Dassault +SUPAERO meeting

Prof. J. Morlier

Facilities

INSTITUT CLEMENT ADER
Université Fédérale Toulouse Midi-Pyrénées / UMR CNRS 5312
3 rue Caroline Aigle
31400 Toulouse, France

Structure

- l'Institut Clément Ader
- Groupe MS2M
- Groupe MSC
- Groupe MICS
- Groupe SUMO
- Axes transverses
- Annuaire

Activités

- Publications
- Agenda scientifique
- Projets et Partenariats
- Moyens
- Thèses

Master Recherche @ ICA

- Master SMMS
- Master DET

Infos pratiques

- Page d'accueil
- Offres d'emploi
- Contact et Accès

Actualités

Bienvenue sur le site de L'**Institut Clément Ader** (**ICA, CNRS UMR 5312**).
L'ICA est un laboratoire de recherche qui s'attache à l'étude des **structures**, des **systèmes** et des **procédés mécaniques**. Nos secteurs d'activités s'inscrivent dans ceux des industries mécaniques avec une attention particulière accordée aux projets des domaines de **l'aéronautique**, de **l'espace**, du **transport** et de **l'énergie**. Nos travaux portent généralement sur la **modélisation du comportement, l'instrumentation** et l'étude de la **durabilité** des structures ou produits considérés. Une part importante de nos recherches porte sur les **matériaux composites**, lesquels prennent aujourd'hui une place importante dans les structures.

ICA France
@ICA_France
Le 16 juin venez écouter Philippe Olivier, Directeur de @ICA_France, nous parler de l'avion du futur au #ForumduCnrs organisé par @CNRSMip.

QUE RESTE-T-IL À DÉCOUVRIR ?
TOULOUSE

Calendrier des évènements scientifiques

Consulter le calendrier de l'ICA

> tous les évènements

Articles récemment publiés

- **P.-M. Nigay, A. Nzihou and T. Cutard**. The impact of the particle size distribution of organic additives on the microstructure of a clay ceramic and its thermal and mechanical properties. *Journal of Materials in Civil Engineering*. 30(4). **2018** [HAL]
- **J.-C. Passieux, R. Bouclier and J.-N. Périé**. A space-time PGD-DIC algorithm: Application to 3D mode shapes measurements. *Experimental Mechanics*. , Online first. **2018** [DOI]
- **F. Blas, F. Ansart, P. Lours, J.-P. Bonino, S. Duluard, V. Vidal, L. Pin, G. Pujol and L. Bonin**. Processing thermal barrier coatings via sol-gel route: Crack network control and durability. *Surface and Coatings Technology*. (334)71-77. **2018** [DOI]

> tous les articles

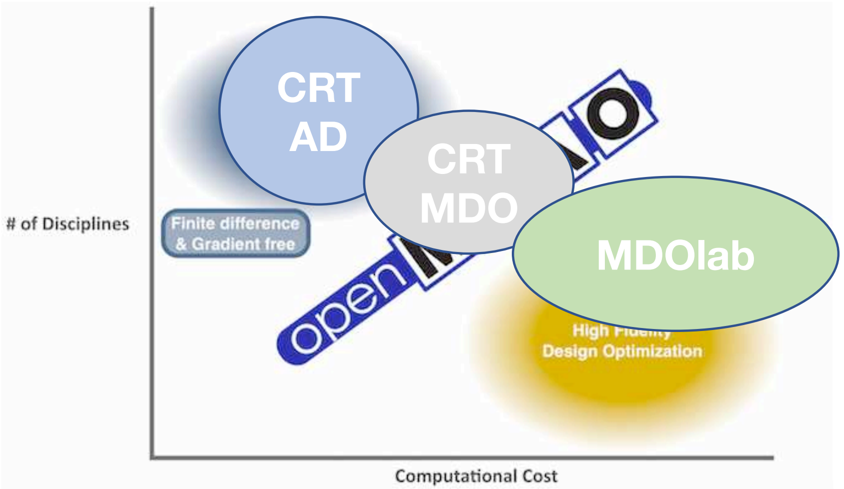
Currently I’m working on the fields:

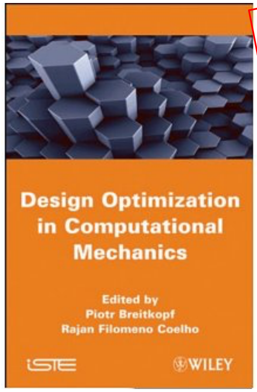
- MDO, Topology optimization, surrogate modeling, machine learning applied to aircraft,

But in the past

- SHM, composites structures, system identification, Neural networks applied to aircraft

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

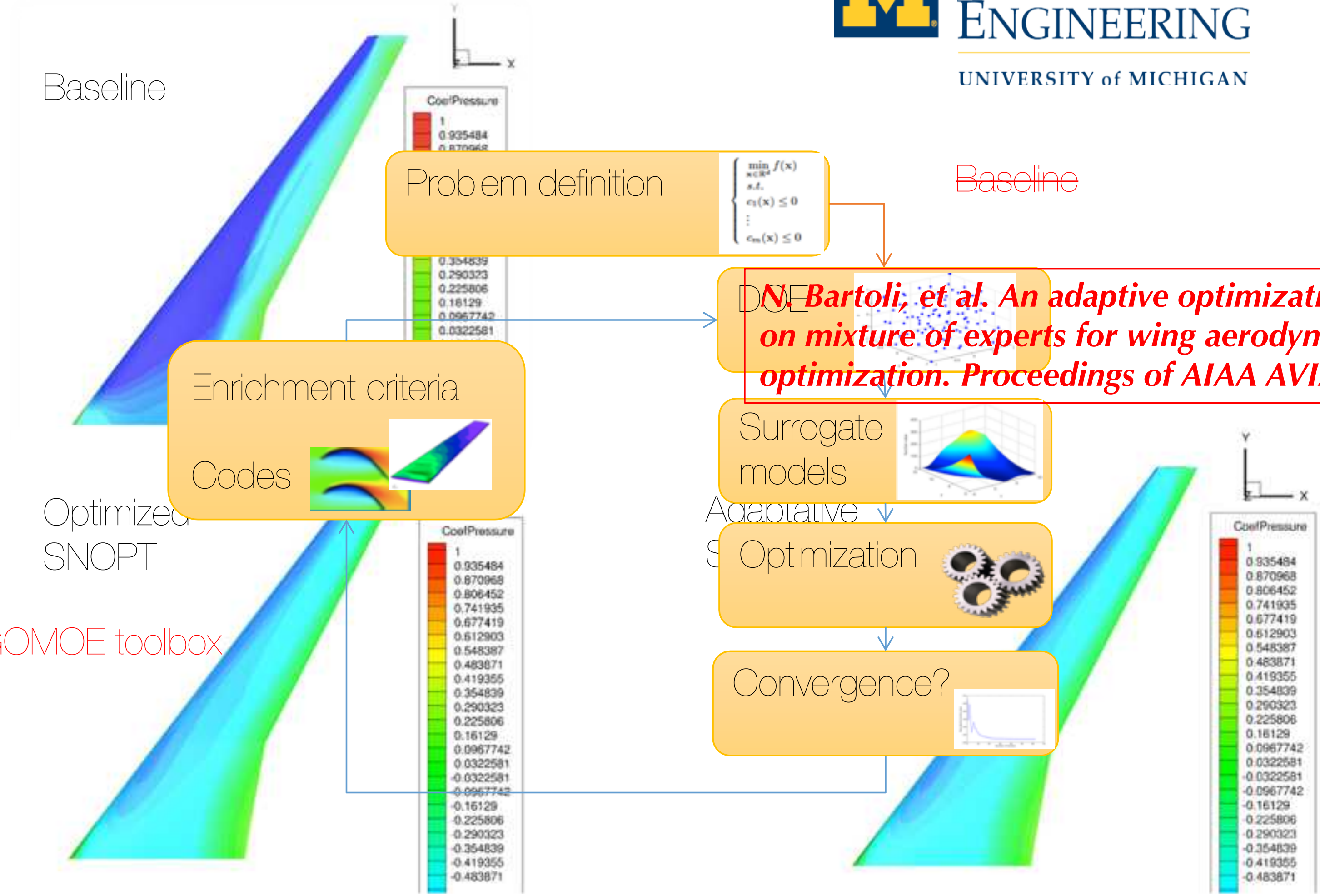
→ Methods applied to AD Aircraft Design,: Put the aircraft structure / aeroelasticity in the loop at the early stage of MDO process

→ compatible with

openMDAO

AIAA Aviation 2017, Collaboration with MDOlab

AEROSPACE ENGINEERING
UNIVERSITY of MICHIGAN



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

Tools: Adflow+ SEGOMOE toolbox

Outlines

1. Overview of Machine learning technics
2. Aerolesticity- Similarity
3. Discrete Continuous Optimization in CSM

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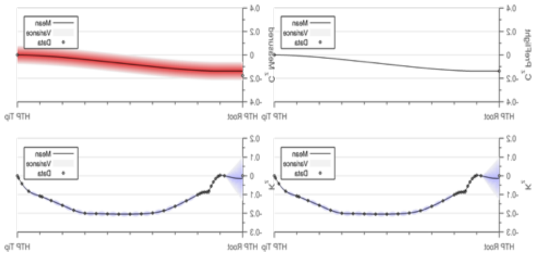
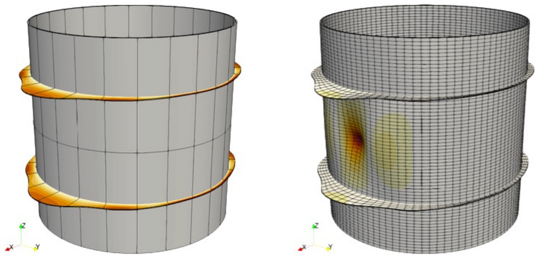
3. Discrete Continuous Optimization in CSM

My Group

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

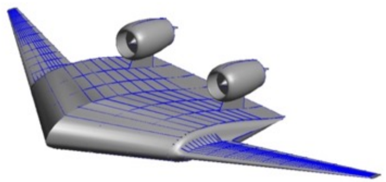
- 5 PhDs, 1 postdoc



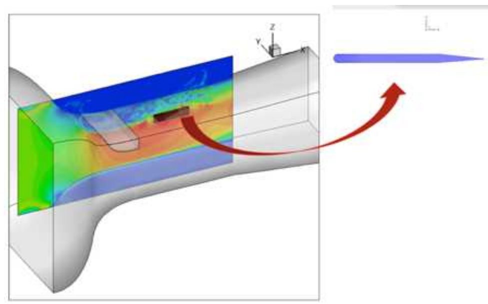


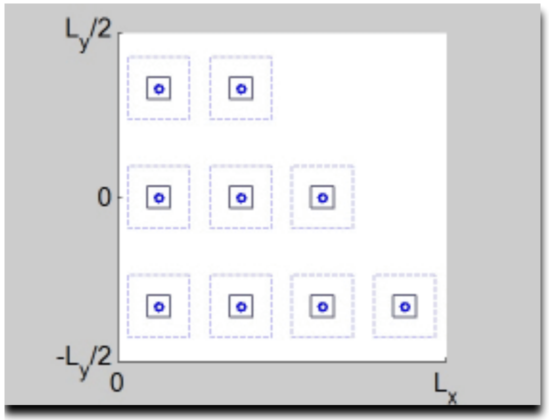
Δ TSFC% solution, Volume fraction =0.39964 Δ TSFC = 2.5276

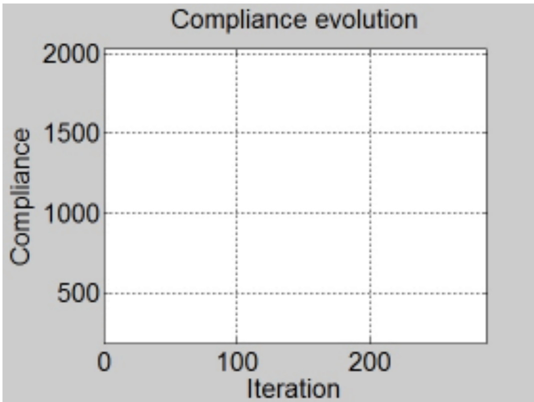
Δ TSFC% solution, Volume fraction =0.49913 Δ TSFC = 1.7554



$$
\begin{aligned}
\min_{\substack{(\boldsymbol{t},\boldsymbol{A}) \in \mathbb{R}^{2N} \\ \boldsymbol{c} \in \Gamma^N}} \quad & W(\boldsymbol{c},\boldsymbol{t},\boldsymbol{A}) \\
\text{Subjected to:} \quad & \boldsymbol{RF}(\boldsymbol{c},\boldsymbol{t},\boldsymbol{A},IL(\boldsymbol{c},\boldsymbol{t},\boldsymbol{A})) \geq 1 \\
& G(\boldsymbol{c},\boldsymbol{t},\boldsymbol{A}) \leq 0 \\
& \underline{t}(\boldsymbol{c}) \leq \boldsymbol{t} \leq \bar{t}(\boldsymbol{c}) \\
& \underline{\alpha}(\boldsymbol{c}) \leq \frac{\boldsymbol{A}}{\boldsymbol{bt}} \leq \bar{\alpha}(\boldsymbol{c})
\end{aligned}
$$







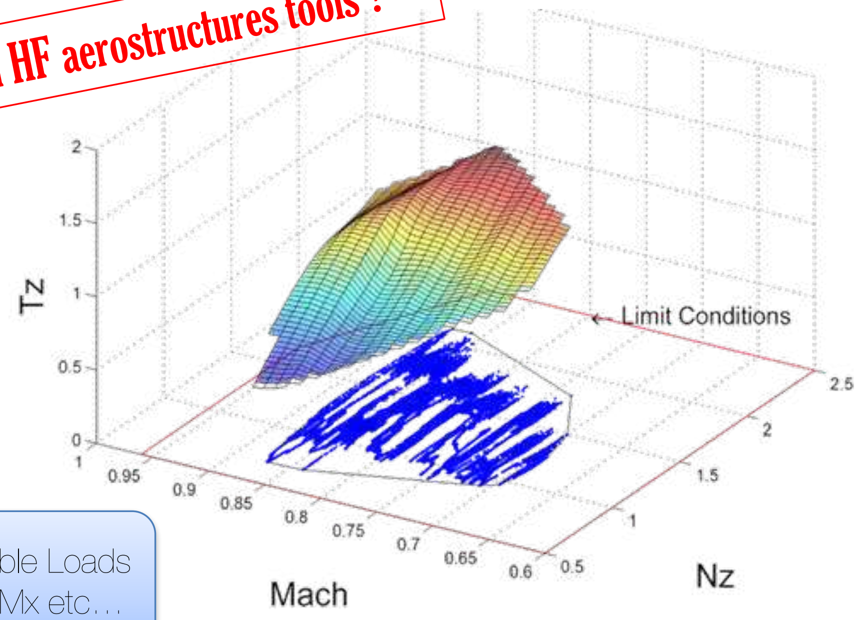
Machine learning for load estimation (Ankit Chiplunkar, AIRBUS FUND)

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 (CIFRE AIRBUS)

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 ?

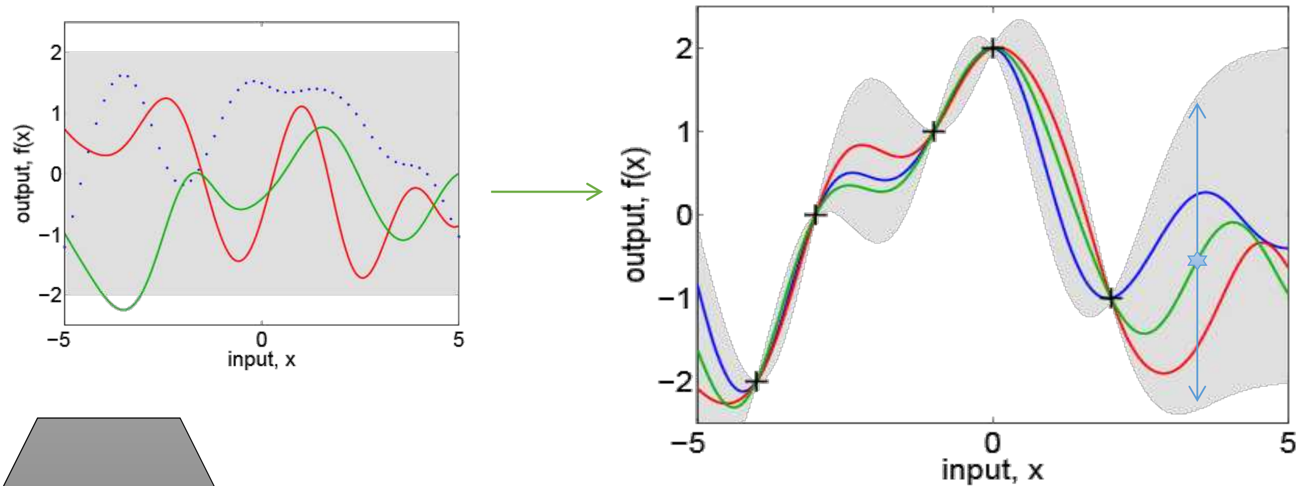


Can we automate the process?

Statistical step

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

Gaussian Process Regression



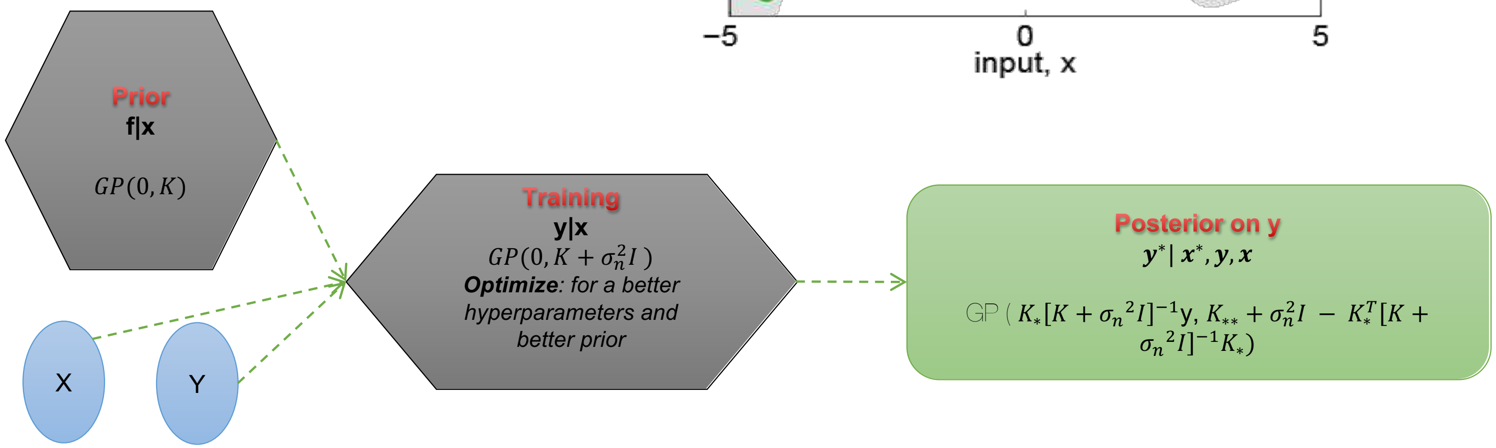
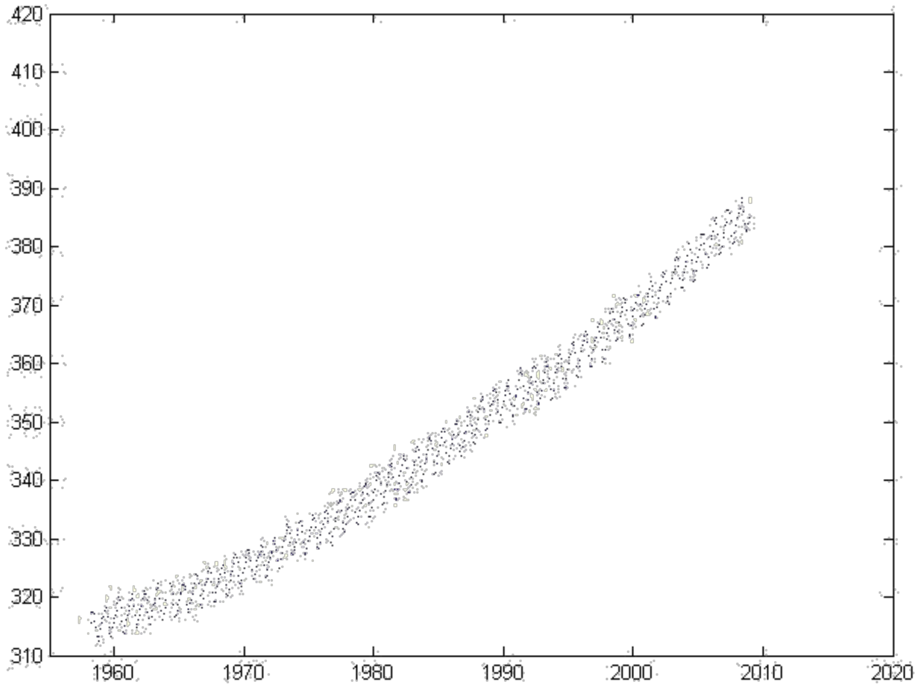


Image Source: http://mlg.eng.cam.ac.uk/teaching/4f13/1314/

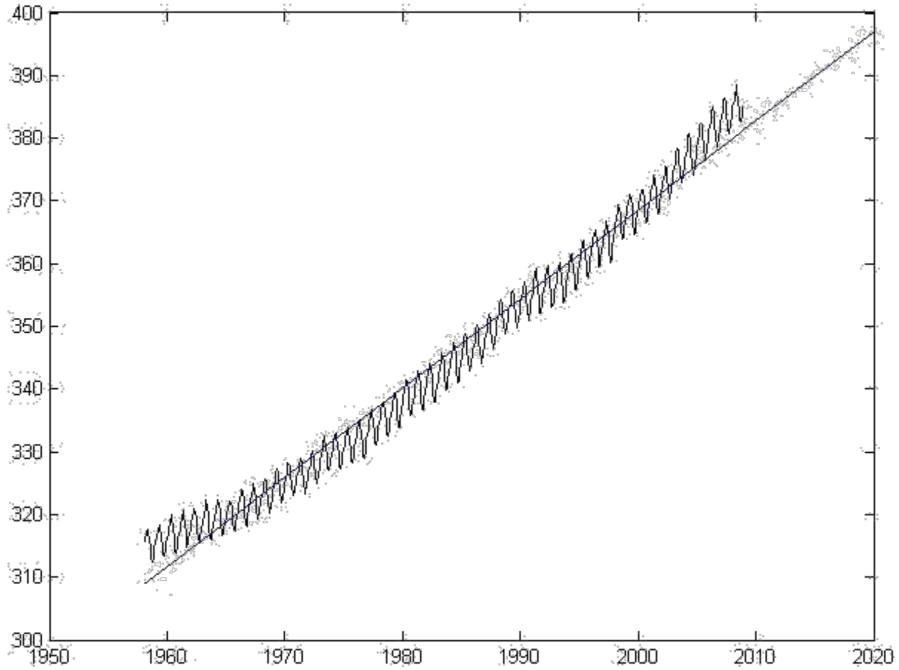
A SIMPle Example



Month-wise data of Co2 concentration in atmosphere at Hawaii

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

Example – Linear Regression



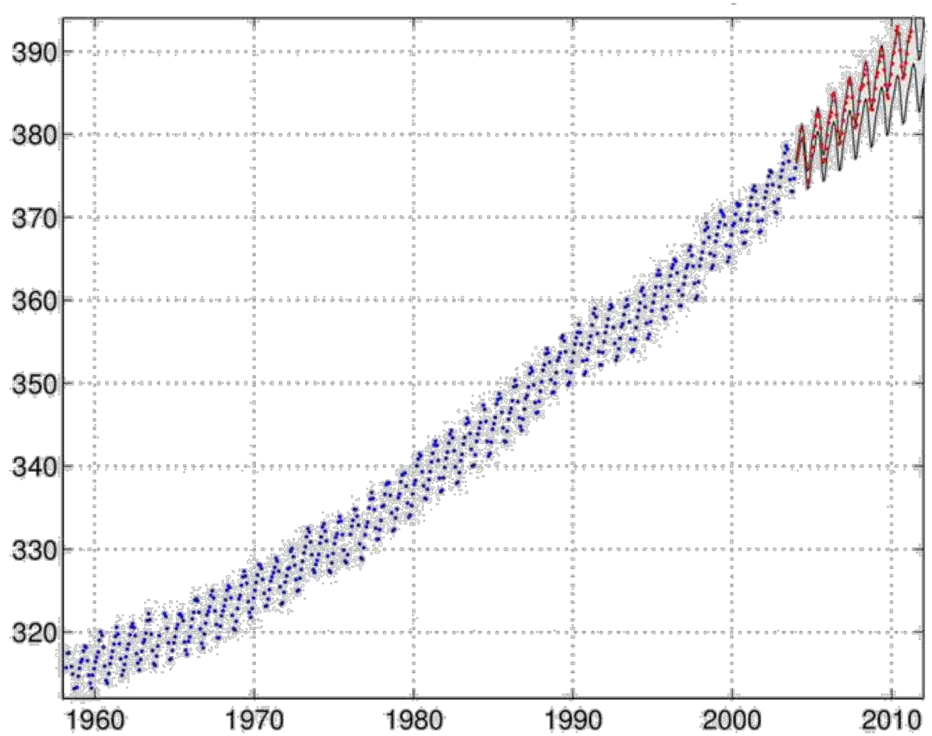
Should we choose a polynomial?

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/

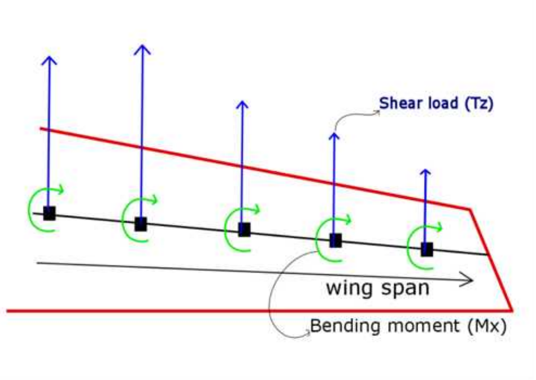
Example – Gaussian Process



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: $f_1 = g(f_2, x)$

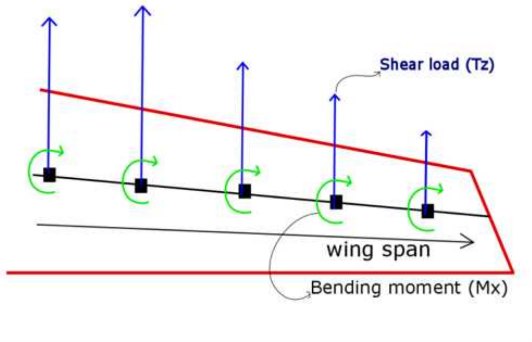
- Earlier examples include **Gradient Enhanced Kriging** (GEK) or **Co-kriging**

- 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.

Multi-Output Gaussian Process – Flight Test examples



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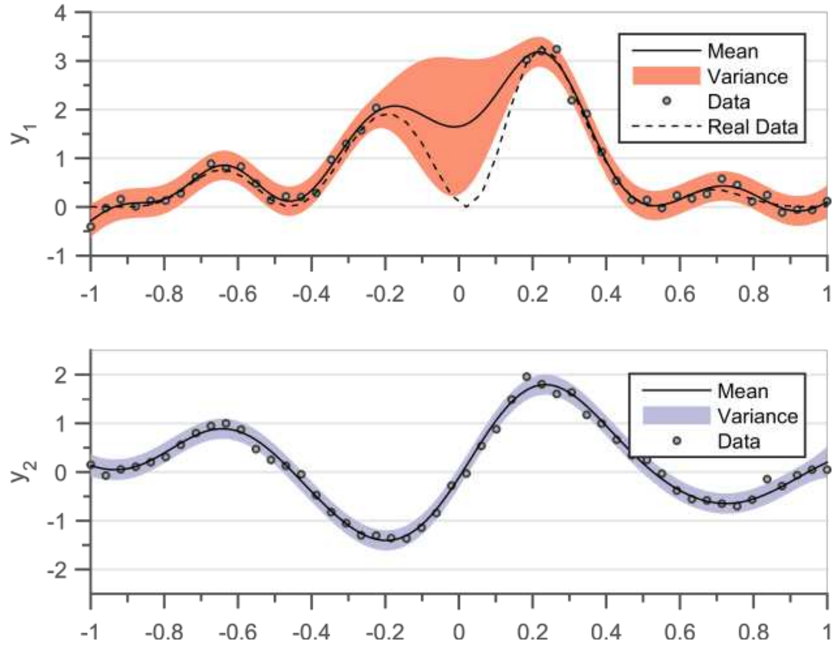
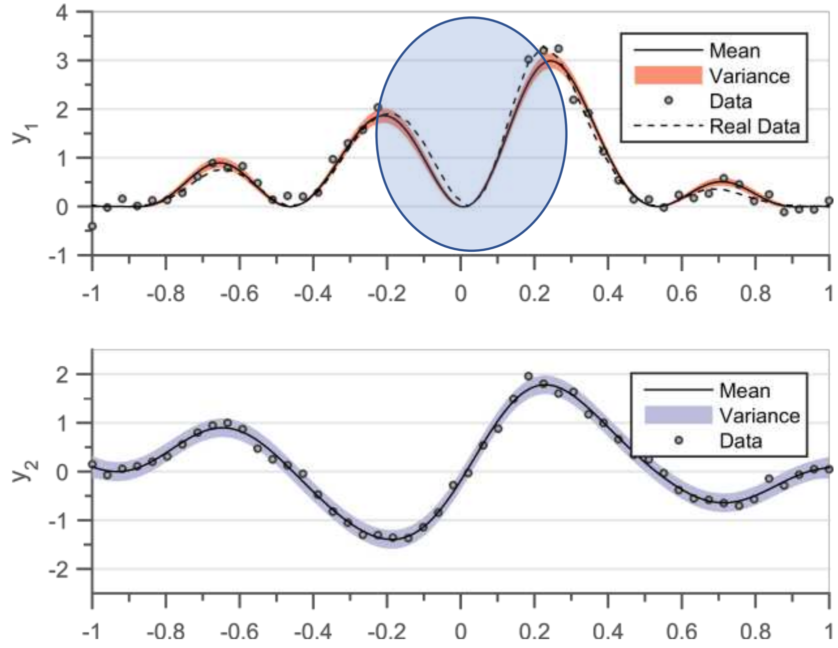
Liu, Weiyu. Development of gradient-enhanced kriging approximations for multidisciplinary design optimization. 2003.

Example 1: Faulty sensors (using synthetic data) $y_1 = (y_2)^2$

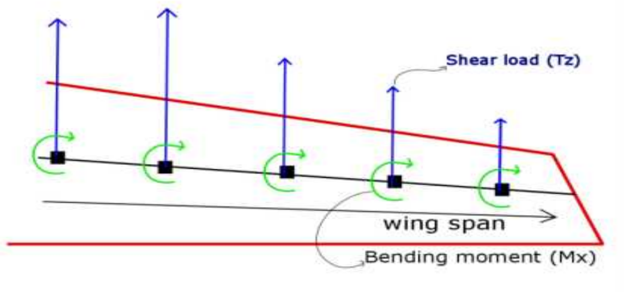


Independent GPs

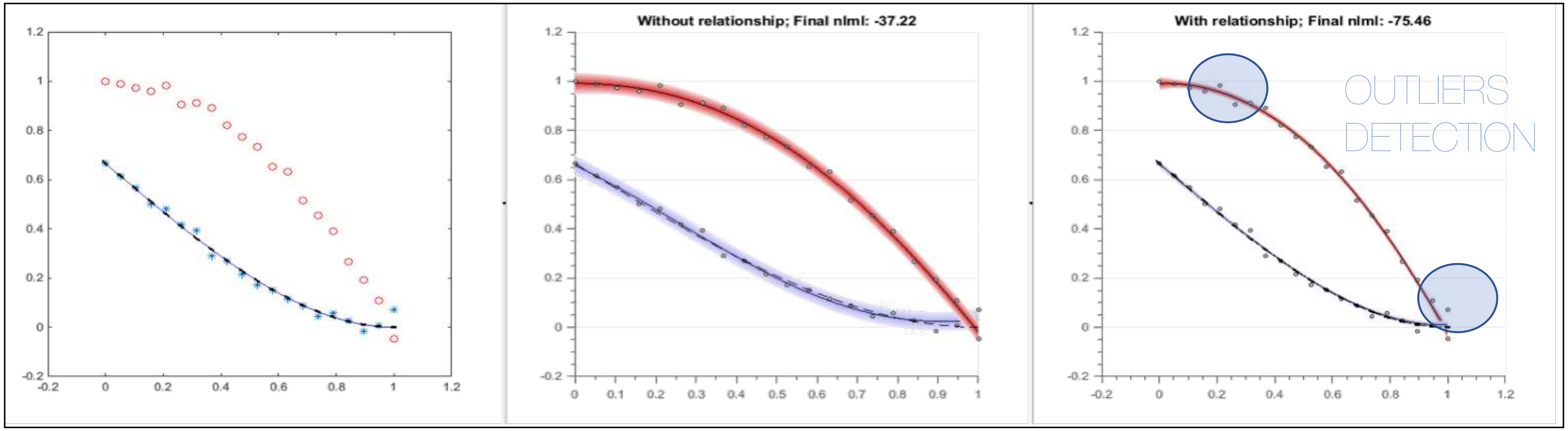


Related GPs

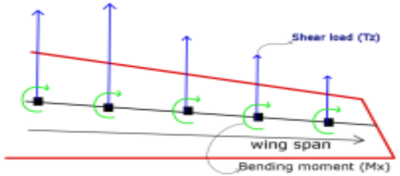
Example 2: use the Relationship between Tz and Mx permits to reduce uncertainties



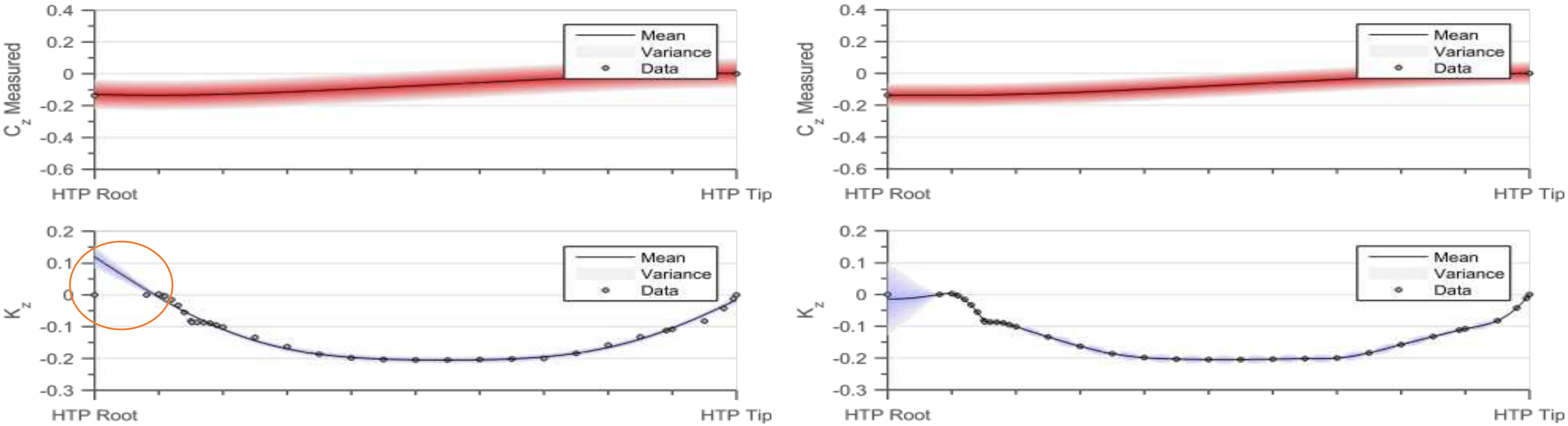
$$Mx = \int_{\eta}^{\eta_{edge}} (x - \eta)\, Tz\, dx$$



Exemple 3: choosing the good kernel



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

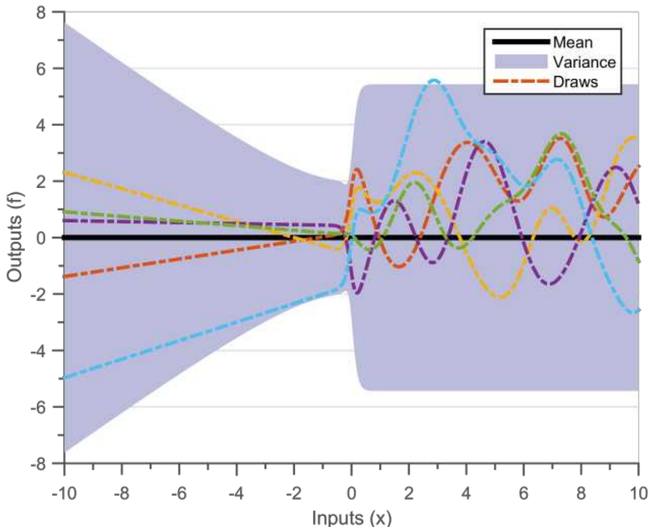


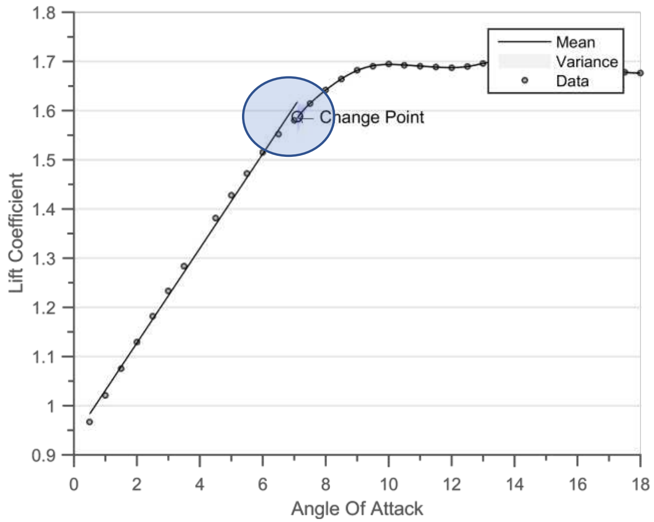
$$k_{SE}(x, x', \theta) = \theta_1^2 exp[-\frac{d^2}{2\theta_2^2}]$$

$$k_{Mat2}(x, x', \theta) = \theta_1^2 \left(1 + \frac{\sqrt{5}d}{\theta_2} + \frac{5d^2}{3\theta_2^2}\right) exp\left[-\frac{\sqrt{5}d}{\theta_2}\right]$$

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

Example 3: Identifying onset of non-linearity

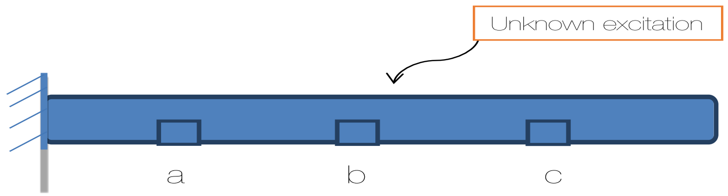


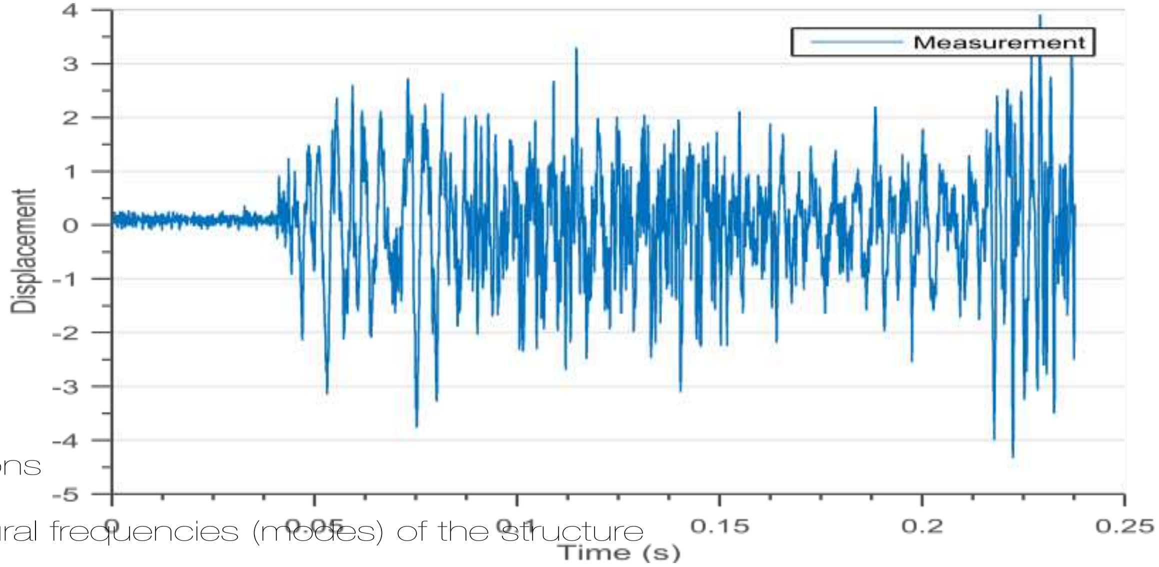


$$k_{CP}(k_1, k_2, x_1, x_2) = sigm(x_1)k_1 sigm(x_2) + (1 - sigm(x_1))k_2(1 - sigm(x_2))$$

- Estimate change in pattern
- Use global optimization to identify the non-lineariity automatically

Example 4: Operational Modal analysis

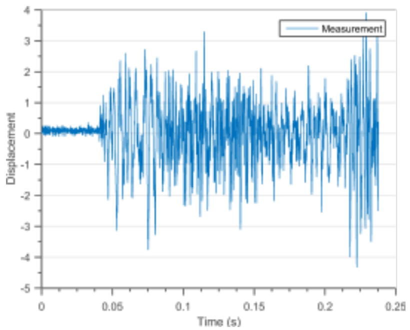


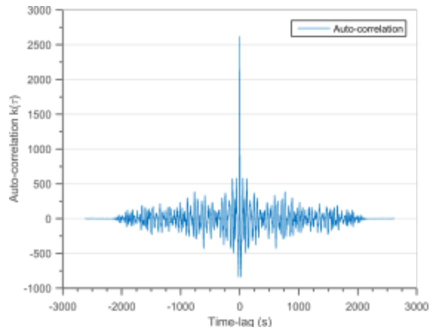


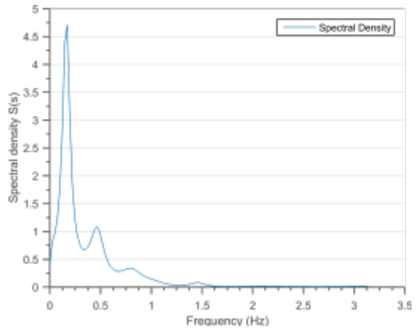
1. Sample is subjected to unknown random excitations
2. Each sensor record time signals
3. Peaks in their power spectral density give the natural frequencies (modes) of the structure

DiazDelaO, F. A., and S. Adhikari. "Structural dynamic analysis using Gaussian process emulators." Engineering Computations 27.5 (2010)

New paradigm: Spectral Mixture

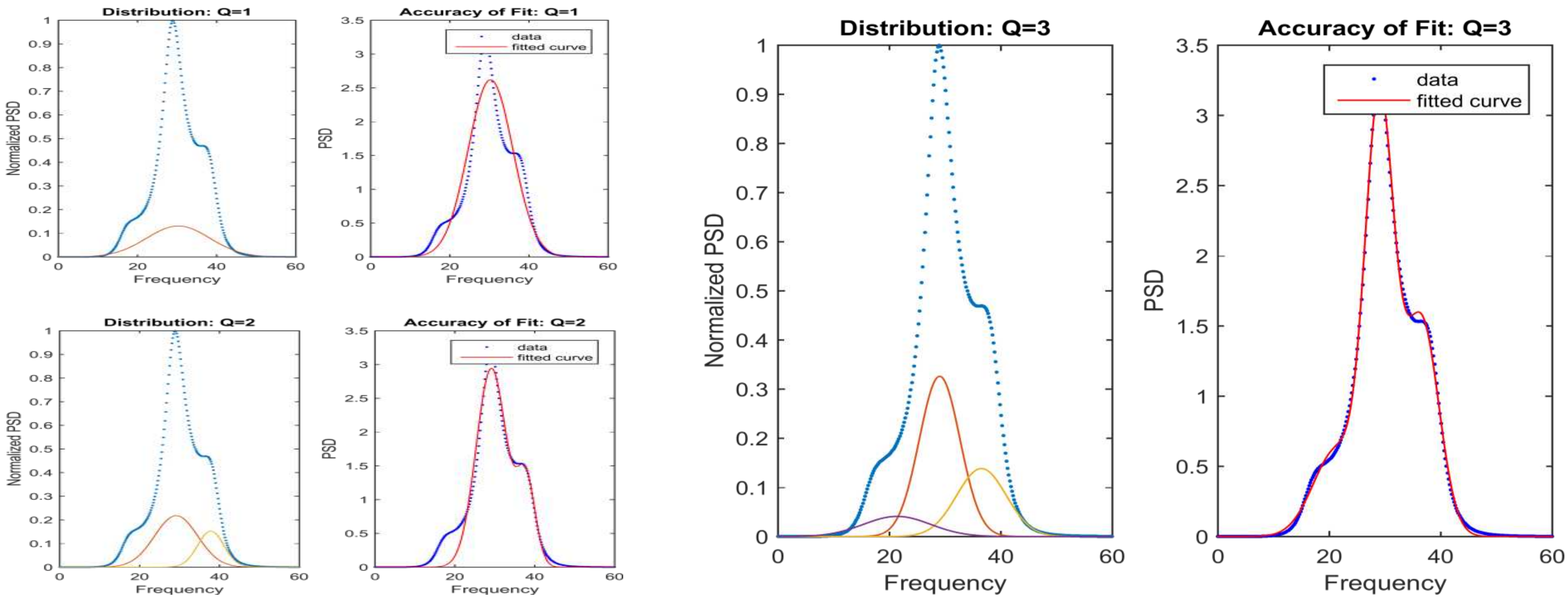






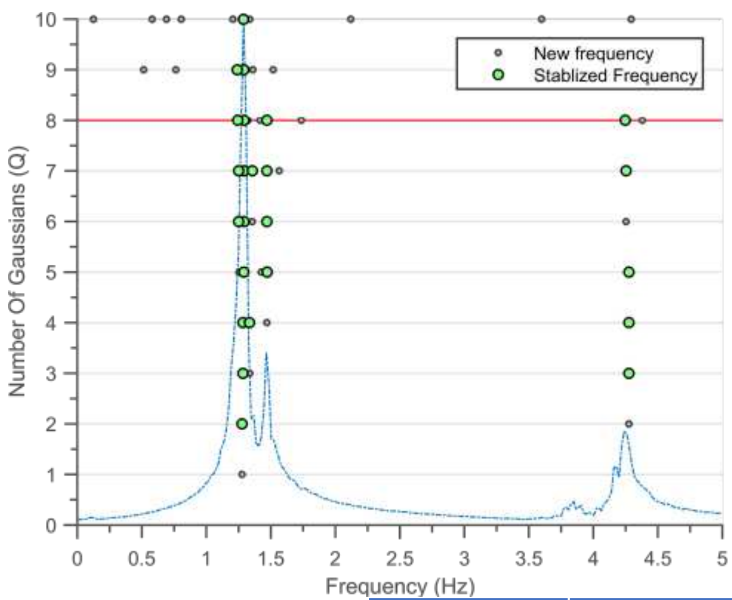
Displacement	Autocorrelation	Power spectral density
$x(t)$	$k(\tau) = \int x(t)x(t-\tau)dt$	$S(s) = Fourier(k(\tau))$
$M\{\ddot{x}(t)\}+C\{\dot{x}(t)\}+K\{x(t)\} = \{f(t)\}$		
	$k(\tau) = \sum A_i exp(-\lambda_i \tau) sin(B_i \tau)$	$S(s) = \frac{\sum a_k(s)^k}{\sum b_l(s)^l}$
Spectral Mixture Covariance		
$x(t) = GP(0, cov_{SM}(t,t'))$	$k_{SM}(d,\mu,\sigma,w) = \sum_{q=1}^{Q} w_q cos(2\pi\mu_q) exp[-2\pi^2 d^2 \sigma_q^2]$	$S_{SM}(s,\mu,\sigma,w) = \sum_{q=1}^{Q} \frac{w_q}{\sqrt{2\pi\sigma_q^2}} \left(\exp\left[-\frac{(s-\mu_q)^2}{2\sigma_q^2}\right] + \exp\left[-\frac{(-s-\mu_q)^2}{2\sigma_q^2}\right] \right)$

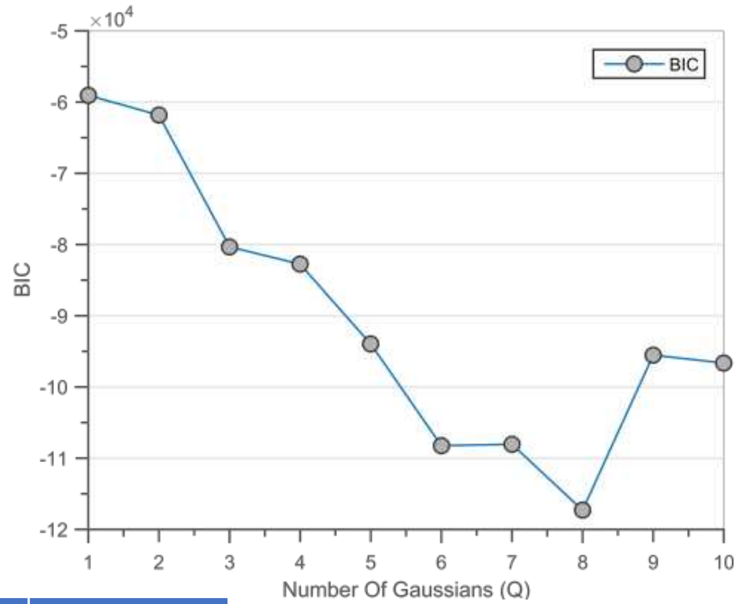
Gaussian Mixture Models



Plataniotis, K. N. and Hatzinakos, D. , Advanced Signal Processing Handbook Theory and Implementation for Radar, Sonar, and Medical

Automatic OMA (Testcase HTC building *)





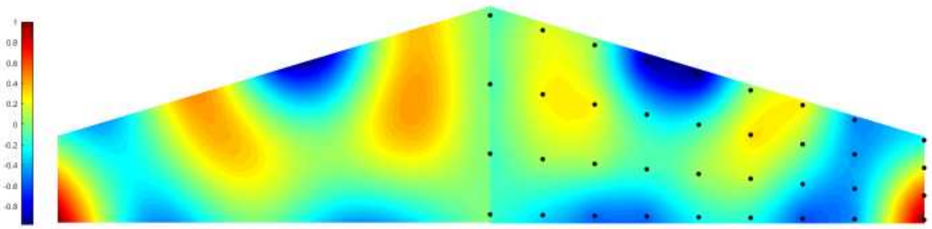
	From paper	GMM
Freq1	1,23	1,242
Freq2	1,27	1,292
Freq3	1,43	1,470
Freq4	3,86	3,866
Freq5	4,25	4,247

*Brincker, Rune, and Palle Andersen. "Ambient response analysis of the heritage court tower building structure." IMAC, 2000
Data from: http://www.brinckerdynamics.com/oma-toolbox/

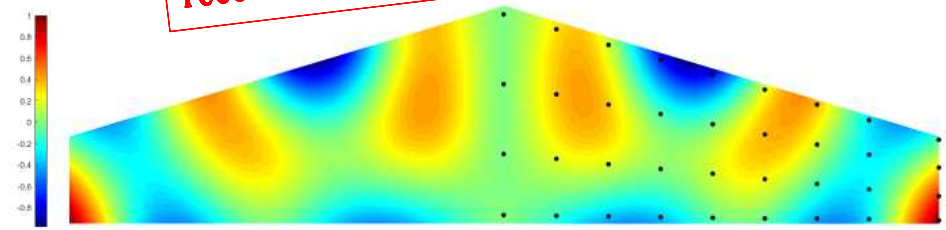
Example 5: Sensor Placement Optimization

- Idea : Reduce in a smart way the number of sensors for GVT by using GP/Kriging for Modeshapes reconstruction
- How: By optimizing the sensor positions and use them as variables in a SPO problem

1/ Better Modeshape reconstruction using GP/Kriging



Comparison between HF FEA results (a) and a Linear Reconstruction with a regular grid of 36 sensors (b), for 9th Mode Shape.



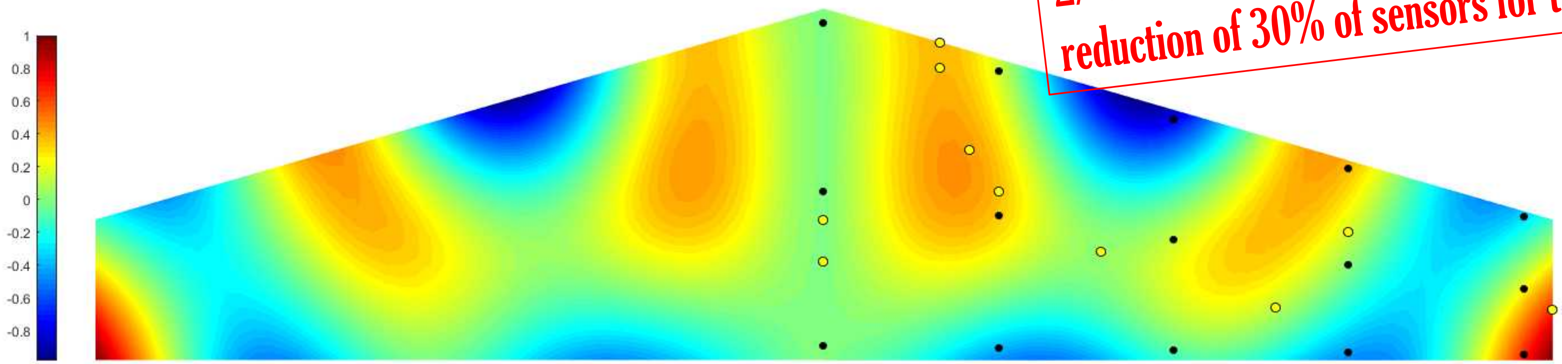
Comparison between HF FEA results (a) and a Kriging Reconstruction with a regular grid of 36 sensors (b), for 9th Mode Shape.

EGO strategy

Jones, D. R., Schonlau, M., & Welch, W. J. (1998). Efficient global optimization of expensive black-box functions. Journal of Global optimization, 13(4), 455-492.

- Idea : Working at fixed budget
- How: Iterative procedure that maximize the trace of MAC (Modal Assurance Criteria)

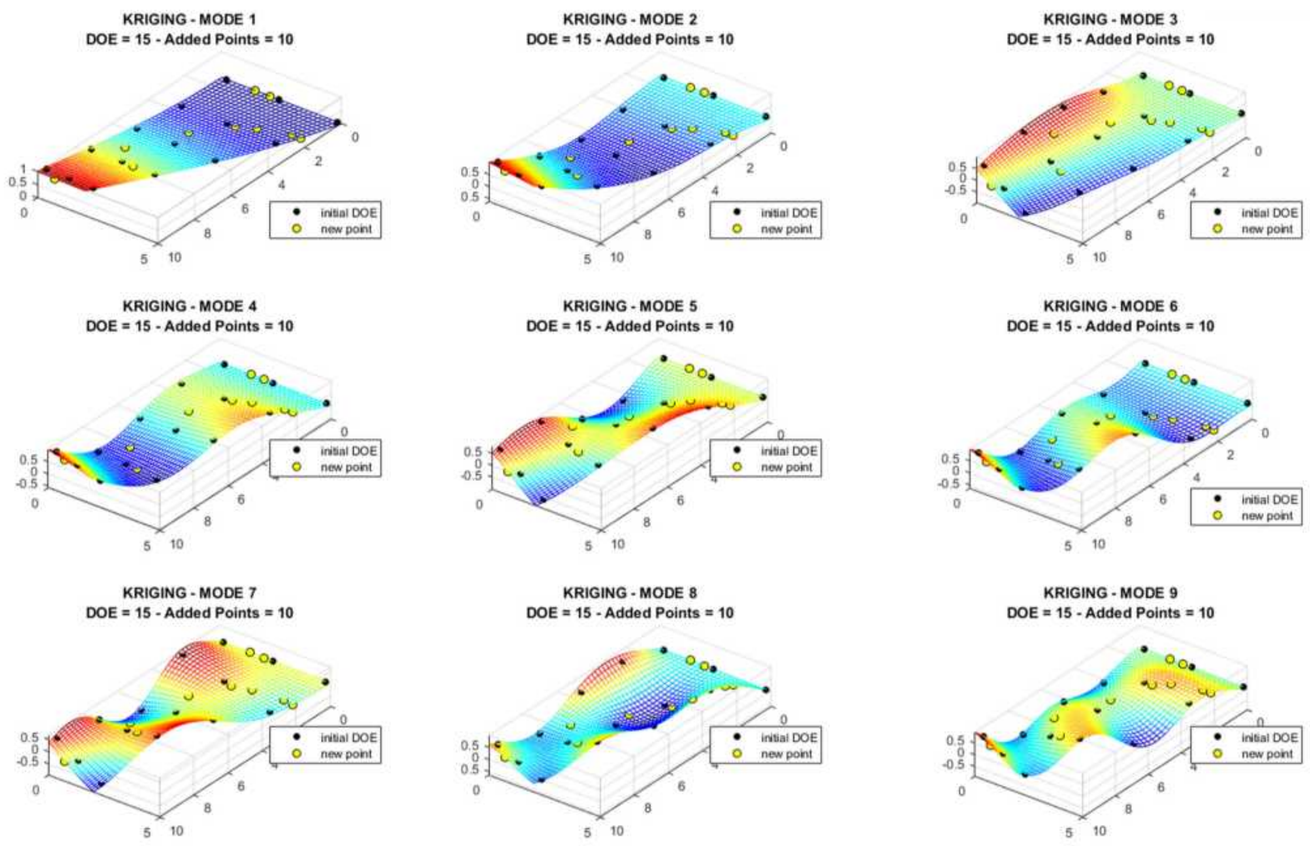
2/ EGO-SPO allows a reduction of 30% of sensors for the entire modal basis.



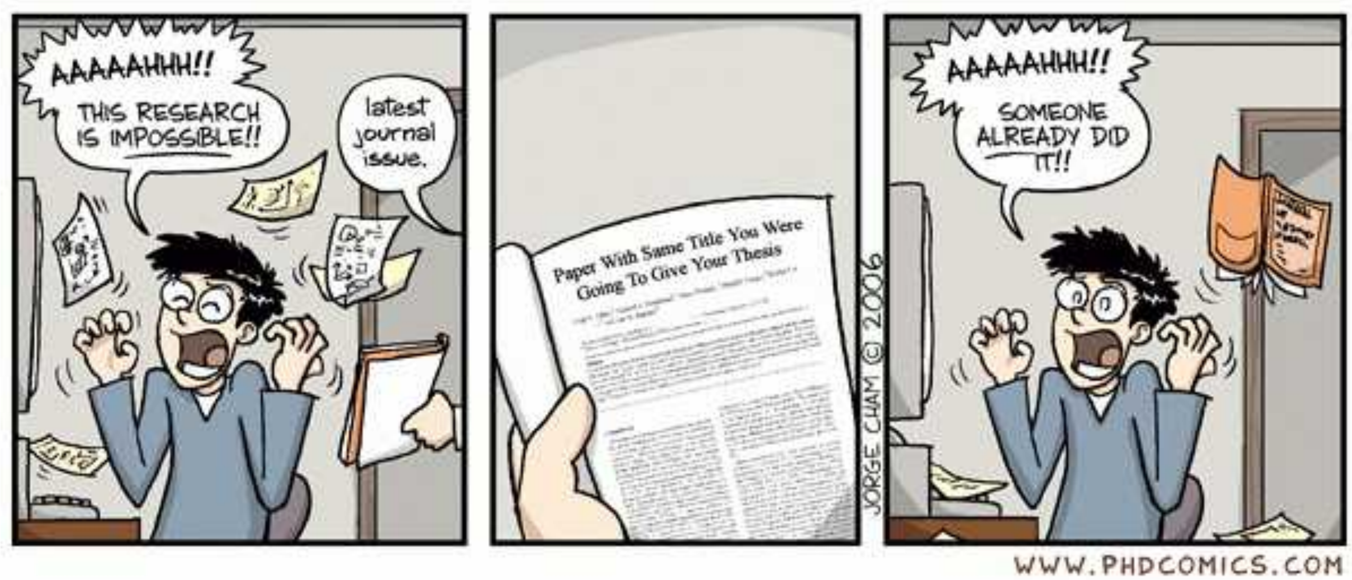
Typical result showing SPO-EGO performance. As example 9th Mode Shape.
(a): HF FEA results. (b): SPO-EGO stategy. The black dots represent the initial DOE (regular grid, 15 sensors).

Results

- Matlab codes (cleaning in profess)
- Compatible with Cliare's inputs



Open questions



- 3D structure

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

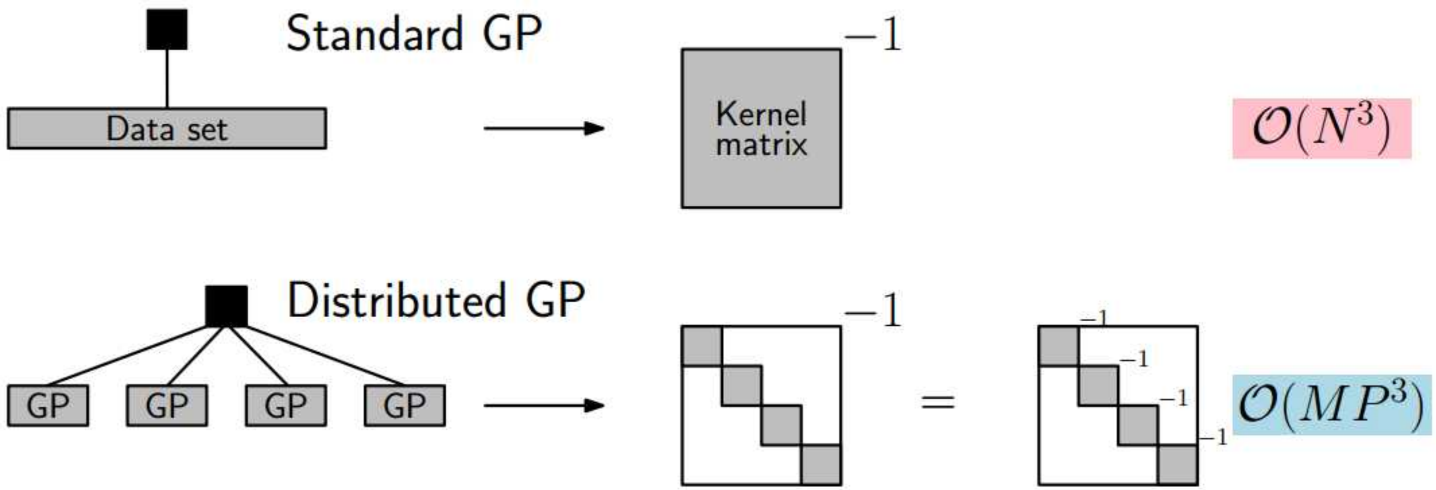
Chiplunkar, E. Rachelson, M. Colombo and J. Morlier. Adding Flight Mechanics to Flight Loads Surrogate Model using Multi-Output Gaussian Processes. AIAA AVIATION 2016

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

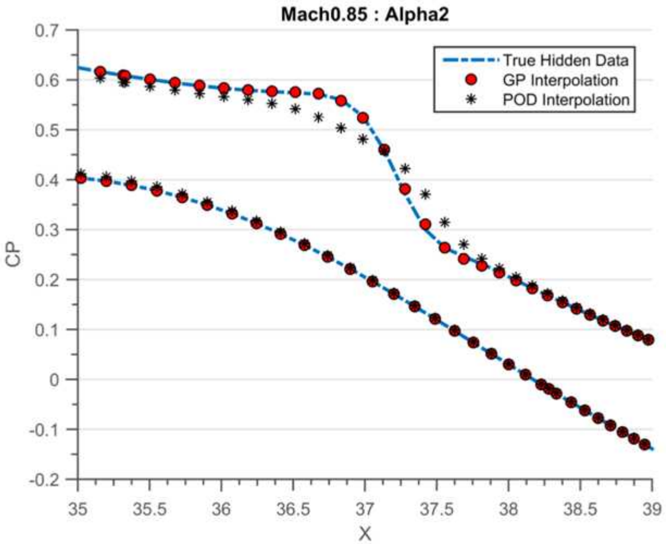
Link to HPC: Distributed Gaussian Process

Learning	Storage	Mean	Variance
$O(n^3)$	$O(n^2)$	$O(n)$	$O(n^2)$

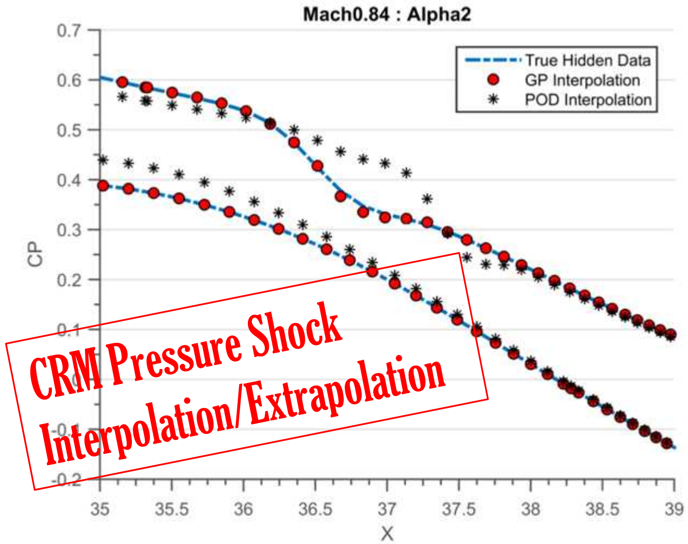


Distributing the dataset into M chunks of size P

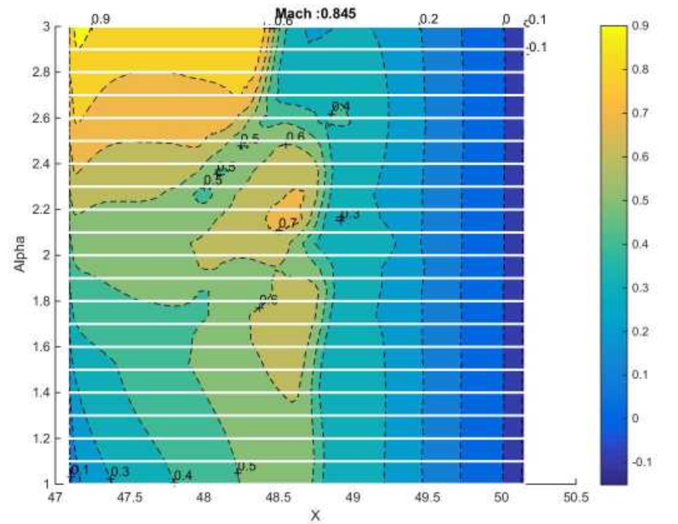
Some others ML applications



(a) Comparison between POD method and Distributed GPs for **interpolation**.



(b) Comparison between POD method and Distributed GPs for **extrapolation**



Outlines

1. Overview of Machine learning technics
2. **Aerolesticity- Similarity**
3. Discrete Continuous Optimization in CSM

Fondation ISAE-SUPAERO
Reconnue d'utilité publique

CEDAR AIRBUS
CHAIR FOR ECO DESIGN OF AIRCRAFT

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

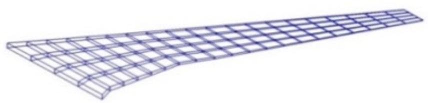
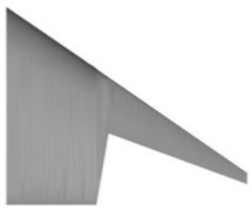
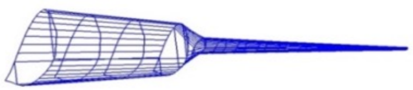
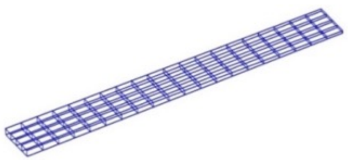
Multifideilty Fidelity

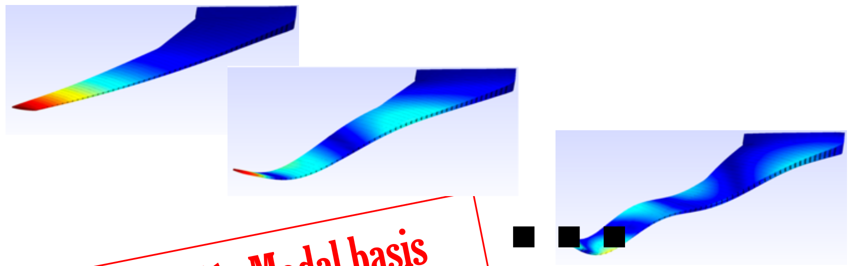
Fidelity Level / Model Type	Low Fidelity	Medium Fidelity	High Fidelity
Geometrical Model	Reduced 1D		Full 3D
Numerical Model/Solution		Panel Method (Panair®) Finite Element (Nastran95®)	

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

CAD= Airconics+ OpenNastran

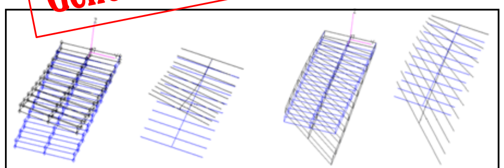
All types of body shape may be reproduced, here some wing examples:

Aerodynamic Surface	Airframe	Wing Type
		CRM
		BWB
		GOLAND



Aircraft DNA: Modal basis

Generalized 1D Beam for low fidelity



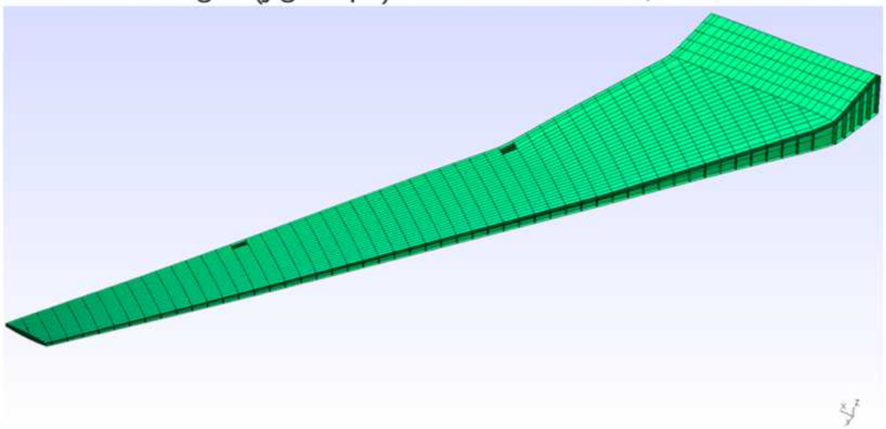
(a) 3D model, $f = 1.98$ Hz (b) stick model, $f = 1.96$ Hz (a) 3D model, $f = 4.05$ Hz (b) stick model, $f = 3.98$ Hz

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 $t_r = 8.89mm$



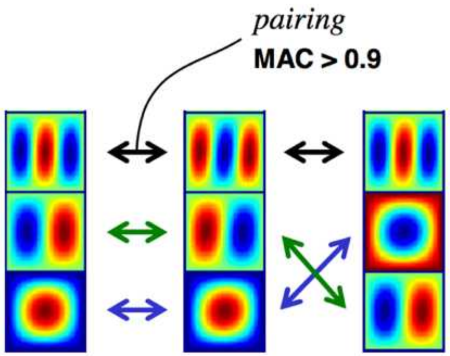
Model provided by T. Achard and C. Blondeau*

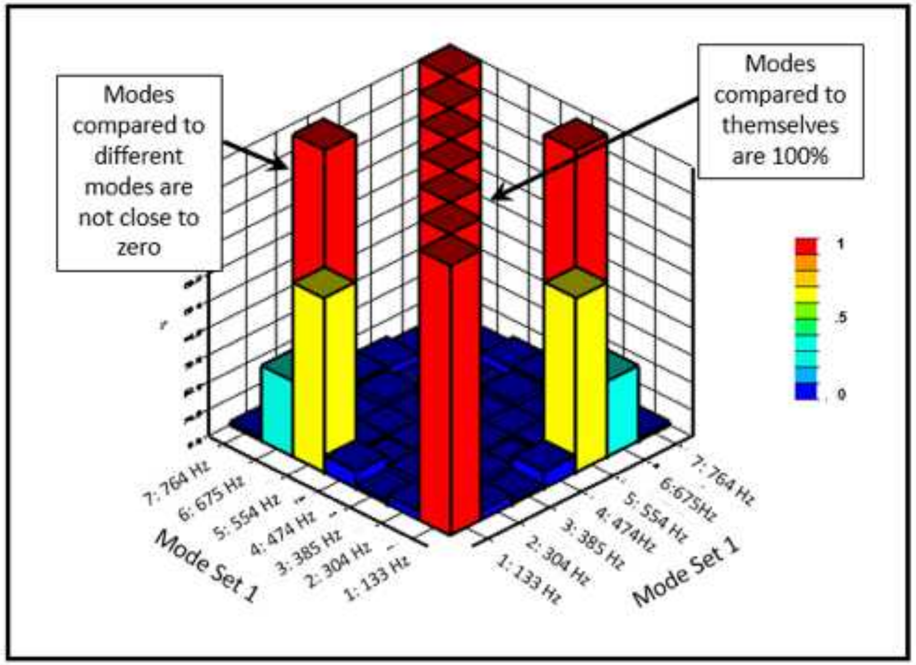
Mode pairing

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

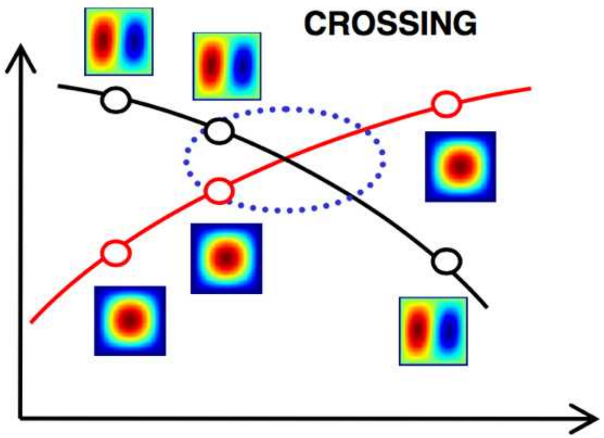
Scaled model: m

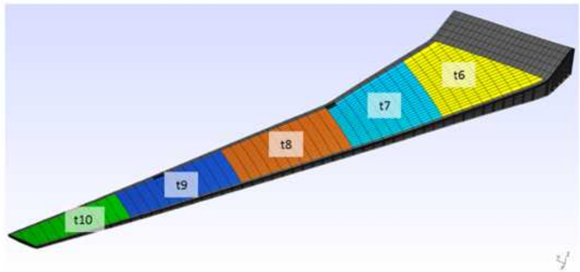
Thickness initialization :Vector of size 10 t1-t10 (meter):

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

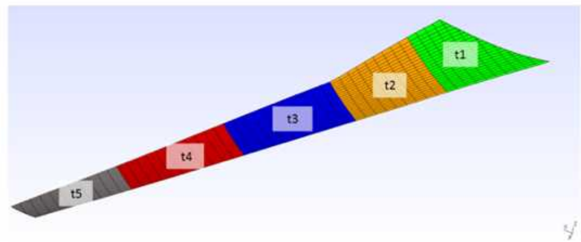
Modes pairing/tracking: Problem definition

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	$\lVert m_r - m_m \rVert = 0$	$\mathbb{R}$	



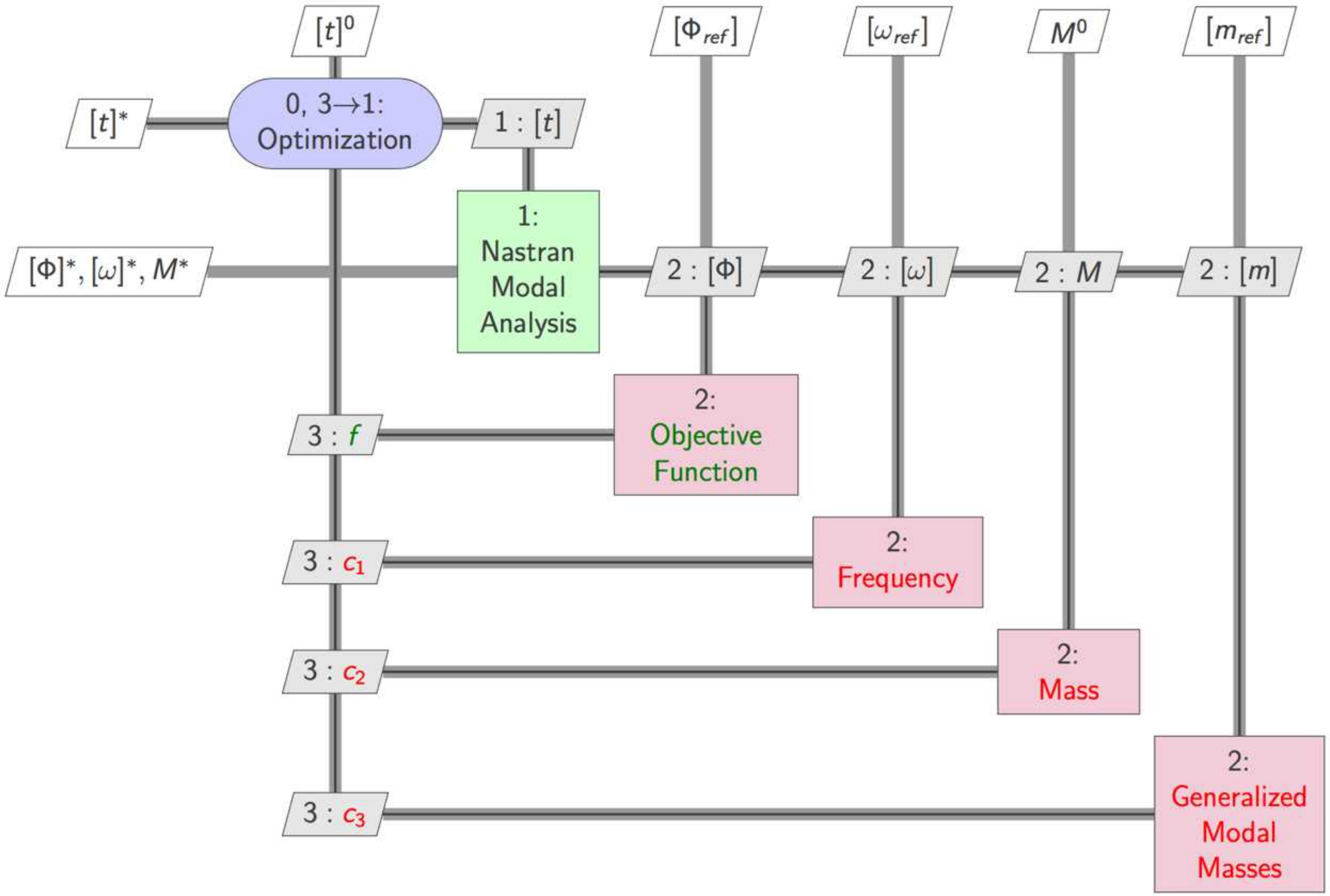


$\rightarrow$ Upper skin panels

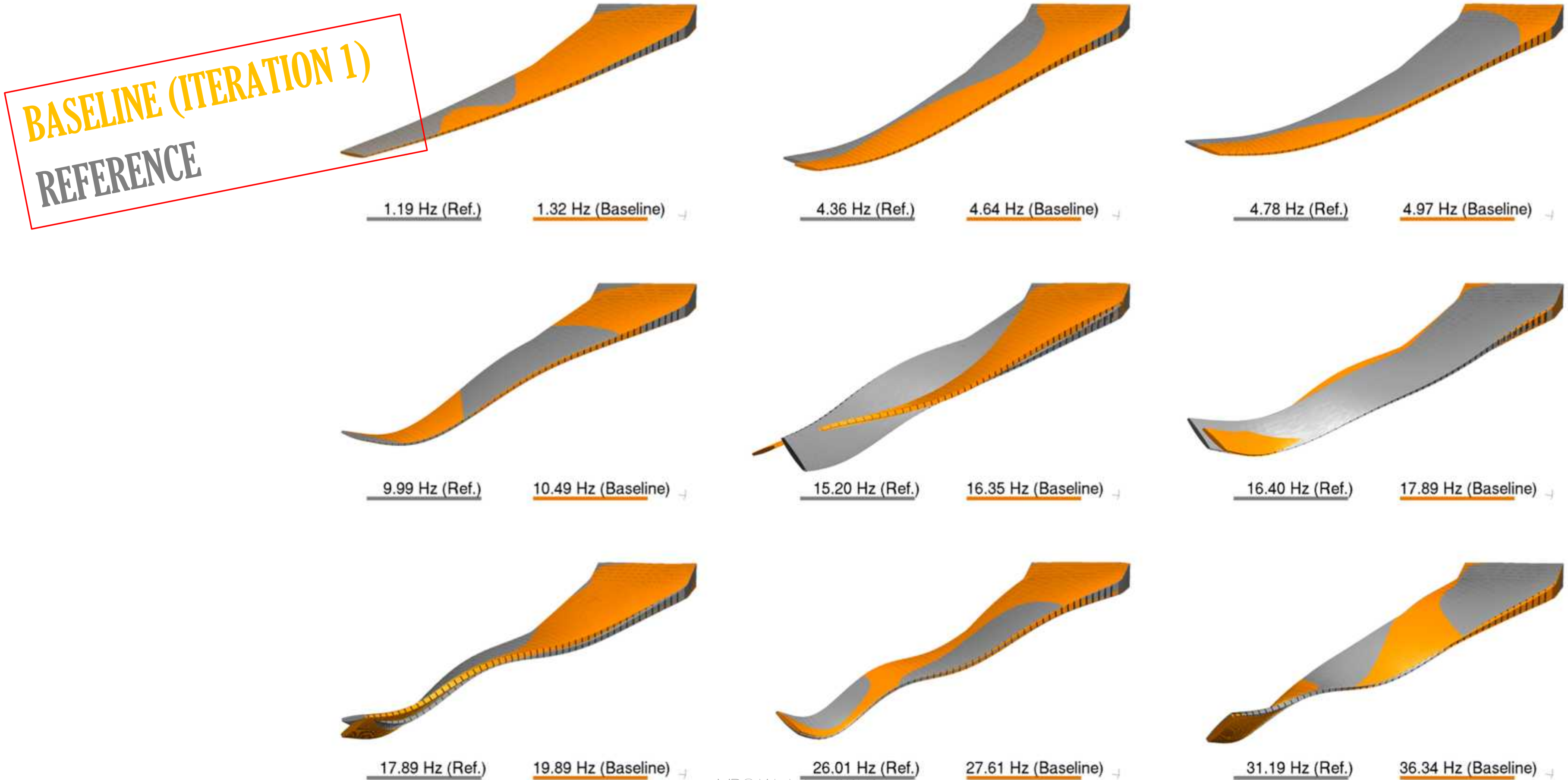


Lower skin panels $\leftarrow$

Modal Optimization



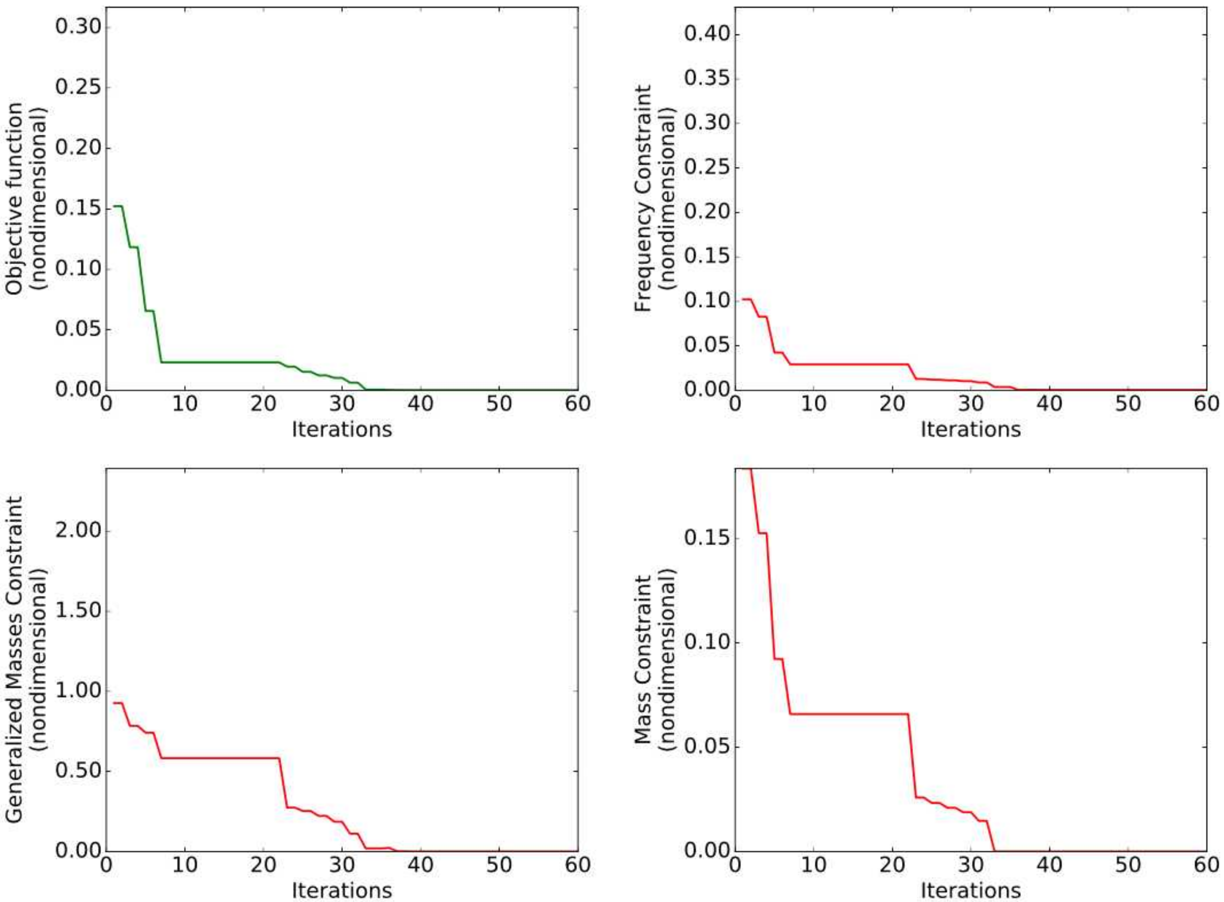
1st Validation CRM Blind Updating



Results of the Optimization (SLSQP)

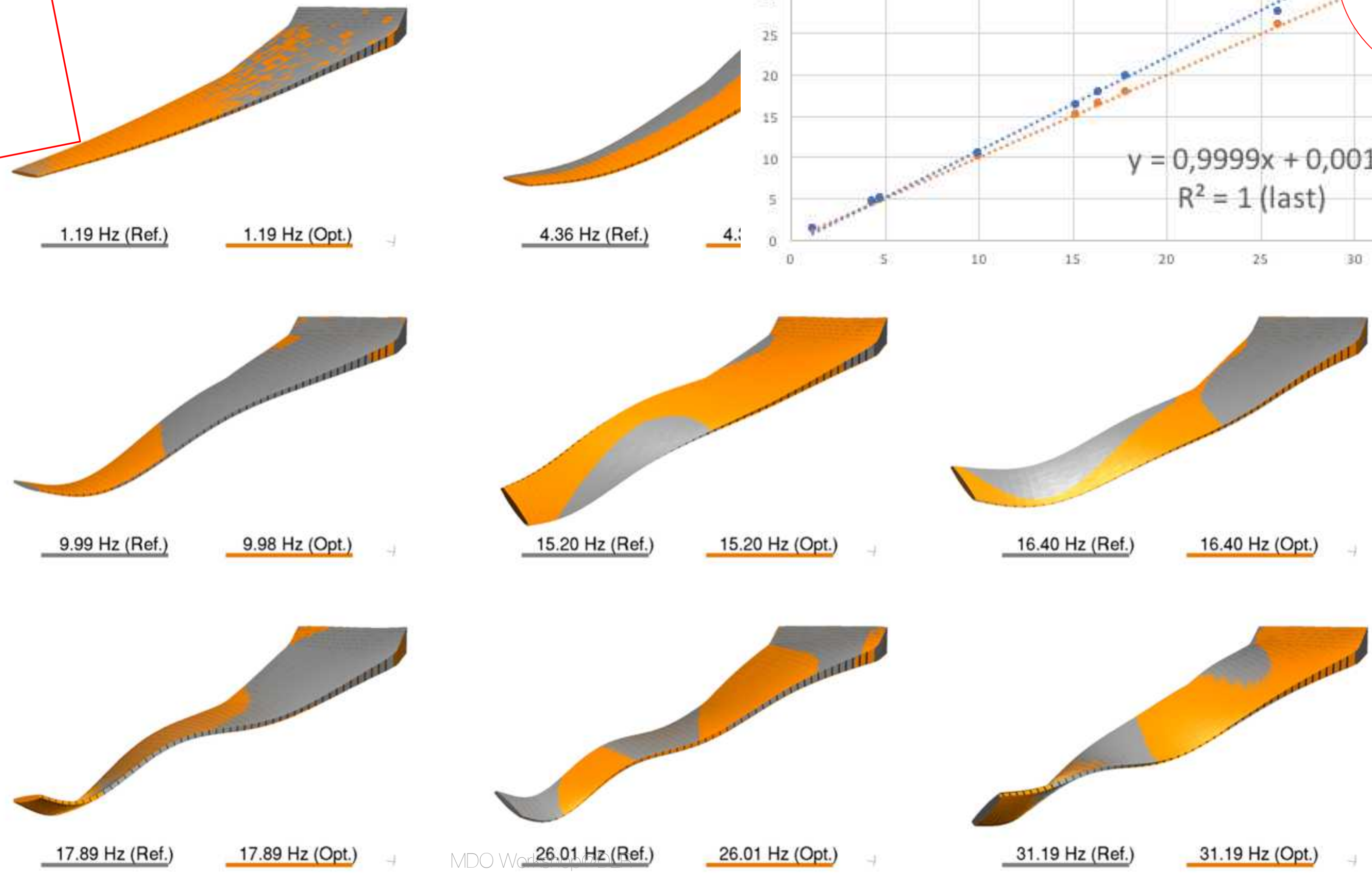
Optimality

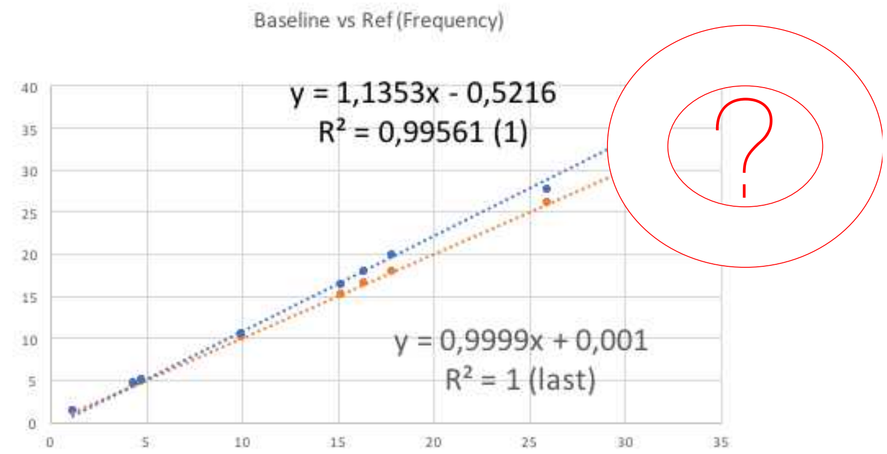
Feasibility



Graphicaly AT CONVERGENCE…

BASELINE (ITERATION Last)
REFERENCE





Open questions

- AIRBUS CIFRE on Flutter Multidisciplinary including Control Law tuning (so called co-design)

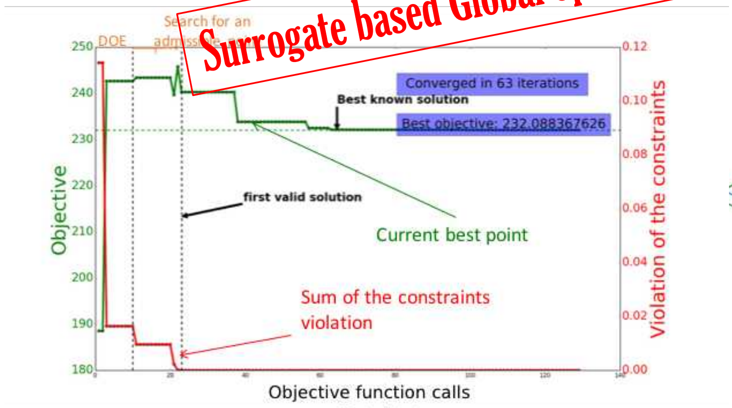
Papers&conf

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

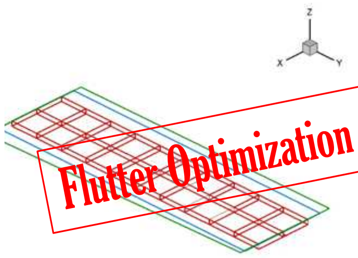
J. Mas Colomer, et al, Static and Dynamic Aeroelastic Scaling of the CRM Wing via Multidisciplinary Optimization. WCSMO12 2017

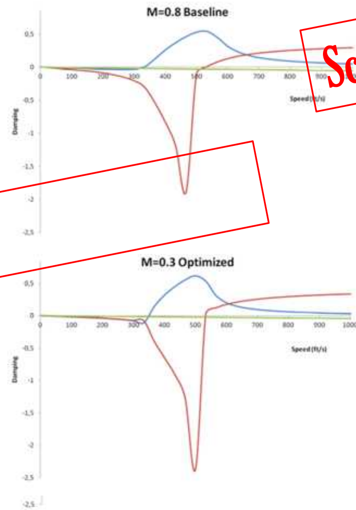
Several Papers in preparation

Surrogate based Global optimization

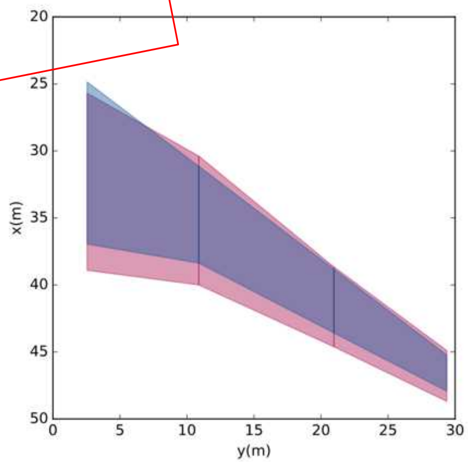


Flutter Optimization





Scaled Aircraft



Optimized planform (red) and baseline (blue).

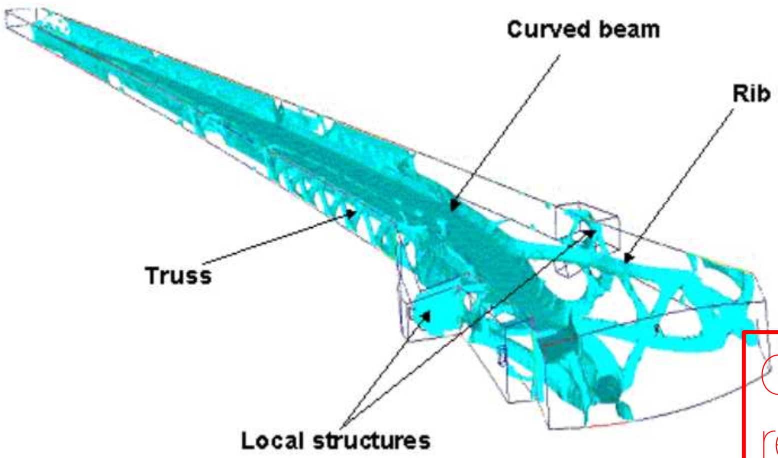
Outlines

1. Overview of Machine learning technics
2. Aerolesticity- Similarity

3. Discrete Continuous Optimization in CSM

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?

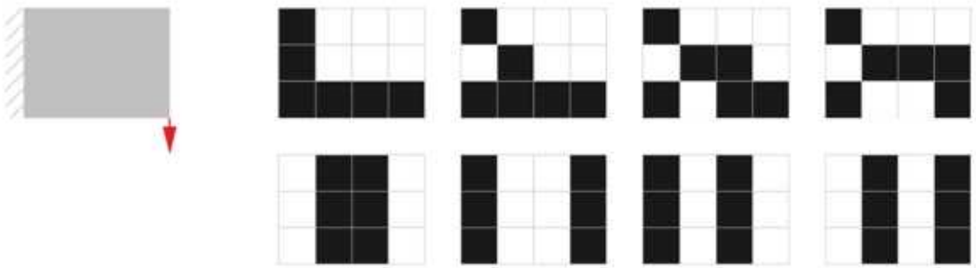
Pixels?

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

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

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

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

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

- Contraints: mass target

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

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

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

Visiting scholar at UoM

Fondation ISAE-SUPAERO Reconnue d'utilité publique
AEROSPACE ENGINEERING UNIVERSITY of MICHIGAN

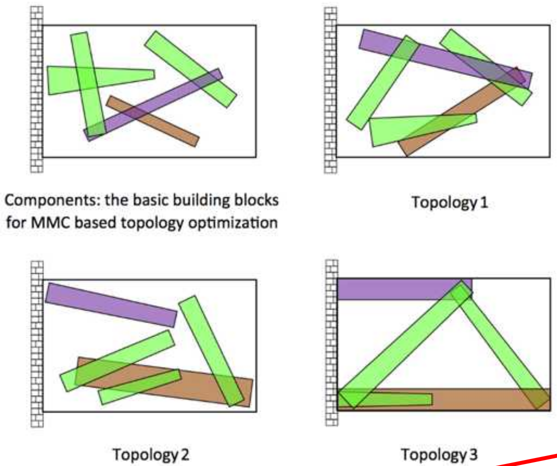
Can we do pattern (structural element) recognition?
Lead an optimization rom a catalog of structural elements?

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]

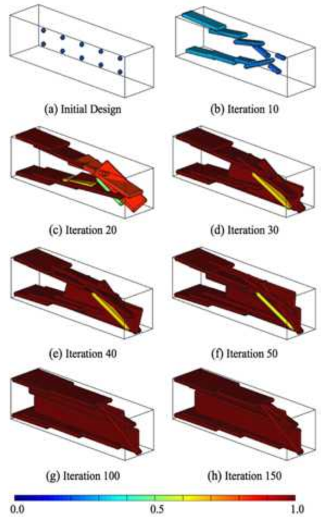


Struct Multidisc Optim
DOI 10.1007/s00158-016-1466-6

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

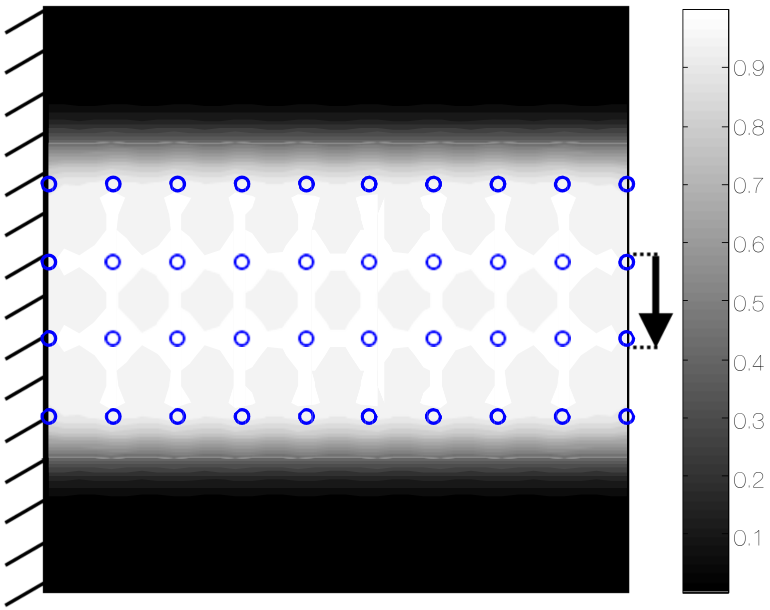
$$C = \mathbf{f}^T \mathbf{u} \qquad \frac{\partial C}{\partial x_j^I}$$

Original Work

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

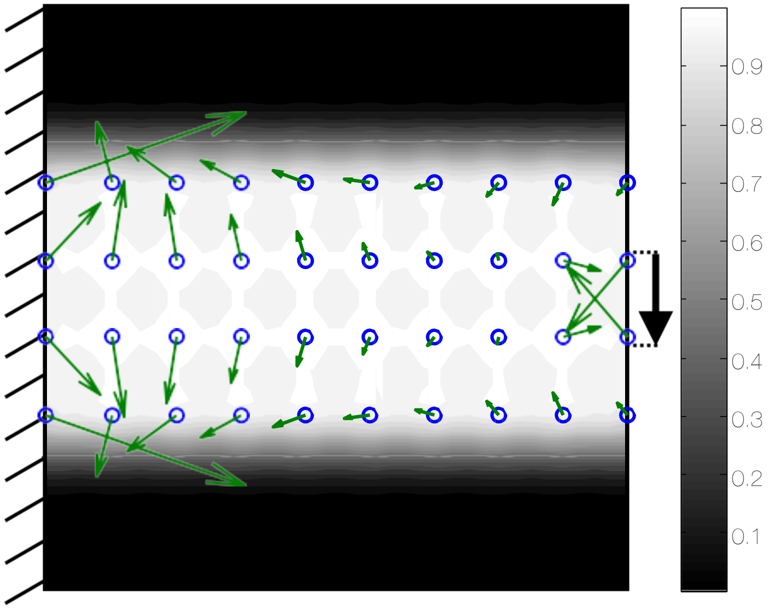
Optimization algorithm

Example of compliance sensitivity



Optimization algorithm

Example of compliance sensitivity



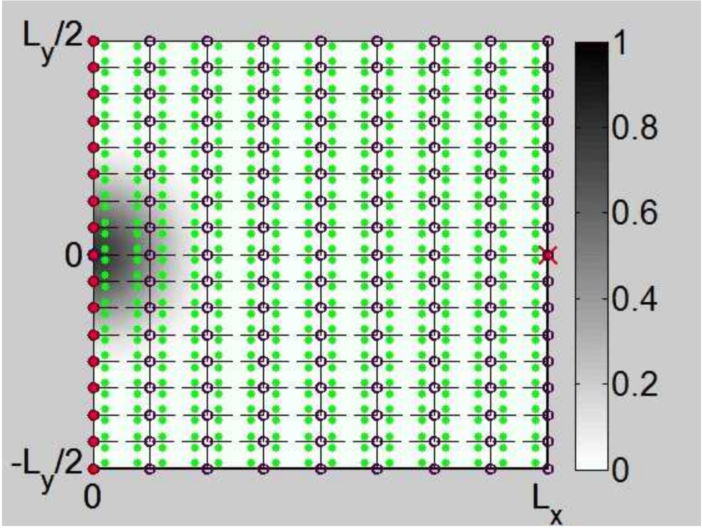
Moving Node Approach (MNA)

- Key idea:

Move material => optimal layout

- Regular discretization = precision

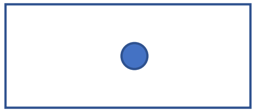
- Material distribution -> mass nodes



The variables (5 per Node)

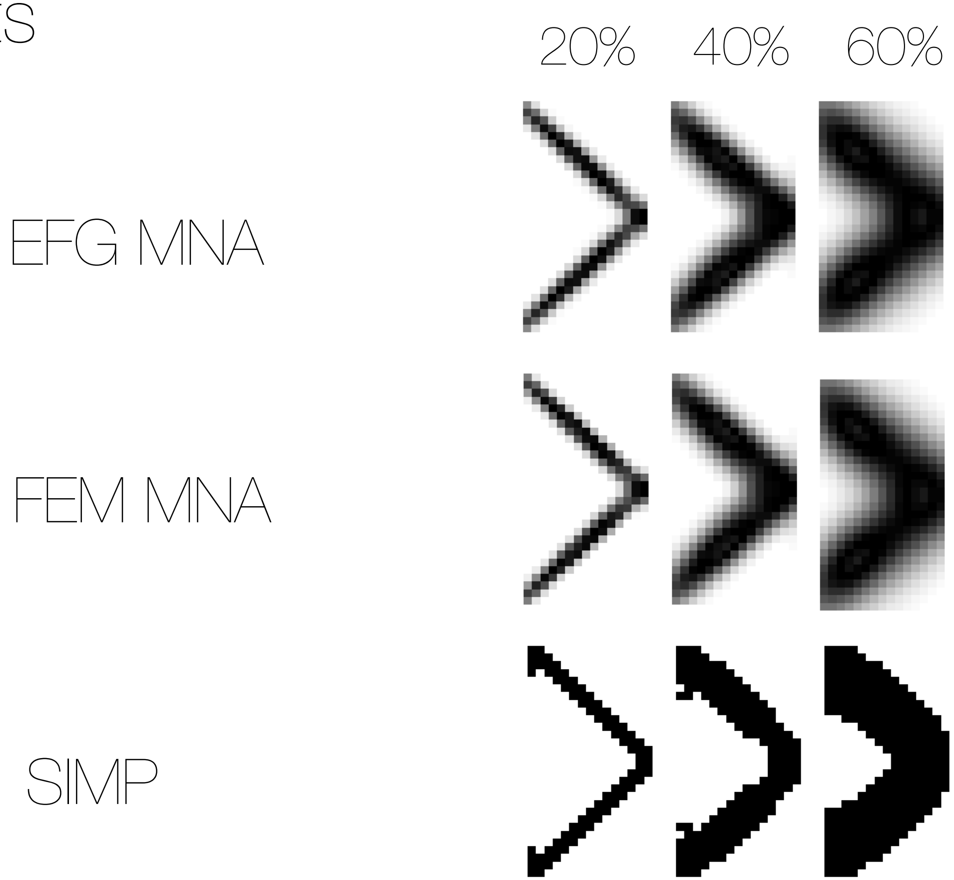
Optimization variables :

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



Deformable Structural Members

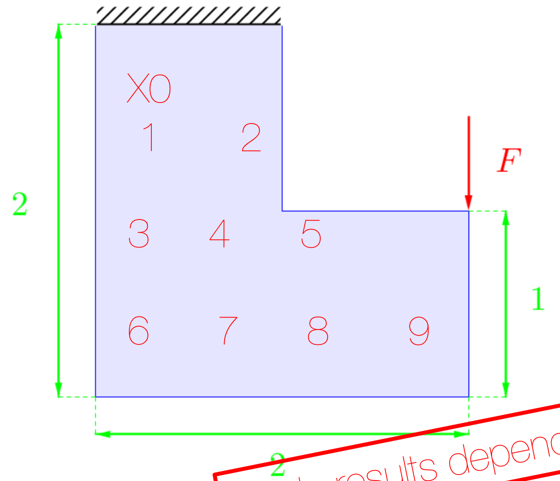
Results

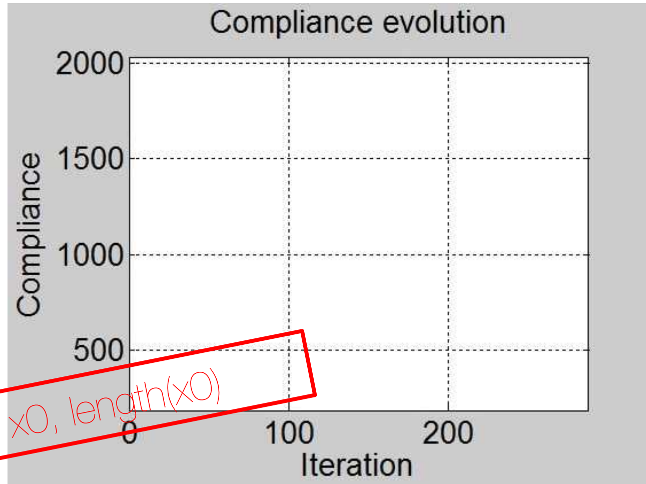


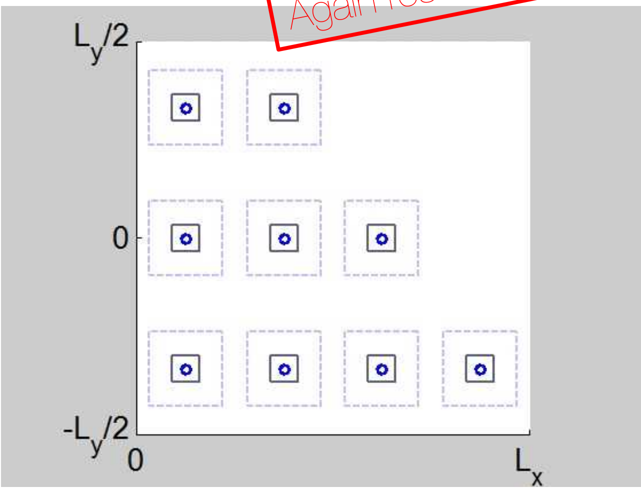
O. Sigmund, "A 99 line topology optimization code written in matlab", Structural and multidisciplinary optimization, vol. 21, no. 2, pp. 120-127, 2001.

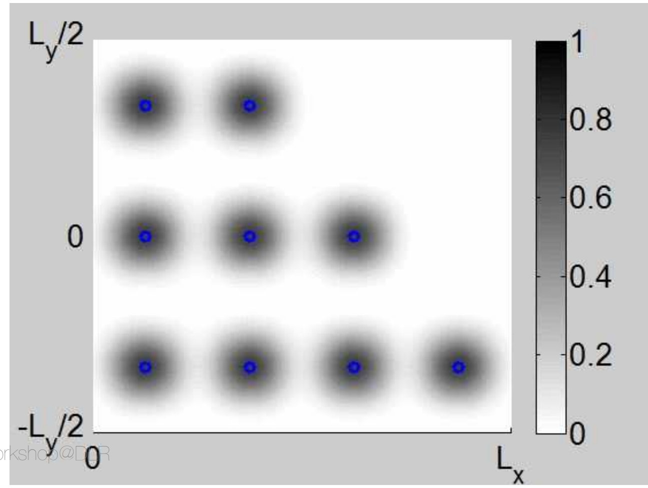
E. Andreassen, A. Clausen, M. Schevenels, B. S. Lazarov, and O. Sigmund, "Efficient topology optimization in matlab using 88 lines of code", Structural and Multidisciplinary Optimization, vol. 43, no. 1, pp. 1-16, 2011.

Our Results on L-Shape 9*5 variables

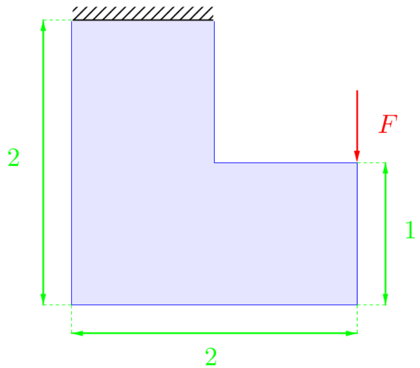




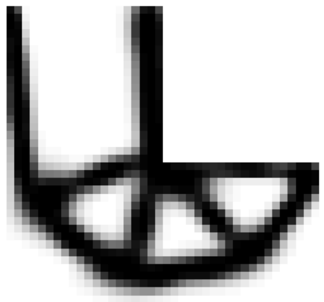




Results on L-Shape (Best solution using a multistart approach)



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

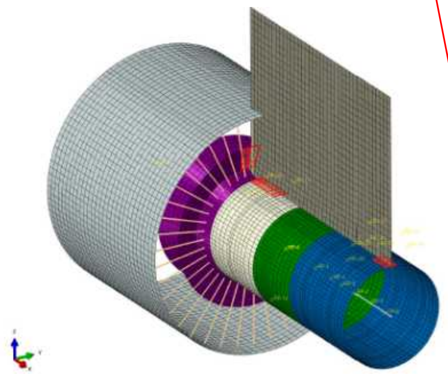
Papers&conf

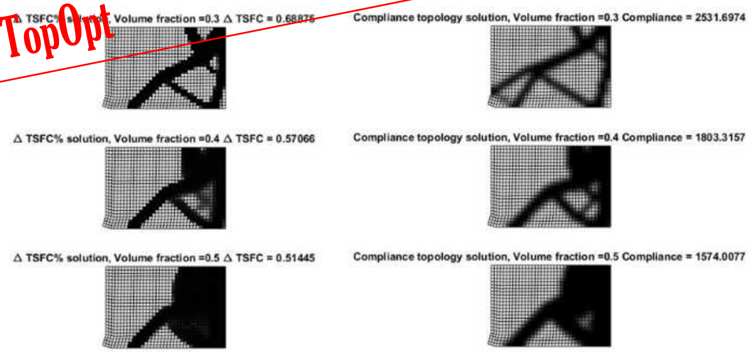
PJ. Barjhoux et al. Mixed Variable Structural Optimization: toward an Efficient Hybrid Algorithm, WCSMO12, 2017

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

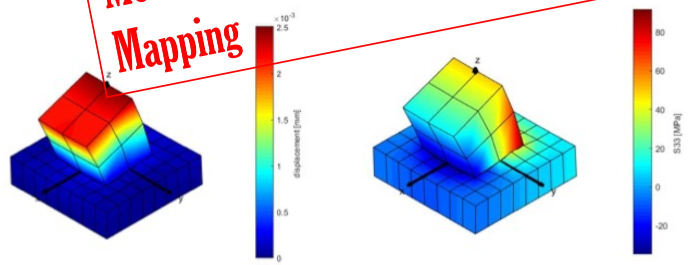
Several Papers in preparation

stress based/performance based TopOpt

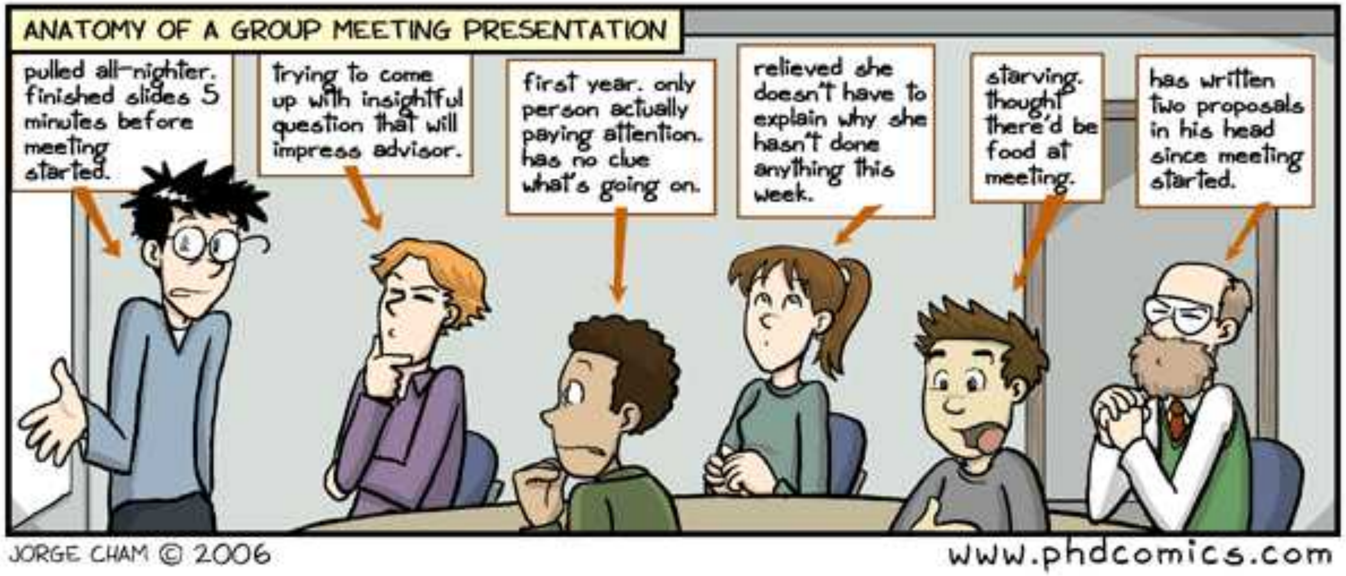




Mesh Tying, error quantification in Mapping



Open questions



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

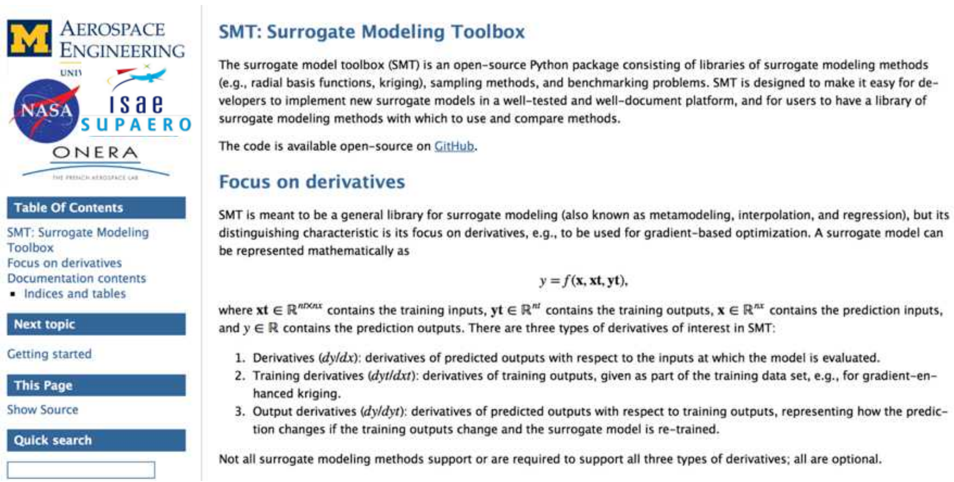
- We also have interesting stuff in FSI-nonlinear transient analysis, Isogeometric (IGA) Shell Structures Optimization …

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



AEROSPACE ENGINEERING

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SMT: Surrogate Modeling Toolbox
Focus on derivatives
Documentation contents
- Indices and tables

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Getting started

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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.