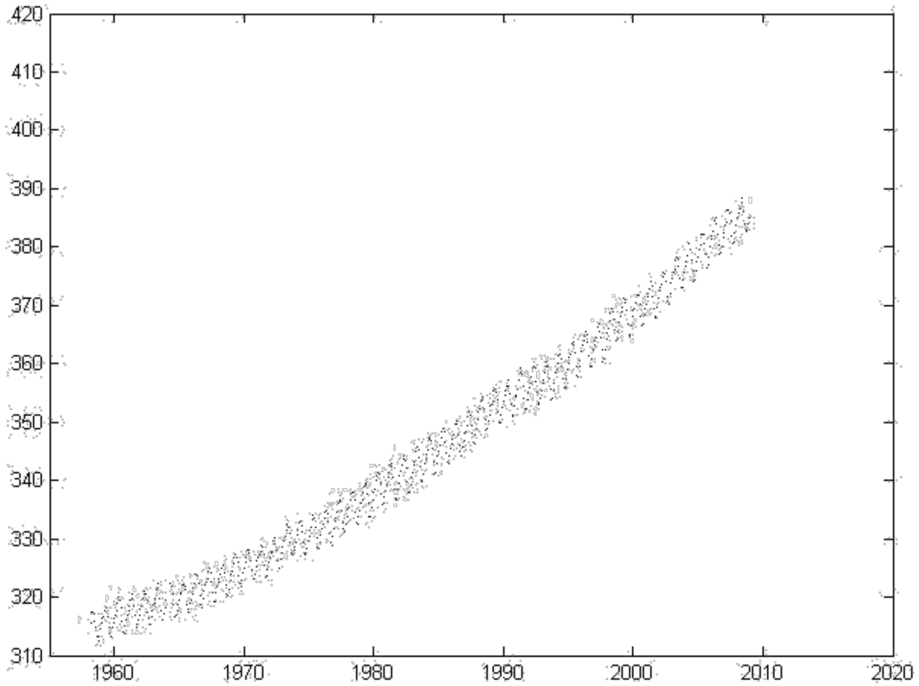
Training
y|x
$GP(0, K + \sigma_n^2 I)$
***Optimize**: for a better hyperparameters and better prior*

Posterior on y
$\boldsymbol{y^*} | \boldsymbol{x^*}, \boldsymbol{y}, \boldsymbol{x}$

GP ($K_*[K + {\sigma_n}^2 I]^{-1}$y, $K_{**} + \sigma_n^2 I \; - \; K_*^T[K + {\sigma_n}^2 I]^{-1}K_*$)

Image Source: http://mlg.eng.cam.ac.uk/teaching/4f13/1314/

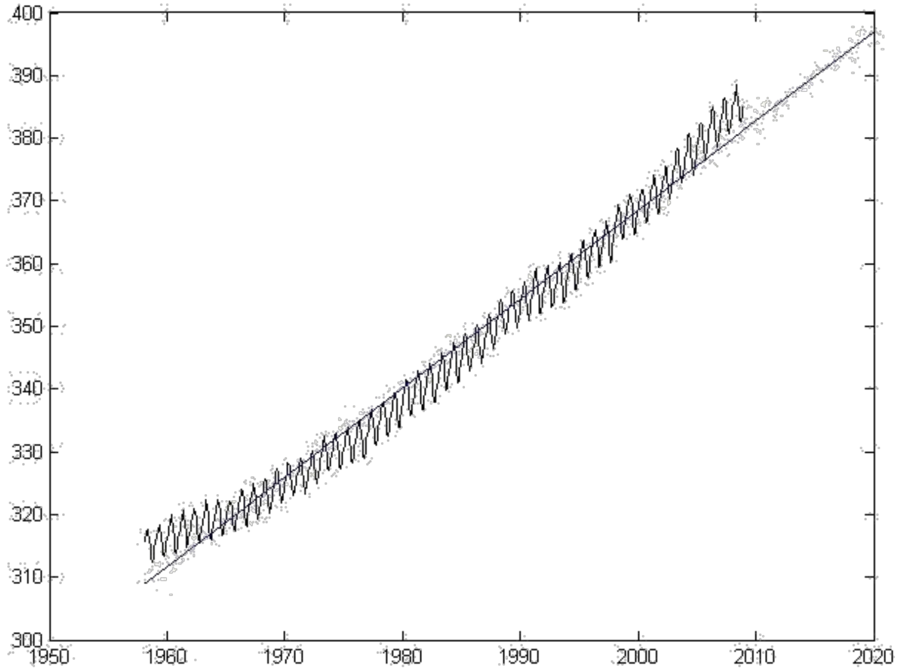
A SIMPle Example



Month-wise data of CO_2 concentration in atmosphere at Hawaii

Image Source: http://mlg.eng.cam.ac.uk/teaching/4f13/1314/

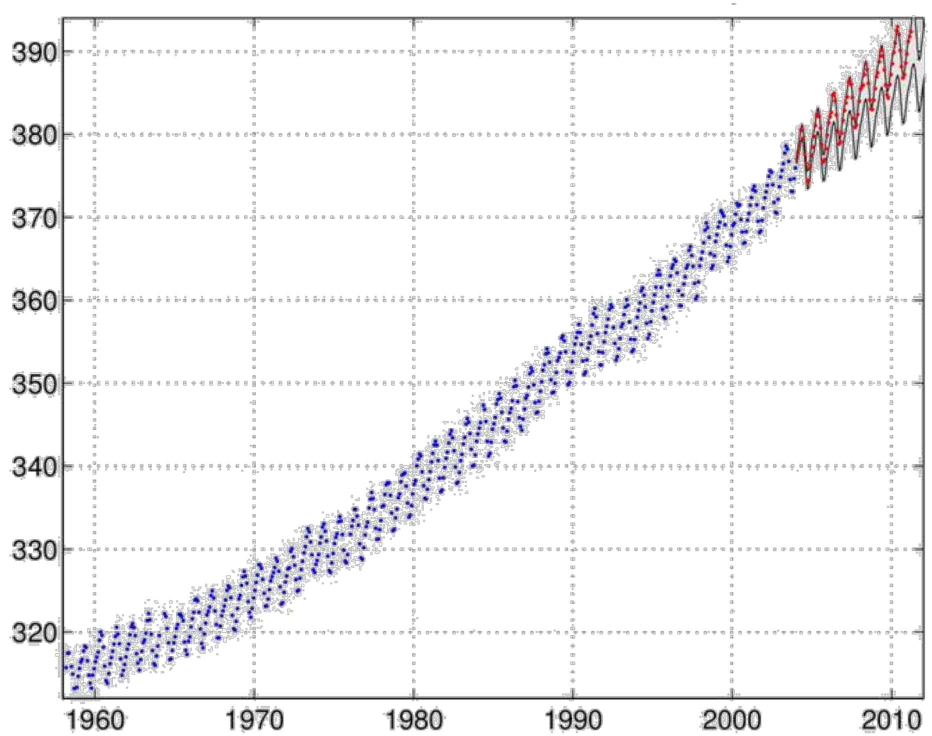
Example – Linear Regression



Should we choose a polynomial?
What degree of polynomial should we choose? (overfitting)
For a given degree, what parameters of polynomial should we choose

Image Source: http://mlg.eng.cam.ac.uk/teaching/4f13/1314/

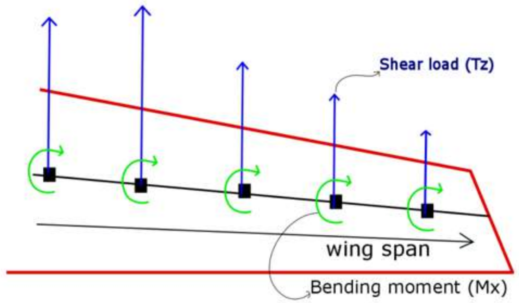
Example – Gaussian Process



Predicted variance after year 2005 in grey, real data-points in red

Image Source: http://mlg.eng.cam.ac.uk/teaching/4f13/1314/

Multi-Output Gaussian Process



Given: $f_1 = g(f_2, x)$

- Earlier examples include **Gradient Enhanced Kriging** (GEK) or **Co-kriging**

- But we want to expand this to integral enhanced kriging, double differential, or any functional relationship between outputs

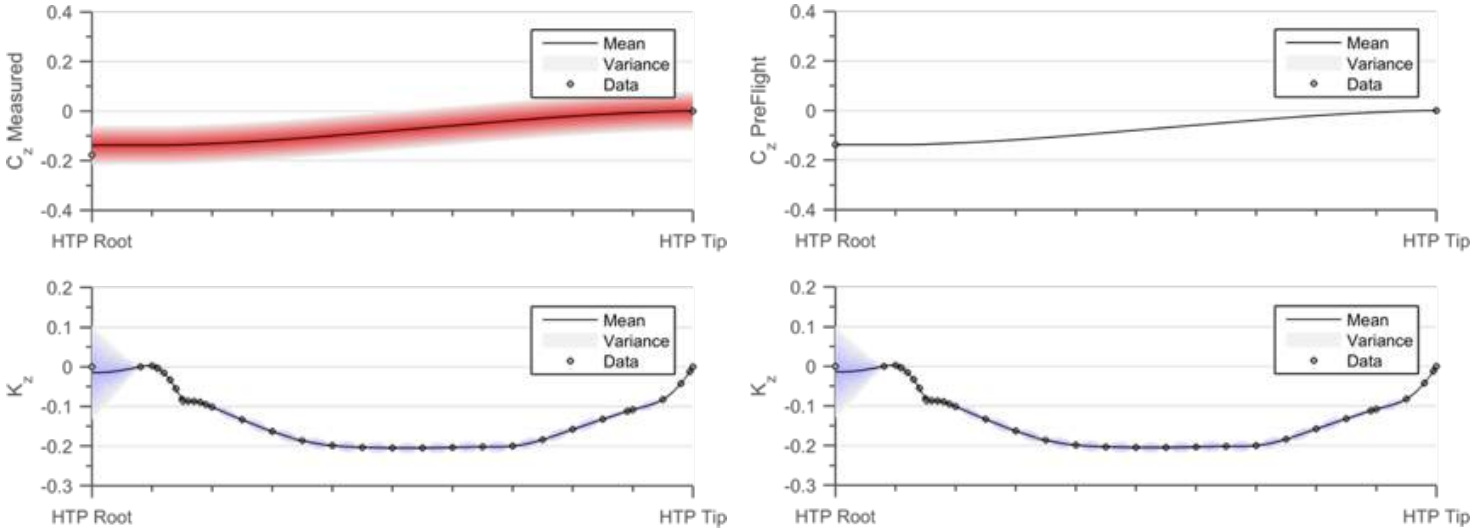
Forrester, A. I. J., Sobester, A. and Keane, A. J. (2007) Multi-fidelity optimization via surrogate modelling. Proceedings of the Royal Society A, 463(2088), 3251–3269, (doi:10.1098/rspa.2007.1900).

LIU, Weiyu. Development of gradient-enhanced kriging approximations for multidisciplinary design optimization. 2003.

Adding Physics based information

$$C_z(\eta) = \int_{\eta_{edge}}^{\eta_{root}} k_Z(\eta) d\eta$$

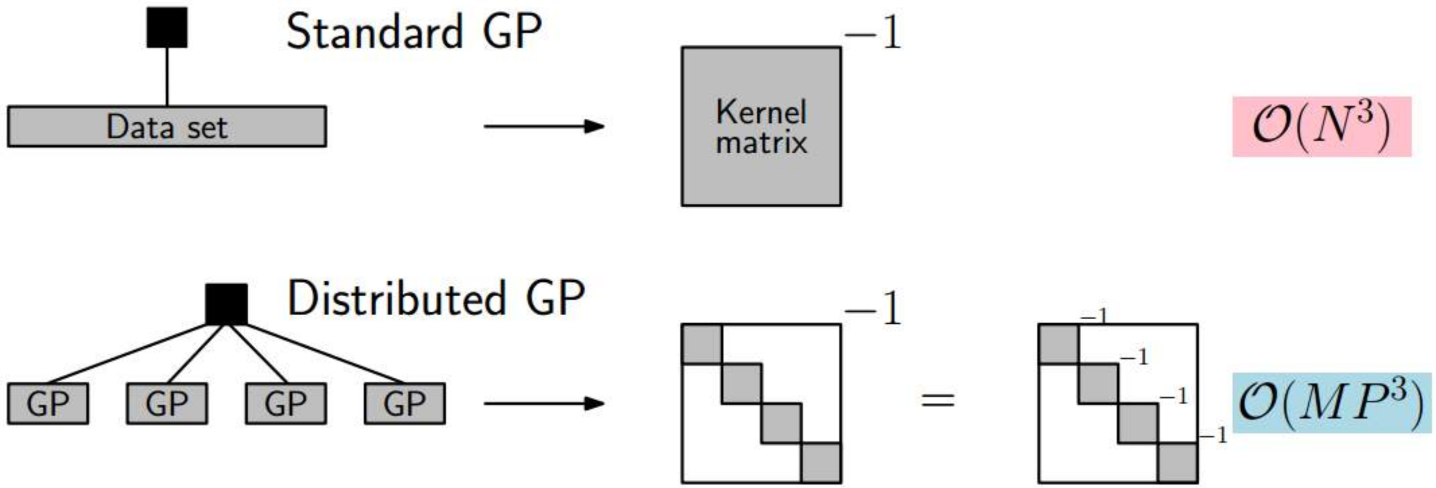
Used in Flight Tests at Airbus



Constantinescu, Emil M., and Mihai Anitescu. "Physics-based covariance models for Gaussian processes with multiple outputs." *International Journal for Uncertainty Quantification* 3.1 (2013).

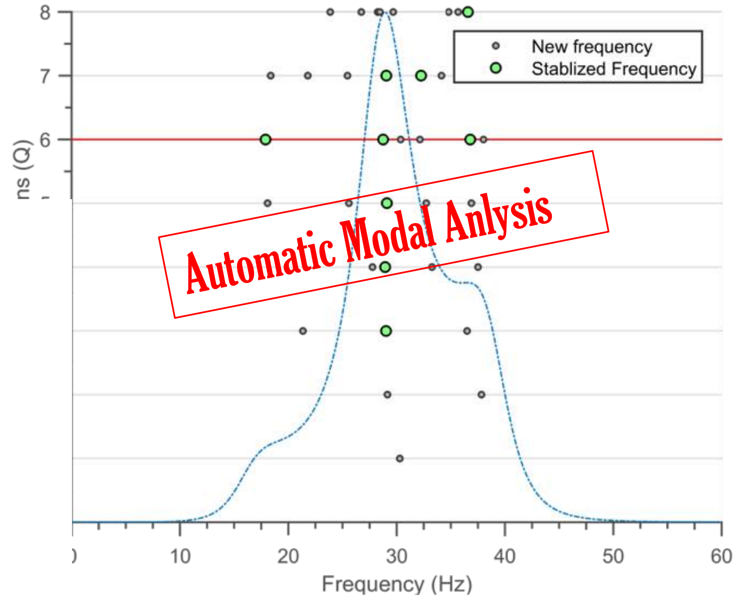
Link to HPC: Distributed Gaussian Process

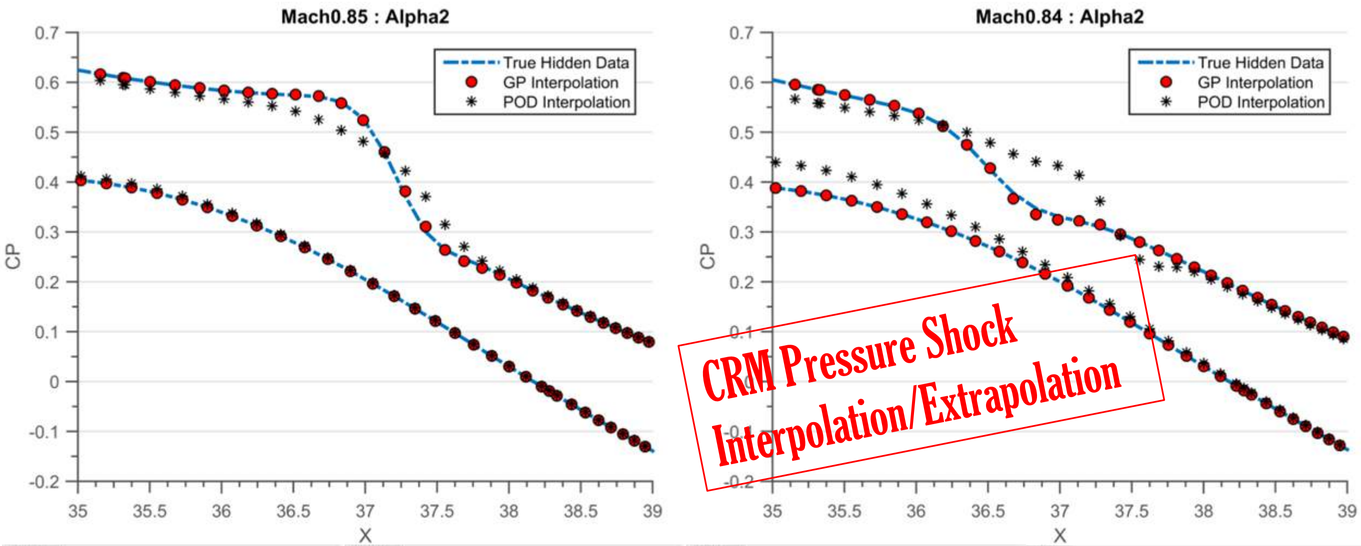
Learning	Storage	Mean	Variance
O(n³)	O(n²)	O(n)	O(n²)

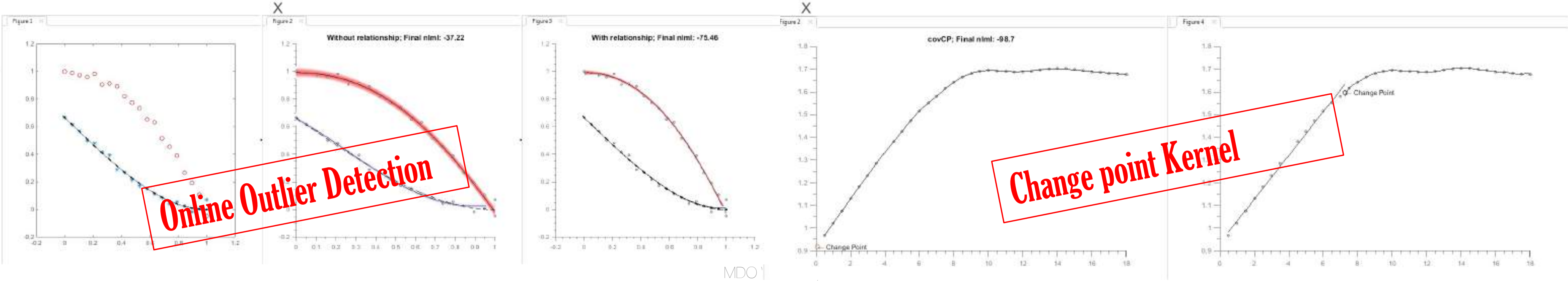


Distributing the dataset into M chunks of size P

Some of ML applications







Papers&conf

Chiplunkar, E. Rachelson, M. Colombo and J. Morlier. Approximate Inference in Related Multi-output Gaussian Process Regression. Lecture Notes in Computer Science. 10163, 88-103. 2017

Chiplunkar and J. Morlier. Operational Modal Analysis in Frequency Domain using Gaussian Mixture Models . Proceedings of IMAC XXXV, 2017

Chiplunkar, E. Bosco and J. Morlier. Gaussian Process for Aerodynamic Pressures Prediction in Fast Fluid Structure Interaction Simulations. Proceedings of WCSMO12 2017

Chiplunkar, E. Rachelson, M. Colombo and J. Morlier. Adding Flight Mechanics to Flight Loads Surrogate Model using Multi-Output Gaussian Processes. AIAA AVIATION 2016

Chiplunkar, E. Rachelson, M. Colombo and J. Morlier. Sparse Physics-Based Gaussian Process for Multi-output Regression using Variational Inferenc. Proceedings of ICPRAM 2016 2016

Several Papers in preparation

Outlines

1. Overview of actual PhDs

2. OpenMDAO+ OpenNastran, but why?

3. Discrete Continuous Optimization in CSM

Objectives

Build a Python written Open Sources Multi-Fidelity Aircraft Preliminary Design Framework, based on Aero-Structure Optimization

Why Python scripted and open source??

- Collaborative Environment.
- Access to a global user community, who proficiently interact with support and solutions.
- Student projects / PhD

Which Optimization Solutions?

- Optimization with aeroelastic constraints
- Applications to BWB, and scaled aircrafts
- New testcases for comparing Gradient vs Surrogate based optimization

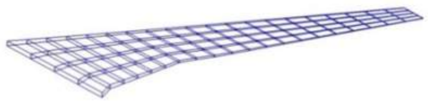
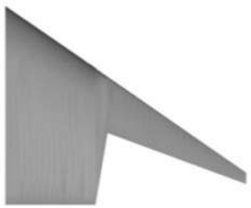
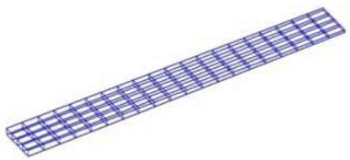
Multifideilty Fidelity

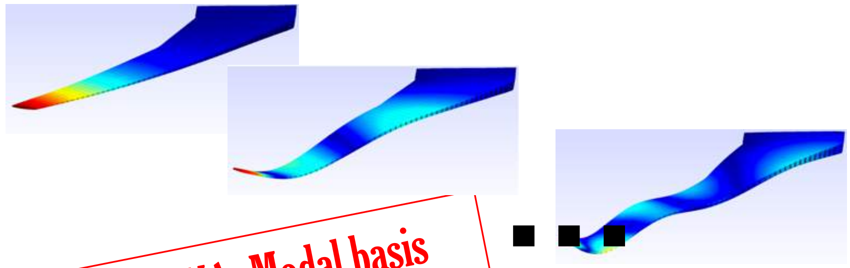
Fidelity Level / Model Type	Low Fidelity	Medium Fidelity	High Fidelity
Geometrical Model	Reduced 1D		Full 3D
Numerical Model/Solution		Panel Method (Panair®) Finite Element (Nastran95®)	

DLM for flutter computation,
Piezo element for control
Work in progress with Adflow compatibility

CAD= Airconics+ OpenNastran

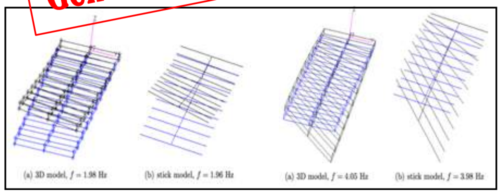
All types of body shape may be reproduced, here some wing examples:

Aerodynamic Surface	Airframe	Wing Type
		CRM
		BWB
		GOLAND



Aircraft DNA: Modal basis

Generalized 1D Beam for low fidelity

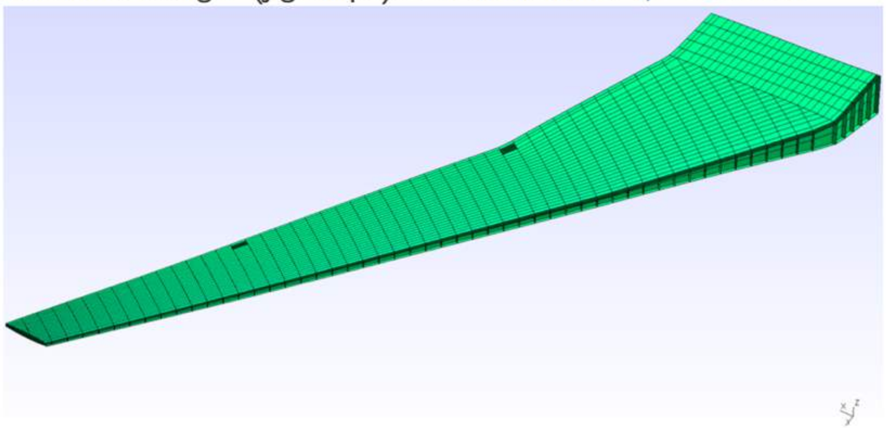


2. Example: Mode tracking strategy

- 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 $t_r = 8.89mm$



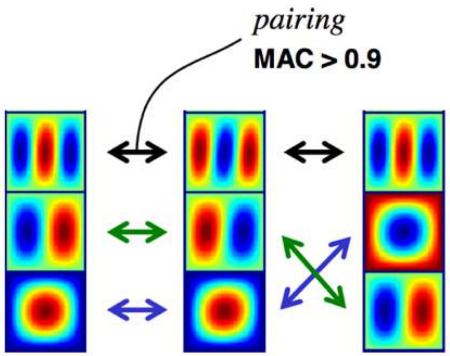
Model provided by T. Achard and C. Blondeau*

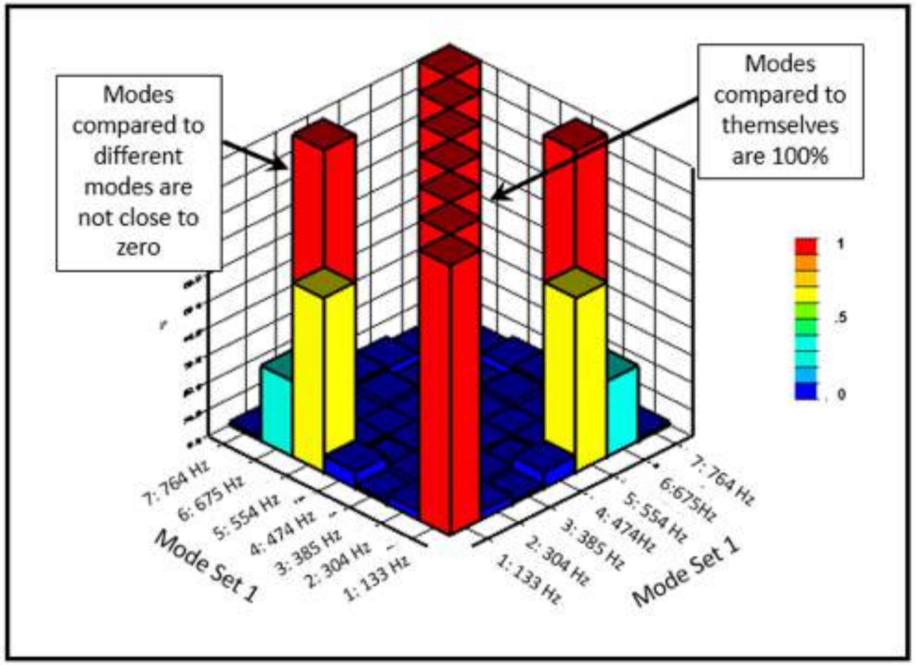
Mode pairing

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

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

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





Reference aircraft: r

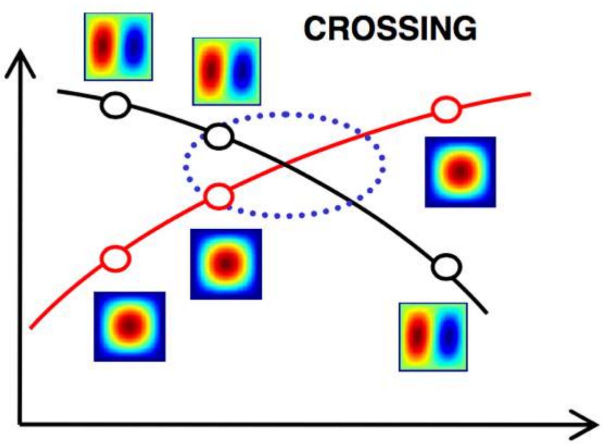
Scaled model: m

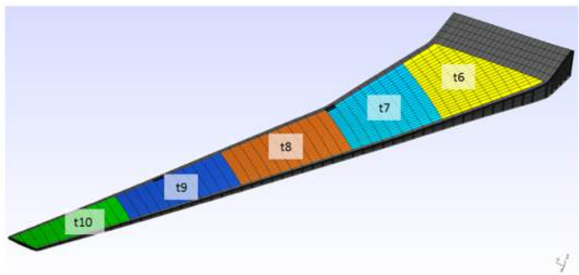
Modes pairing/tracking: Problem definition

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])

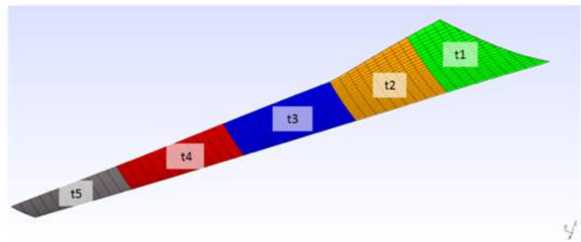
Objective Function		**Dimension**	**Bounds**
Mode shape difference minimization	$\min(N - \mathrm{trace}(\mathrm{MAC}([\Phi_r], [\Phi_m])))$	$\mathbb{R}$	
Design Variables			
Skin thicknesses vector	$[t]$	$\mathbb{R}^{10}$	$[0.0889, 26.67]$ mm
Constraints			
Reduced frequency matching	$\lVert\omega_r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



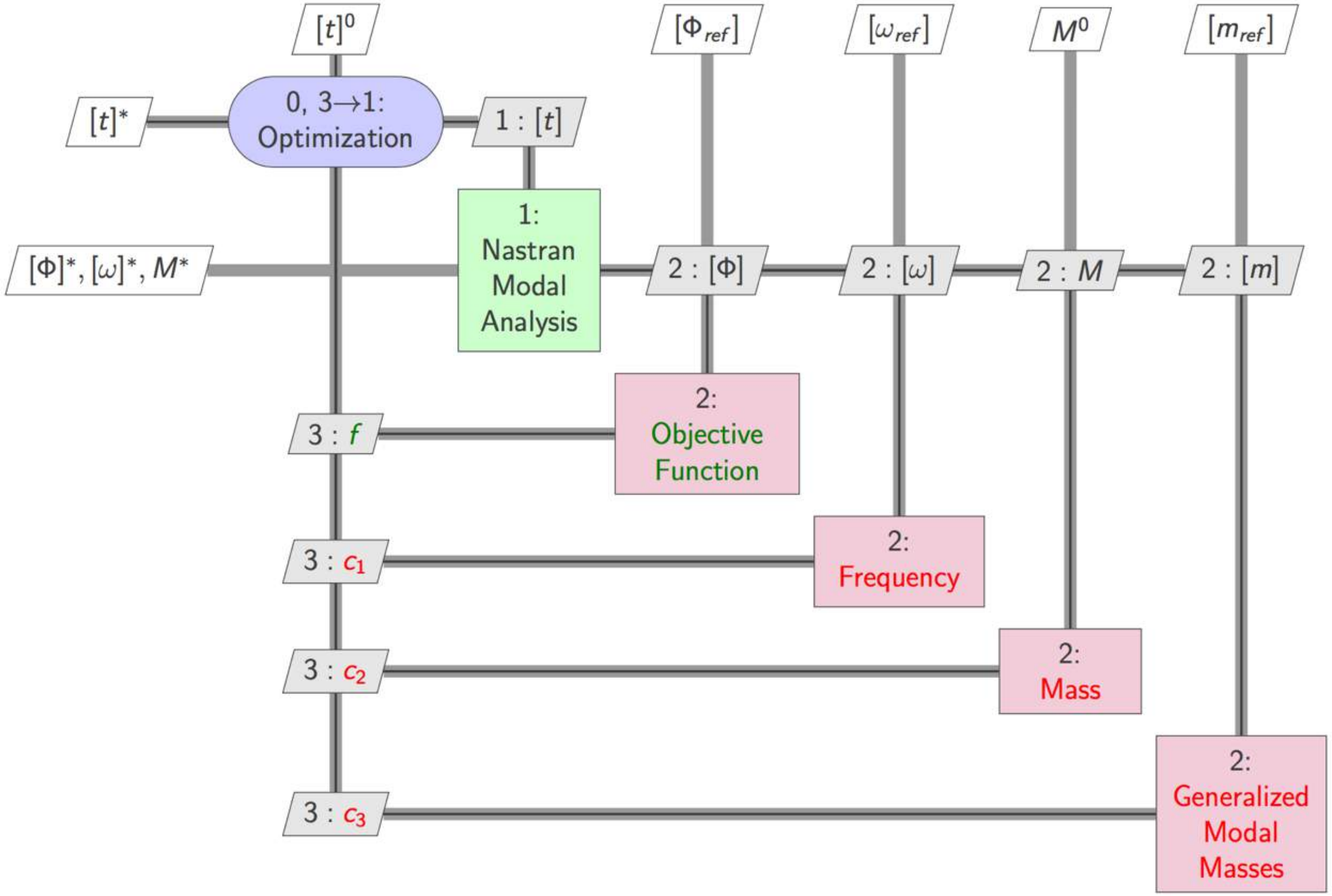


→ Upper skin panels

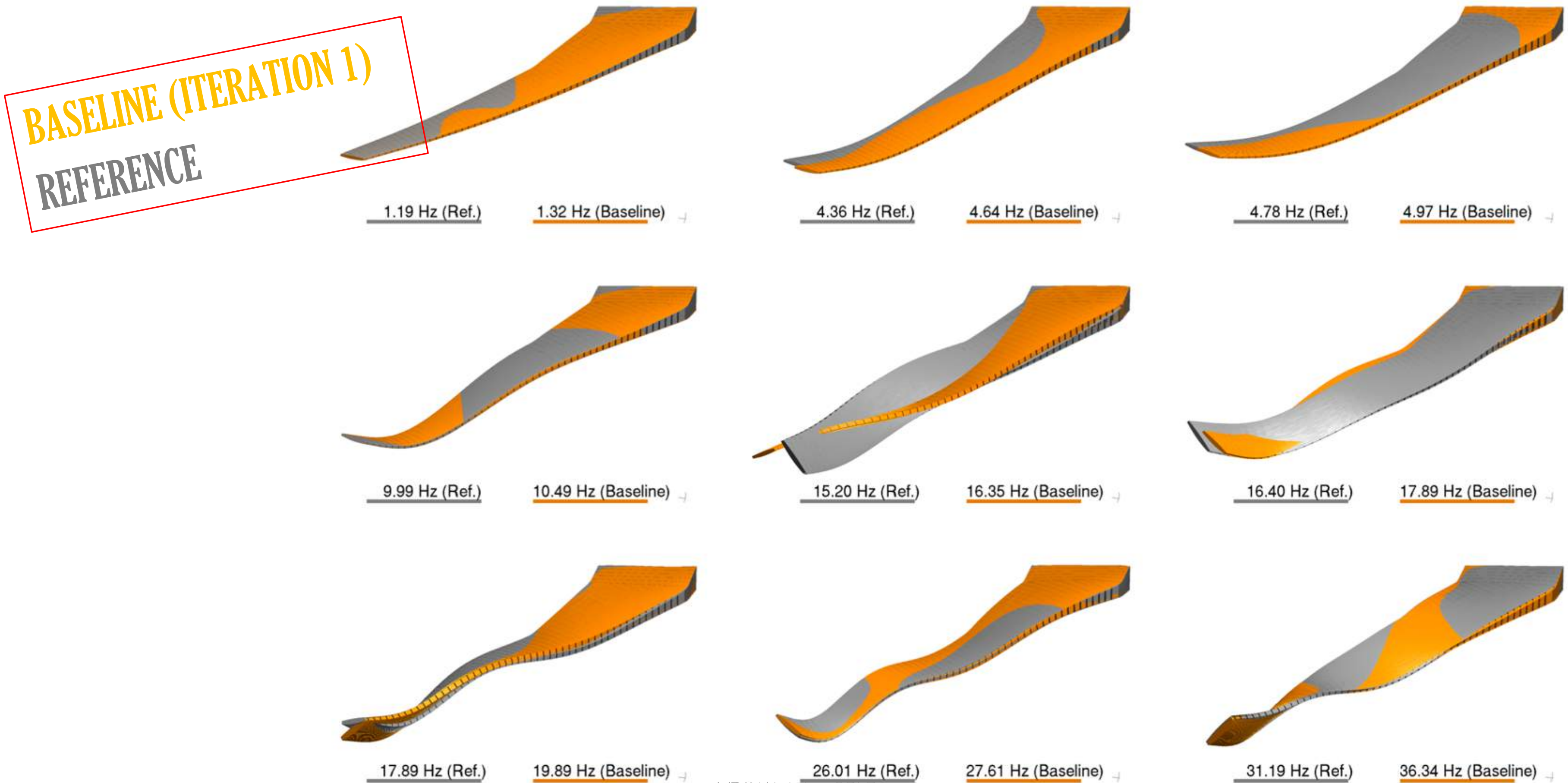
Lower skin panels ←



Modal Optimization



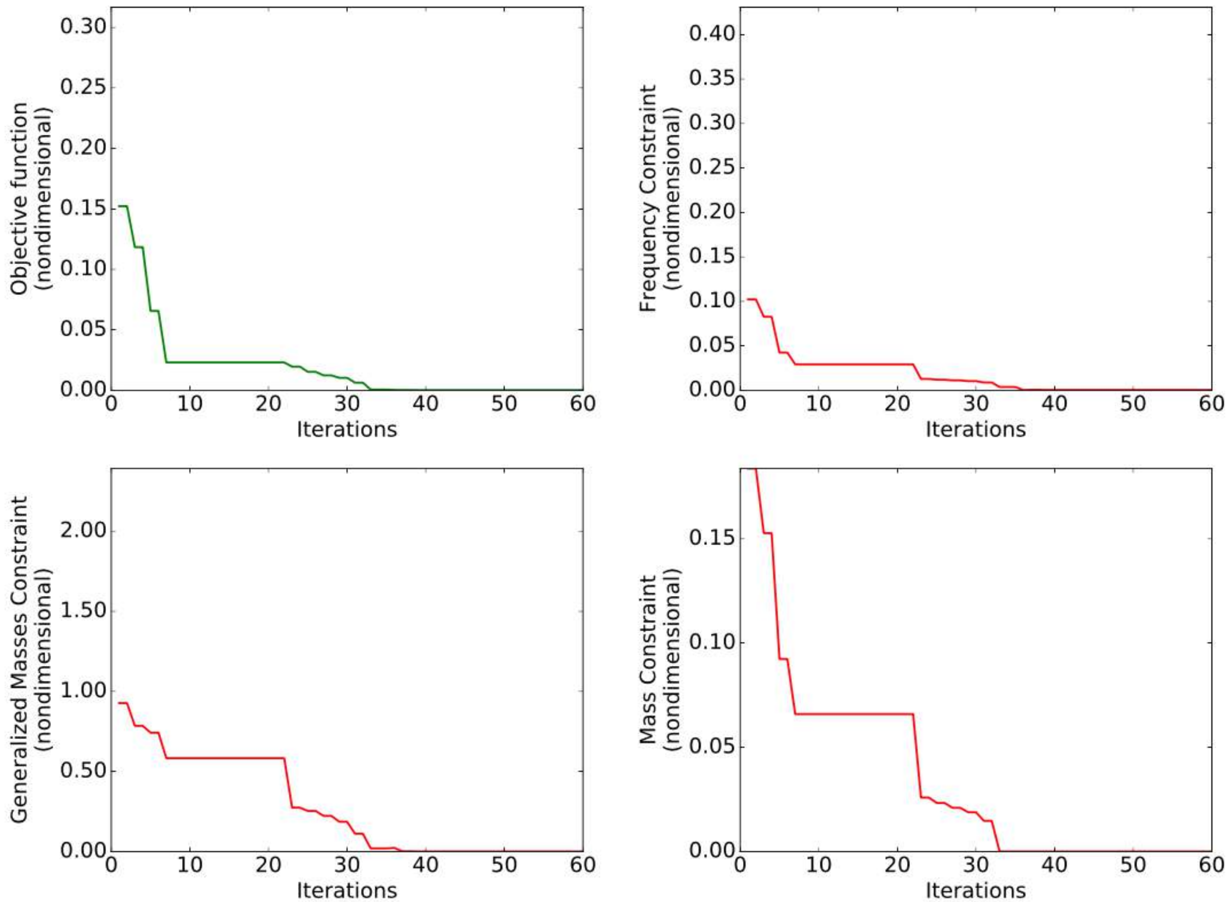
1st Validation CRM Blind Updating



Results of the Optimization (SLSQP)

Optimality

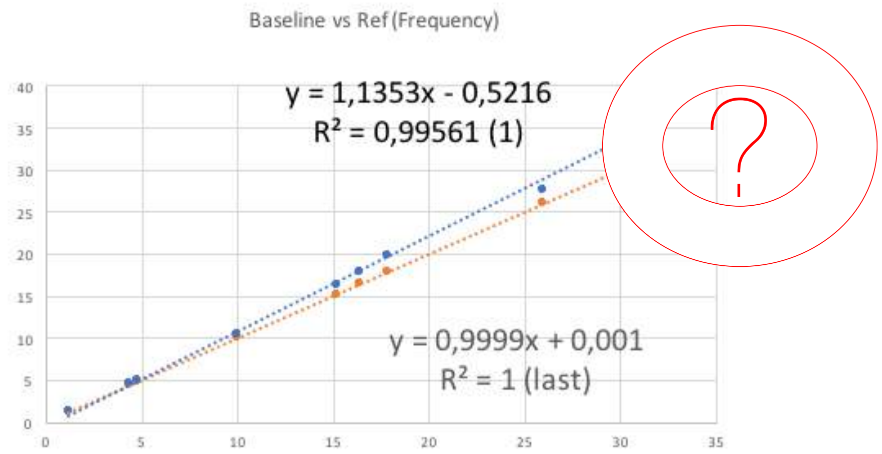
Feasibility

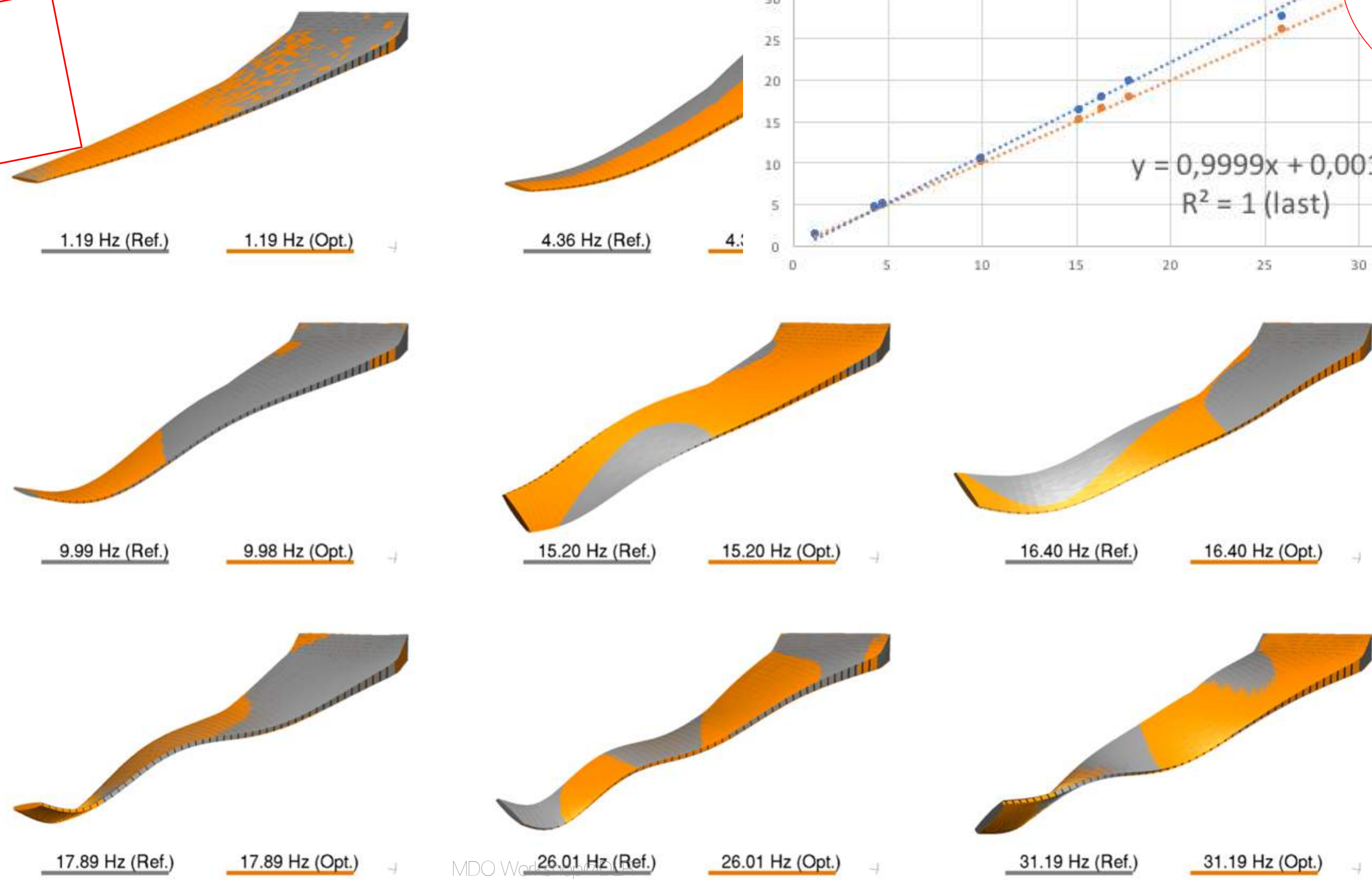


Graphicaly AT CONVERGENCE…

BASELINE (ITERATION Last)

REFERENCE



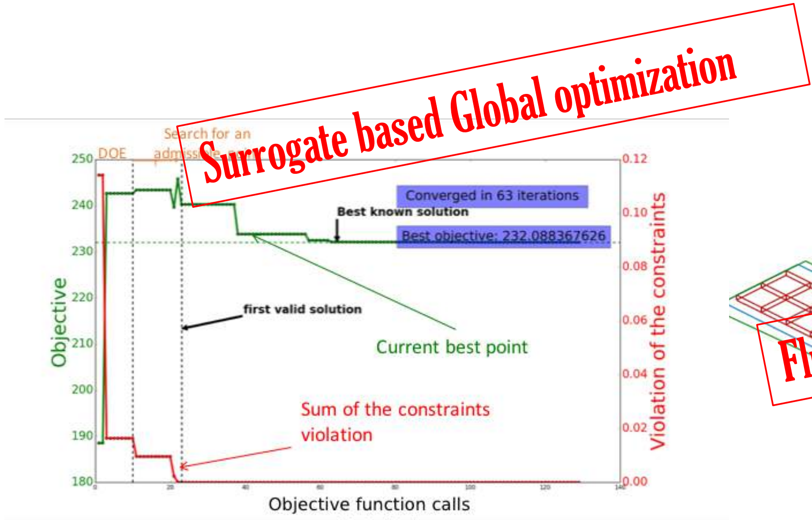


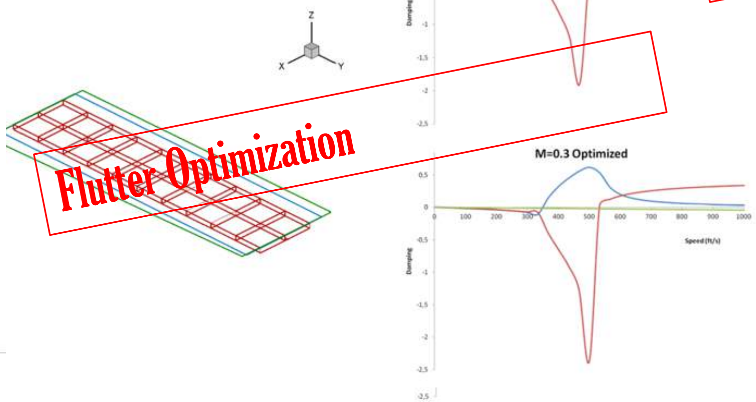
Papers&conf

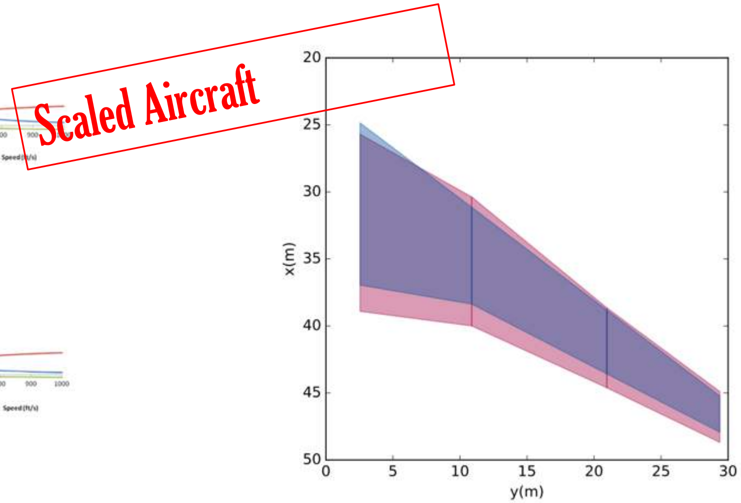
J. Mas Colomer et al Similarity Maximization of a Scaled Aeroelastic Flight Demonstrator via Multidisciplinary Optimization. AIAA SCITECH 2017

J. Mas Colomer, et al, Static and Dynamic Aeroelastic Scaling of the CRM Wing via Multidisciplinary Optimization. WCSMO12 2017

Several Papers in preparation







Optimized planform (red) and baseline (blue).

Outlines

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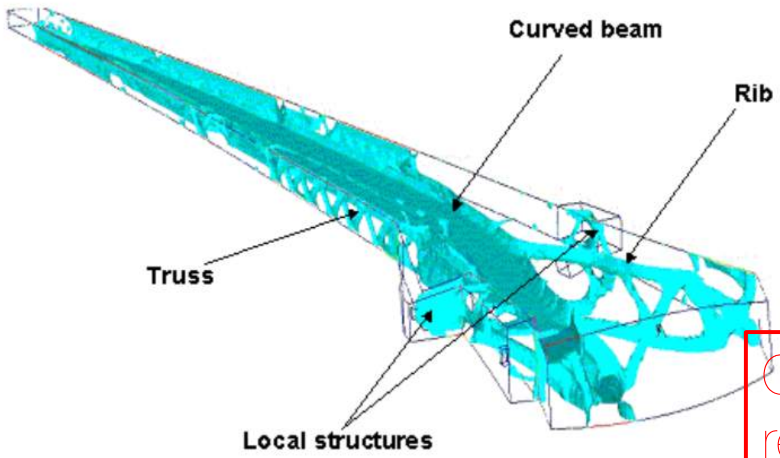
Starting point*, Open at least 2 questions ??

*L.Krog, S.Grihon, A.Marasco, Smart design of structures through topology optimisation, 8th World Congress on Structural and Multidisciplinary Optimization, June 1 - 5, 2009, Lisbon,



Identified features:
- **Curved beam** for carrying bending loads
- Large **rib**-like structure connecting the gear rib area to the forward root joint
- **Truss**-like spar structures
- **Local structures** around gear-rib and pylon areas

Can we do pattern (structural element) recognition?
Can we process an optimization from a catalog of structural elements?

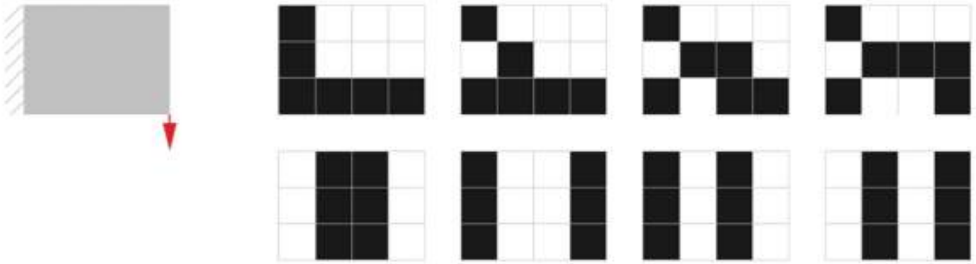
Pixels?

When the size of the FE model is increasing, the SIMP optimization problem is …

Chris Columbus *et al,* Pixels, movie 2015

Pixels

- Finding a solution by checking all the possible combinations IS impossible since the number of topologies nT increases exponentially with the number of finite elements n
- nT = 2^n,



The legal (top) and some illegal (bottom) topologies with 4 by 3 elements

Division into elements (pixels or voxels) and binary decision for each or example 10,000 elements --> 210,000 possible configurations!

Intuitive Problem? Quadratic Form

- Objective function; Strain energy

$$\min c(\mathbf{x}) = \mathbf{U}^T \mathbf{F} = \mathbf{U}^T \mathbf{K}\mathbf{U} \qquad x_e = \frac{\rho_e}{\rho_0} \text{ with} \tag{4}$$

$$\text{with } \mathbf{K} = \mathbf{K}_0 \sum_{e=1}^{N} x_e^p \qquad \text{one can write:}$$

$$\min c(\mathbf{x}) = \sum_{e=1}^{N} (x_e)^p \mathbf{u}_e^T \mathbf{k}_0 \mathbf{u}_e \tag{5}$$

Transform discrete variables continuously
(TO USE gradient-based algorithms)
Cheap derivatives!

- Contraints: mass target

$$\frac{V(\mathbf{x})}{V_0} = f = const \quad \Leftrightarrow \quad \sum_{e=1}^{N} V_e x_e - V_0 f = 0 = h(\mathbf{x})$$

$$0 < \rho_{\min} \le \rho_e \le 1$$

$$\frac{\partial c}{\partial \rho_e} = -p(\rho_e)^{p-1} \mathbf{u}_e^T \mathbf{k}_0 \mathbf{u}_e$$

Context & Objectives

- Reminder on variables types:

Can we do pattern (structural element) recognition?
Can we process an optimization from a catalog of structural elements?

- variable
  - Numerical
    - Continuous
    - Discrete
      - integer
      - non integer
  - Categorical
    - Ordinal
    - Nominal

e.g.: Height, diameter

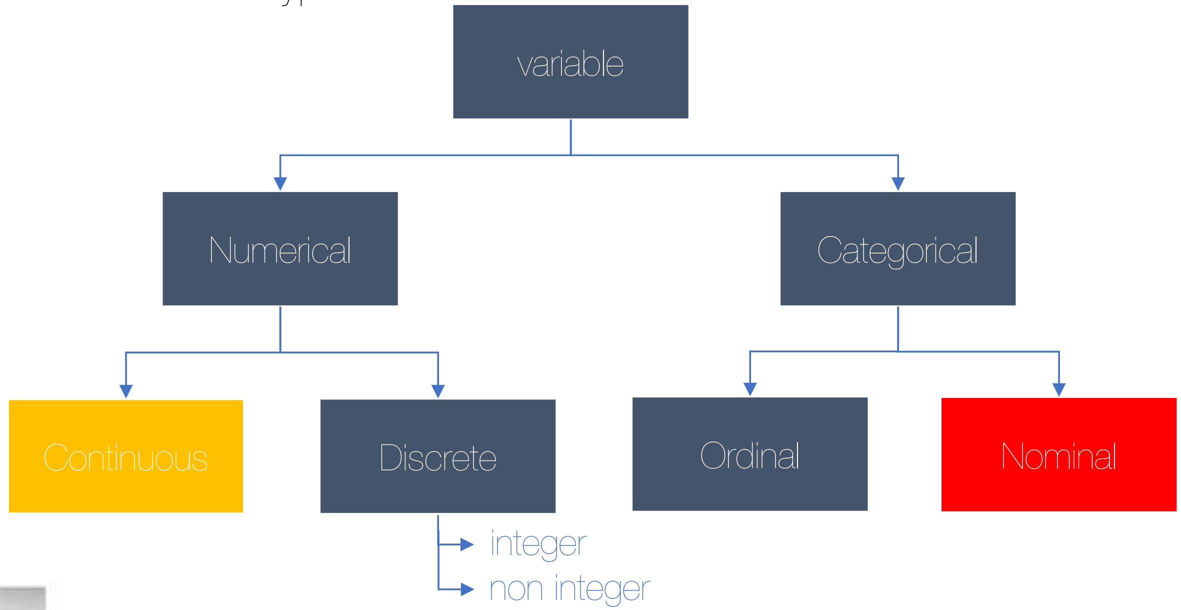
e.g.: number of holes

e.g.: cross-section shape

M. Herrera et al, Metamodel-assisted optimization based on multiple kernel regression for mixed variables, Structural and Multidisciplinary Optimization, 2014.

Context & Objectives

- Reminder on variables types:



e.g.: Height, diameter

e.g.: number of holes

e.g.: cross-section shape

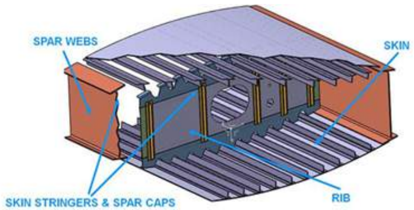
Modified B&B

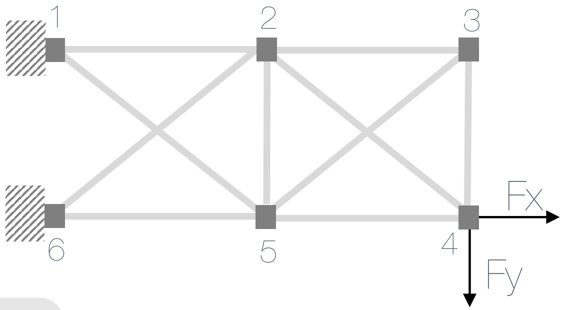
- Branch & bounds : elements

A. H. Land and A. G. Doig, An Automatic Method of Solving Discrete Programming Problems, Econometrica, 1960.
R. J. Dakin, A tree-search algorithm for mixed integer programming problems, The Computer Journal, 1965.

Test case description

- academic test case : generic description





Problem formulation :

$$\min_{\substack{A \in \mathbb{R}^{10} \\ c \in \Gamma^{10}}} W(c, A)$$

Subject to

$$RF(c, A, \Phi(c, A)) \geq 1$$

$$G(c, A) \leq 0$$

$$\underline{A}(c) \leq A \leq \overline{A}(c)$$

$$\sigma_i \leq \sigma_{tens,\, i}$$

$$-\sigma_i \leq \sigma_{compr,\, i}$$

$$-\sigma_i \leq \sigma_{local\ buckl,i}$$

$$-\sigma_i \leq \sigma_{euler\ buckl,i}$$

$$u_y(c, A) \leq \overline{u_y}$$

- Minimize mass
- Under constraints
- With respect to Areas A

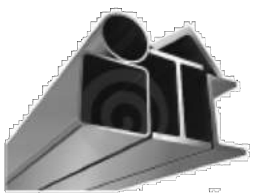
  $c \left\{ \begin{array}{l} \text{Materials M} \\ \text{Shapes S} \end{array} \right.$
- 1 bar = 1 choice of A, M, S

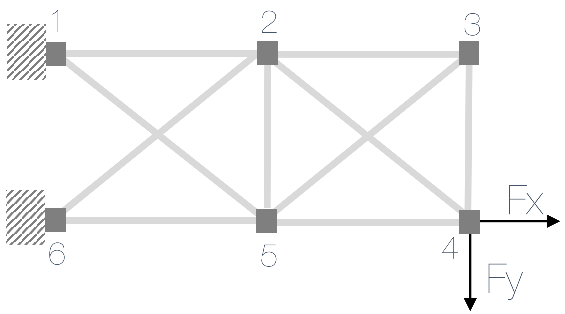
Test case description

- test case :
  leads to curse of dimensionality (numerical example)

For each bar, with a choice among 6 couples of (M, S) :

- 3 cross-sections





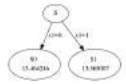
- 2 materials : Titane, Aluminium

6^10 possible choices combinations

Solution example

- Branch and bound : toward a baseline solution

2 catalogs : Material '0', Material '1'
Displ. bound : 25 mm

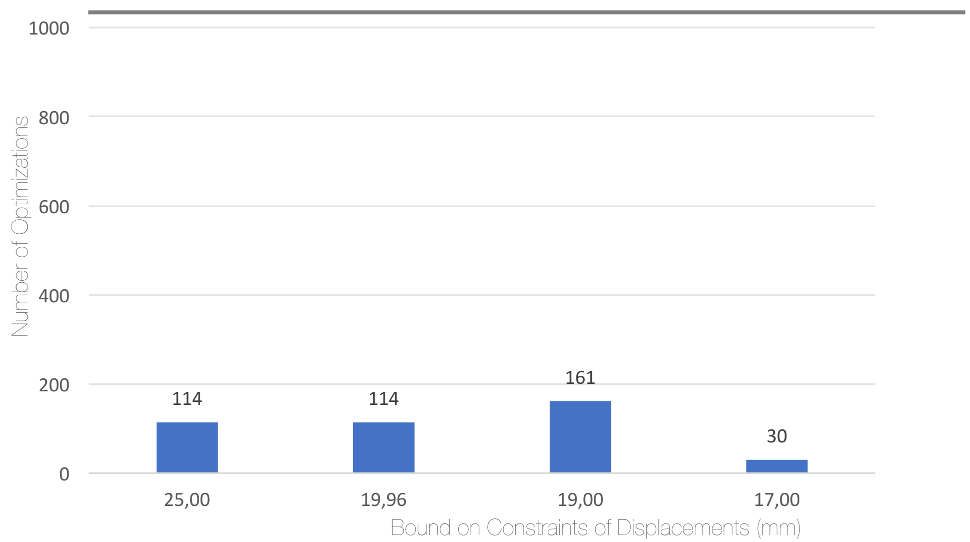


Solution example

- Branch and bound : computation cost / efficiency
  - 2 catalogs case :

2 catalogs : Material '0', Material '1'
Displ. bound : 25 mm

Number of Optimizations



Number of nodes at last level of the tree

$$= 2^{10} = 1024$$

  - 4 catalogs case :

    0,7% of the combinatory (7'000/1'000'000)

Visiting scholar at UoM

Can we do pattern (structural element) recognition?

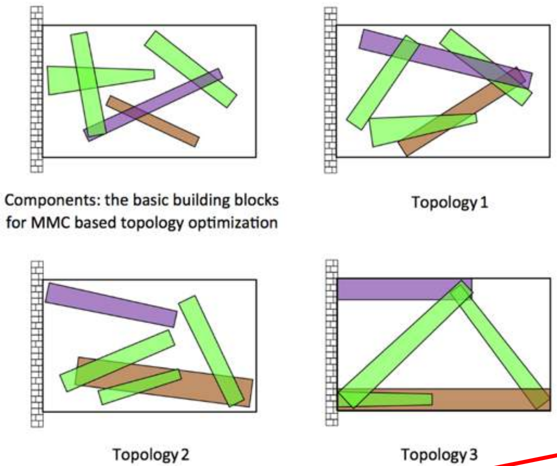
Lead an optimization rom a catalog of structural elements?

Struct Multidisc Optim (2016) 53:1243–1260
DOI 10.1007/s00158-015-1372-3

RESEARCH PAPER

A new topology optimization approach based on Moving Morphable Components (MMC) and the ersatz material model

Weisheng Zhang[1] · Jie Yuan[1] · Jian Zhang[1] · Xu Guo[1]

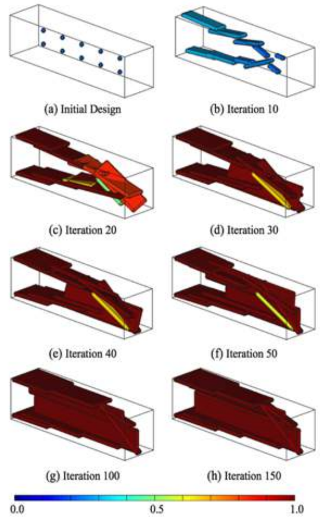


Struct Multidisc Optim
DOI 10.1007/s00158-016-1466-6

RESEARCH PAPER

A geometry projection method for the topology optimization of plate structures

Shanglong Zhang[1] · Julián A. Norato[1] · Arun L. Gain[2] · Naesung Lyu[3]



Explicit Topology Optimization

Optimization algorithm

Nodal movement

- Optimization algorithm based on decoupling
- Movement of nodes
  - Direction of the movement

- Measure performance of structure by compliance
  - Move mass nodes in the direction of decreasing compliance

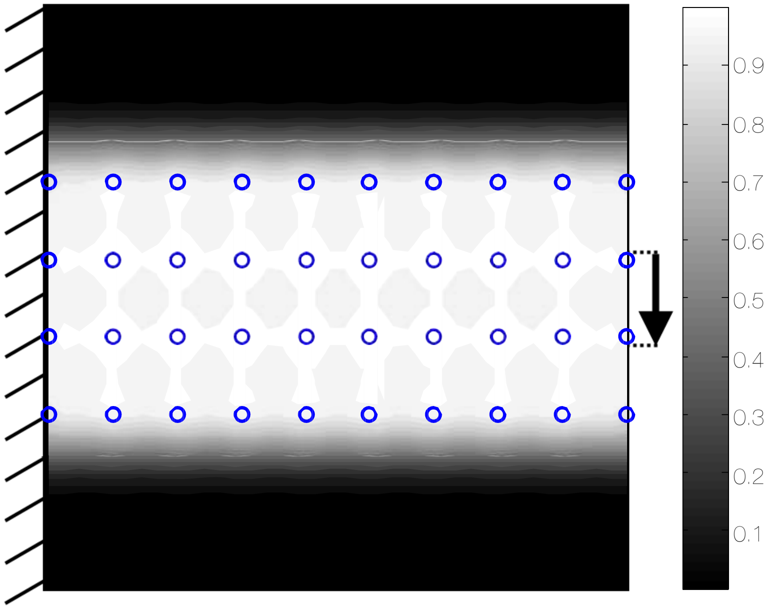
$$C = \mathbf{f}^T \mathbf{u} \qquad \frac{\partial C}{\partial x_j^I}$$

Original Work

J. T. Overvelde, "The moving node approach in topology optimization", Master's thesis, TU Delft, Delft University of Technology, 2012.

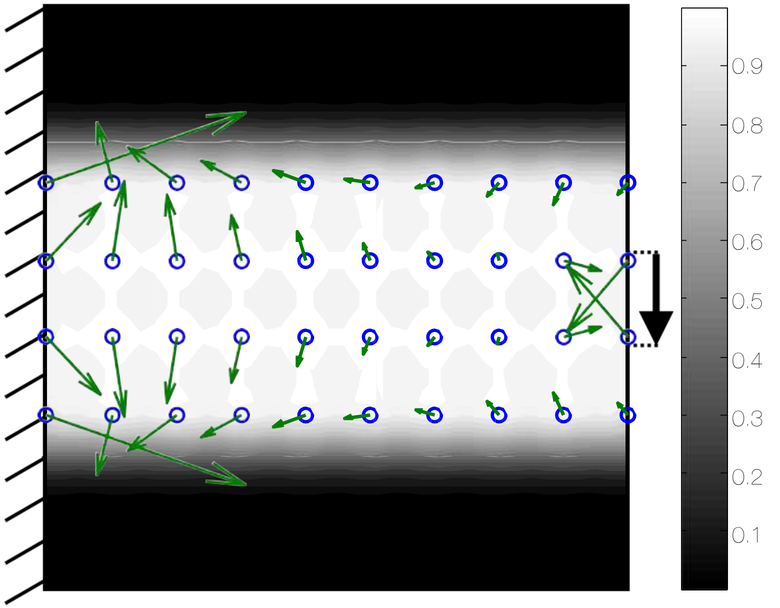
Optimization algorithm

Example of compliance sensitivity



Optimization algorithm

Example of compliance sensitivity



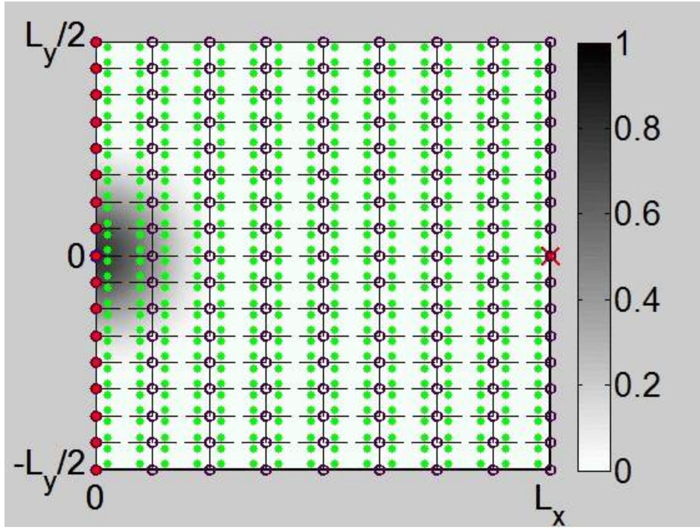
Moving Node Approach (MNA)

- Key idea:

Move material => optimal layout

- Regular discretization = precision

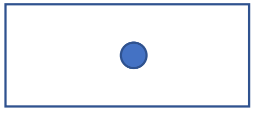
- Material distribution -> mass nodes



The variables (5 per Node)

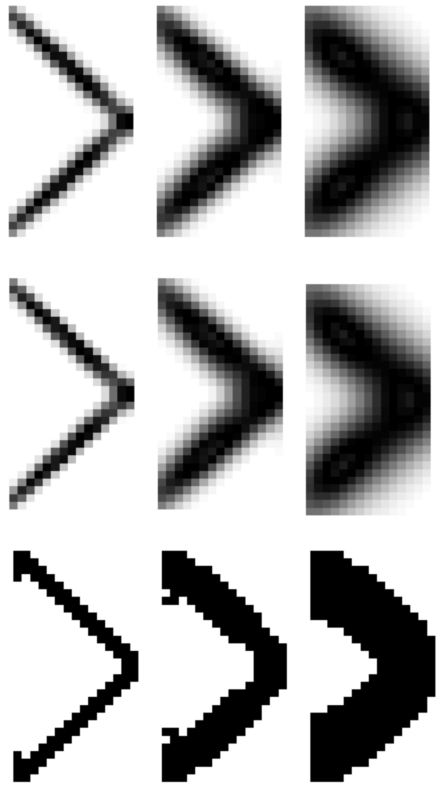
Optimization variables :

- Positions (x,y)
- Orientation (\theta)
- Dimensions (Lx,Ly)



Deformable Structural Members

Results

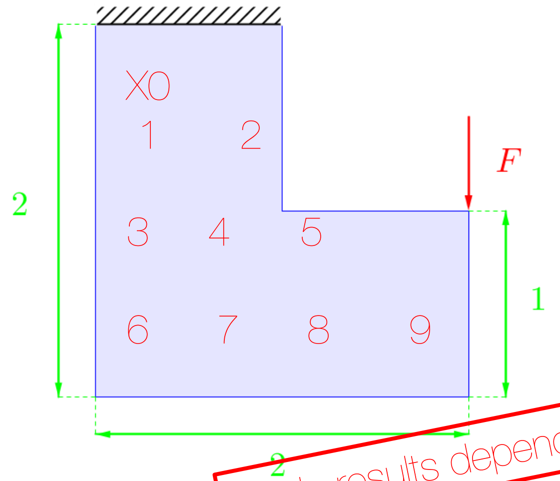


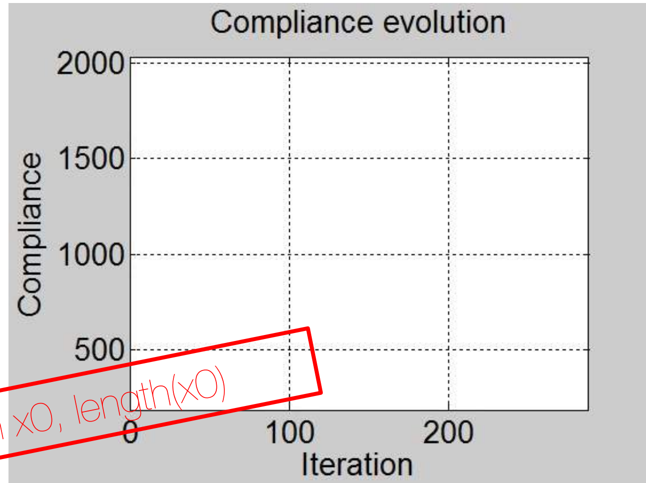
O. Sigmund, "A 99 line topology optimization code written in matlab", Structural and multidisciplinary optimization, vol. 21, no. 2, pp. 120-127, 2001.

E. Andreassen, A. Clausen, M. Schevenels, B. S. Lazarov, and O. Sigmund, "Efficient topology optimization in matlab using 88 lines of code", Structural and Multidisciplinary Optimization, vol. 43, no. 1, pp. 1-16, 2011.

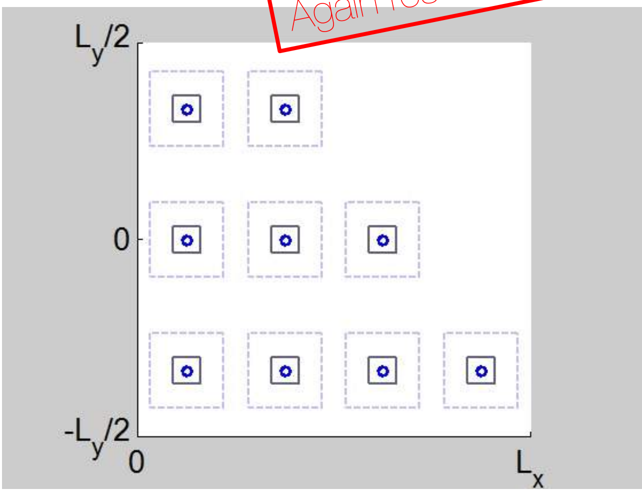
Length(x0)

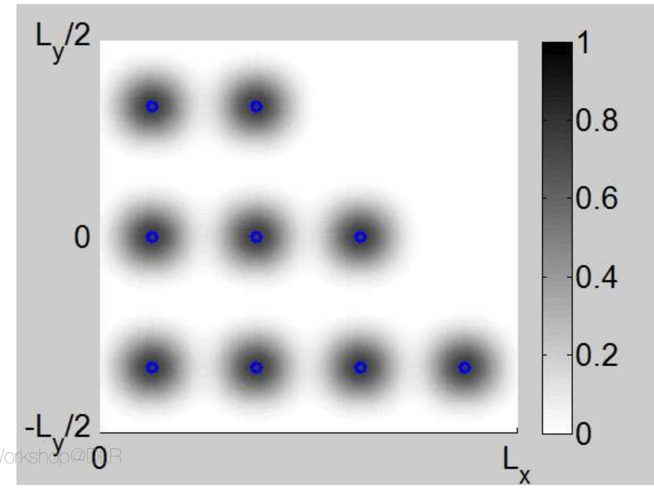
Our Results on L-Shape 9*5 variables



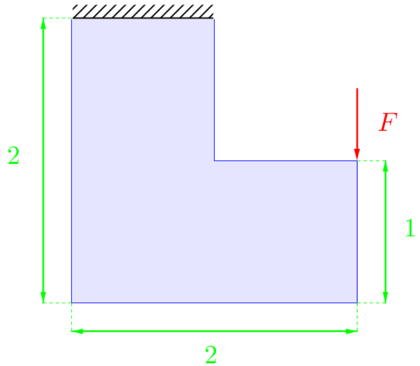


Again results dependent on x0, length(x0)

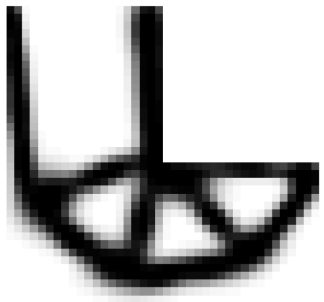




Results on L-Shape (Best solution using a multistart approach)



MNA



C = 127

SIMP

C = 94

```
disp('MNA')
topmna(x0,nelx,nely,volfrac,3,[ratio;aspect],tolchange);

disp('SIMP')
top88(nelx,nely,volfrac,3,2,1)
```

TopMNA include Few hyperparameters, starting from a « dense » regular grid with Fusion/merging/Recognition of beam elements

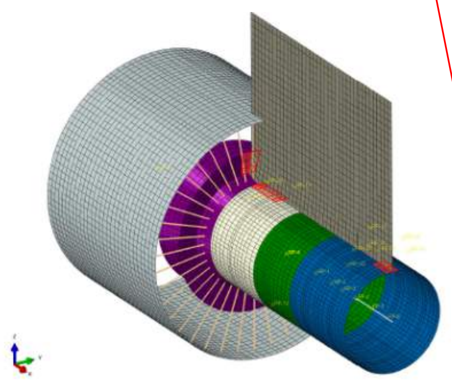
Papers&conf

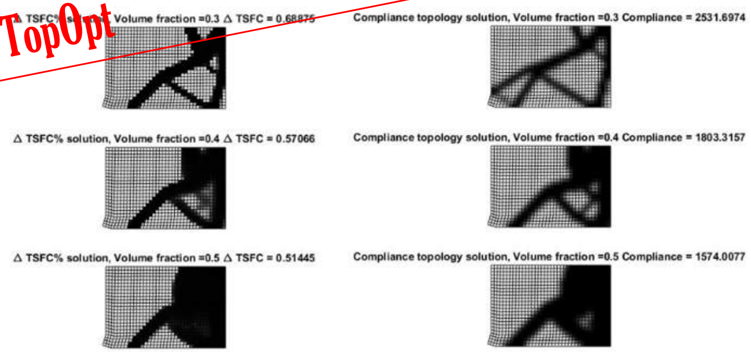
PJ. Barjhoux et al. Mixed Variable Structural Optimization: toward an Efficient Hybrid Algorithm, WCSMO12, 2017

G. Raze et al, Optimisation topologique sans maillage : vers la reconnaissance d'éléments structuraux, CSMA 2017

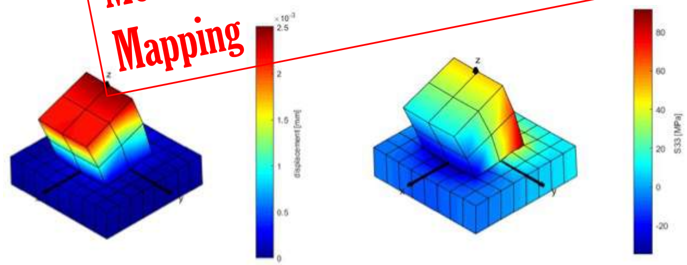
Several Papers in preparation

stress based/performance based TopOpt





Mesh Tying, error quantification in Mapping



Conclusions

- New Surrogate and ML technics for an automated optimal design process
- structural/aeroelastic constraints at the early stage of the MDO loop
- A new step toward a catalogue based-multimaterial structures design

→ Teach/apply our (simplified) methodologies in 2 MDO courses (MsC level) at SUPAERO with ONERA/AIRBUS

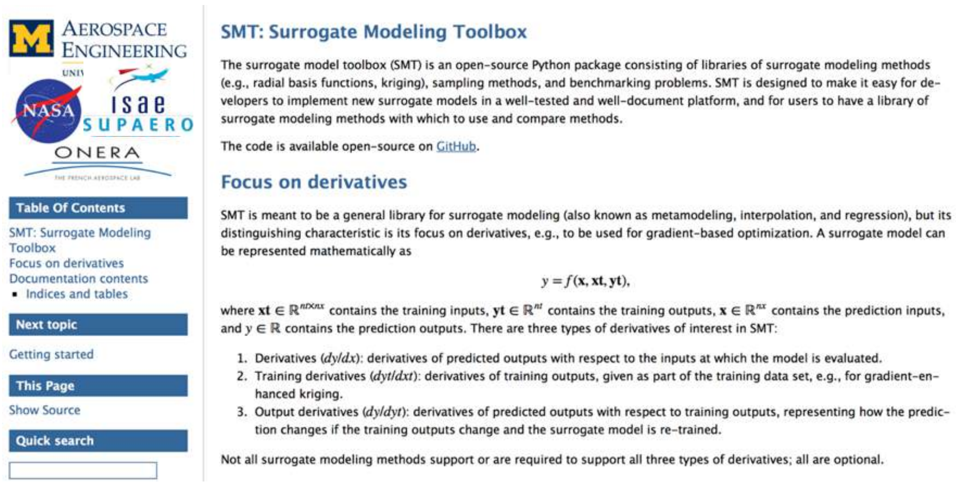
- We also have interesting stuff in FSI-nonlinear transient analysis, Isogeometric (IGA) Shell Structures Optimization …

http://www.institut-clement-ader.org/pageperso.php?id=jmorlier

- Thanks to My co-workers: Joaquim Martins, Nathalie Bartoli, Emmanuel Benard, Claudia Bruni Emmanuel Rachelson, Nicolas Gourdain, John Hwang, Mohamed Bouhlel, Thierry Lefebvre, Youssef Diouane, Sylvain Dubreuil, Christian Gogu and PhDs Pierre-Jean Barjhoux, Simone Coniglio, Elisa Bosco, Joan Mas Colomer, Ankit Chiplunkar, and MsC Ghislain Haine, …

Surrogate modeling in HD, focus on derivatives

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.