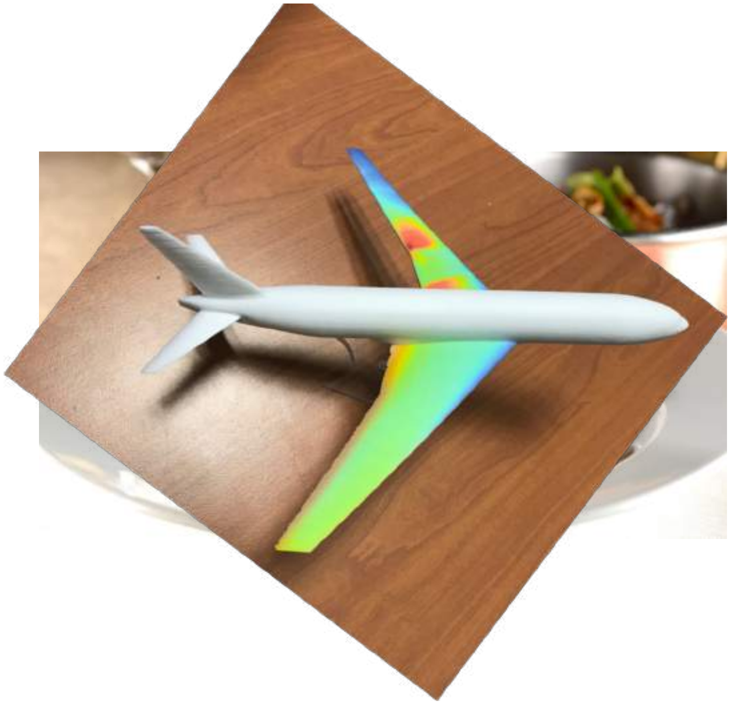


A 3-ingredient recipe for Accelerating Aerospace Engineering Design: **MDO**, **Surrogate** and **Ecodesign**

Prof. Joseph Morlier

AE Seminar at TUD

ISAE
Institut Supérieur de l'Aéronautique et de l'Espace
SUPAERO

Key Figures at a Glance

1909

200
PhD students

130
Professors & Researchers

60 M€
Budget

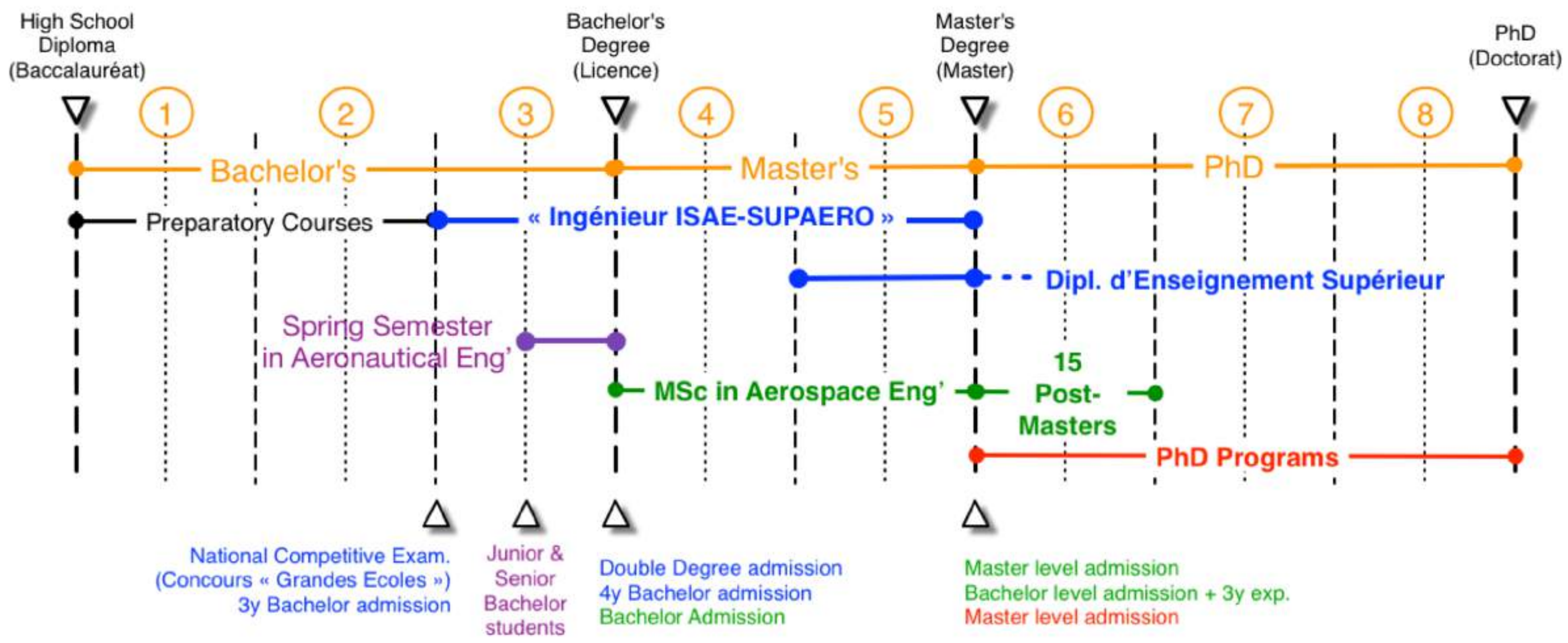
30%
Foreign Students

1 700
Students on campus

650
students graduated a year

> 130
Academic Agreements

ISAE-SUPAERO Programs & Bologna Process



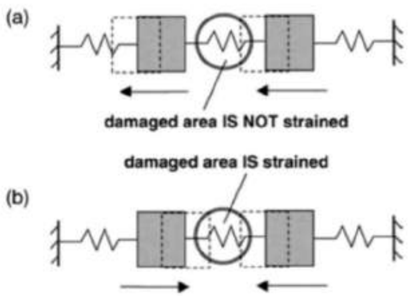
Toulouse: Aerospace Activities

Thanks to all my Students and Colleagues

INSTITUT CLÉMENT ADER

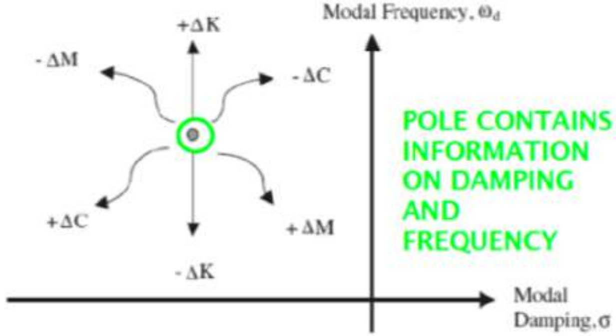
Before 2012

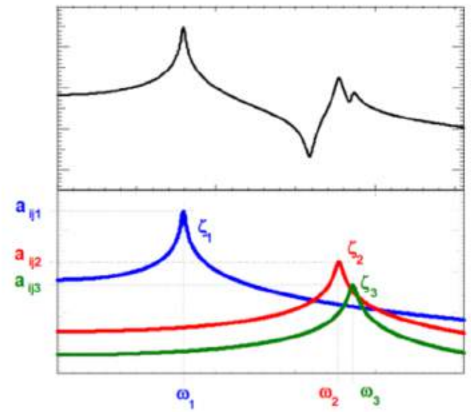
- SHM on composites (Modal analysis, EMI)

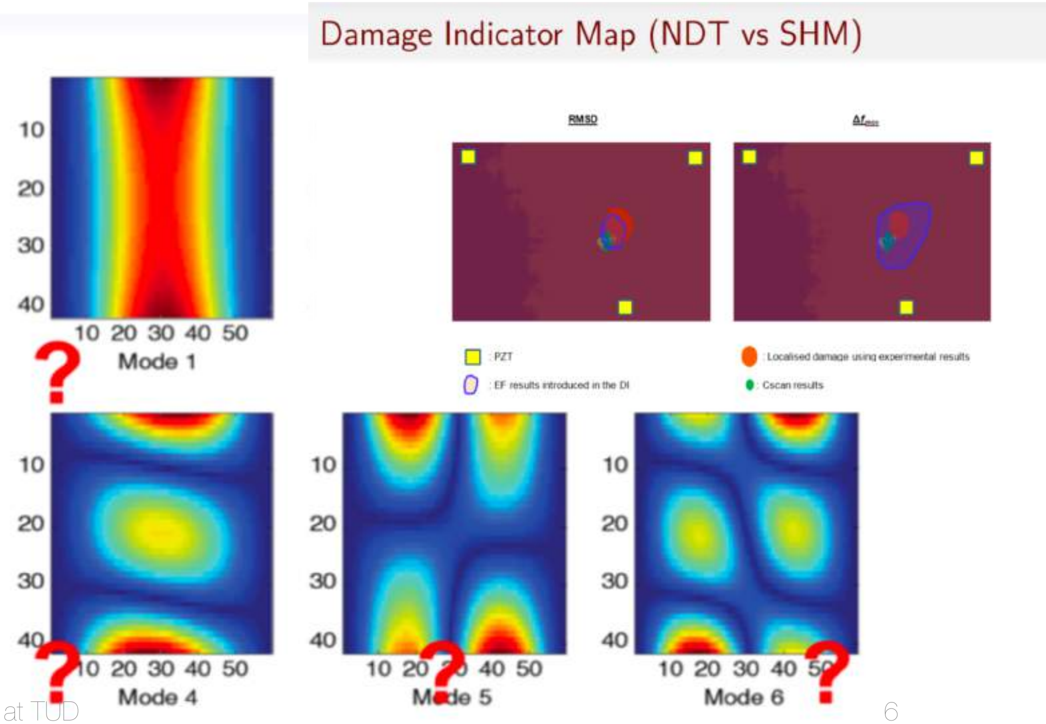


- Detection by change in damping, change in modeshapes

- Methodology for damage recognition using Artificial Neural Networks







Research Experiences

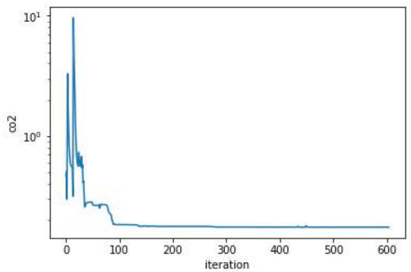
- PhD in Bordeaux SHM of civil engineering structures in 2005
- Ass. Prof in SUPAERO in 2006 SHM of composites structures
- Full Professor in Structural and Multidisciplinary Design Optimization since 2012

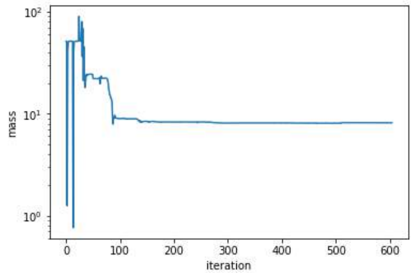
As a visiting Researcher

- in Beijing, Sino French lab on Applied Mathematics (summer 2006)
- In University of Michigan @MDOlab (summer 2017)
- **ANR Grant 2021** (French Science Foundation) →TUD in **May 2022** (and also to brainstorm regularly with **Kunal Masania since 1 year**)

?

CO_2 footprint

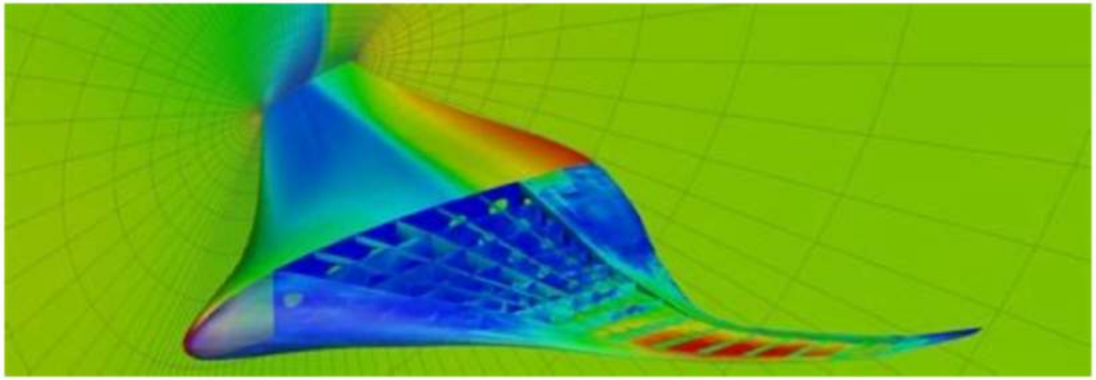




Vs Mass minimization

Popularization ONERA-SUPAERO

https://www.linkedin.com/pulse/optimization-mdo-connecting-people-joseph-morlier/



http://mdolab.engin.umich.edu

Optimization [MDO] for connecting people?

Publié le 14 février 2019 Modifier l'article | Voir les stats

joseph morlier
Professor in Structural and Multidisciplinary Design Optimization, ... any idea?
2 articles

74 31 3 0

Popularization 2

https://www.linkedin.com/pulse/possible-build-aircraft-wing-lego-joseph-morlier/?articleId=6627240732975480832

https://www.tripadvisor.fr/LocationPhotoDirectLink-g187529-d574612-i349532022-Museum_of_Natural_Science_Museo_de_Ciencias_Naturales-Valencia_Province_o.html

Is it possible to build an aircraft wing in LEGO® ?

Publié le 17 février 2020 | Modifier l'article | Voir les stats

joseph morlier
Professor in Structural and Multidisciplinary Design Optimization, ... any idea?

5 articles

Au programme

Duration	Description	Agenda
10’	MDO	Examples
10’	Surrogate	SMT
10’	Ecodesign	Lighter and Greener
4’	Conclusions	And future works?

« Tools/Results » oriented presentation

For theoretical background, have a look to

[1] Bouhlel, M. A., Hwang, J. T., Bartoli, N., Lafage, R., Morlier, J., & Martins, J. R. (2019). A Python surrogate modeling framework with derivatives. Advances in Engineering Software, 135, 102662.

[2] Coniglio, S., Morlier, J., Gogu, C., & Amargier, R. (2019). Generalized Geometry Projection: A Unified Approach for Geometric Feature Based Topology Optimization. Archives of Computational Methods in Engineering, 1-38.

[3] Duriez, E., Morlier, J., Charlotte, M., & Azzaro-Pantel, C. (2021). A well connected, locally-oriented and efficient multi-scale topology optimization (EMTO) strategy. Structural and Multidisciplinary Optimization, 1-24.

[4] Mas Colomer, J., Bartoli, N., Lefebvre, T., Martins, J. R., & Morlier, J. (2021). An MDO-based methodology for static aeroelastic scaling of wings under non-similar flow. Structural and Multidisciplinary Optimization, 63(3), 1045-1061.

[5] Duriez, E., Guadano Martin, Morlier, J. (2022). HALE multidisciplinary ecodesign optimization with material selection, under review

[6] Duriez, E., Morlier, J., Charlotte, M., & Azzaro-Pantel, C. (2022). Ecodesign with topology optimization. Procedia CIRP.

Au programme

Duration	Description	Agenda
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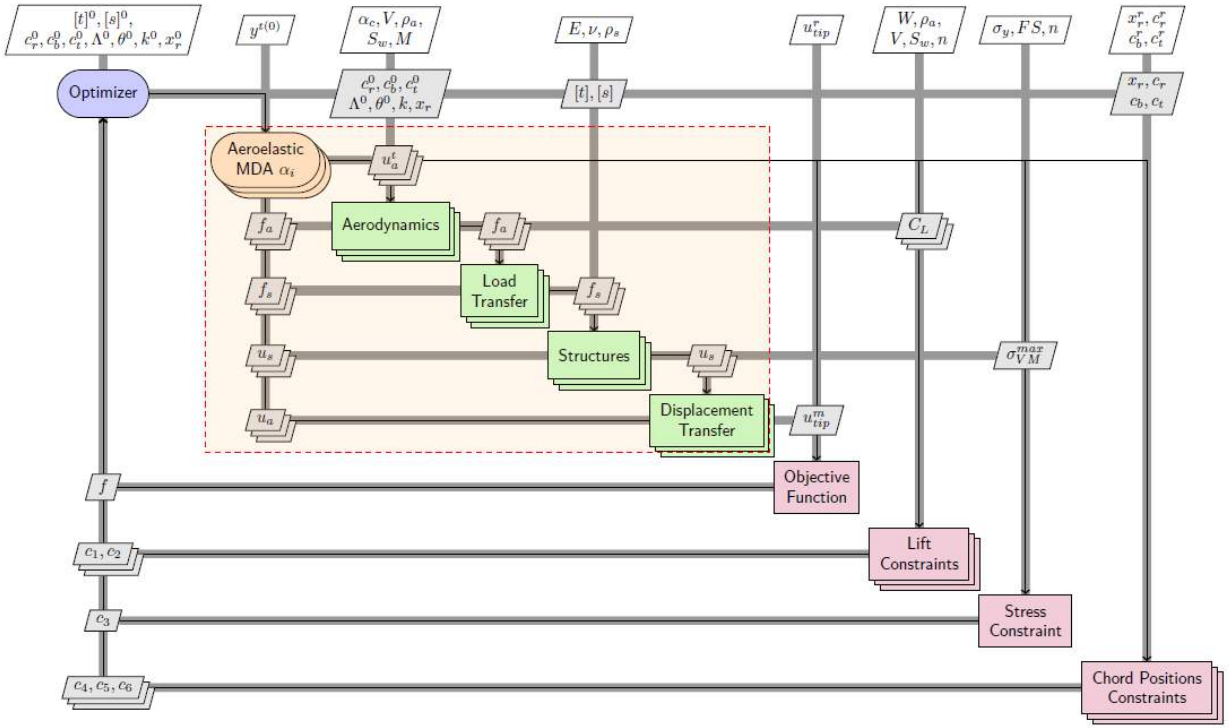
MDO

ONERA
THE FRENCH AEROSPACE LAB

AEROSPACE ENGINEERING
UNIVERSITY of MICHIGAN

Multidisciplinary Design Optimization

- Multidisciplinary Design Optimization (MDO) focuses on solving optimization problems spanning across multiple interacting disciplines



A way to fully automate the design process

Wing span
Airfoil shapes
Structural sizing

Fuel burn

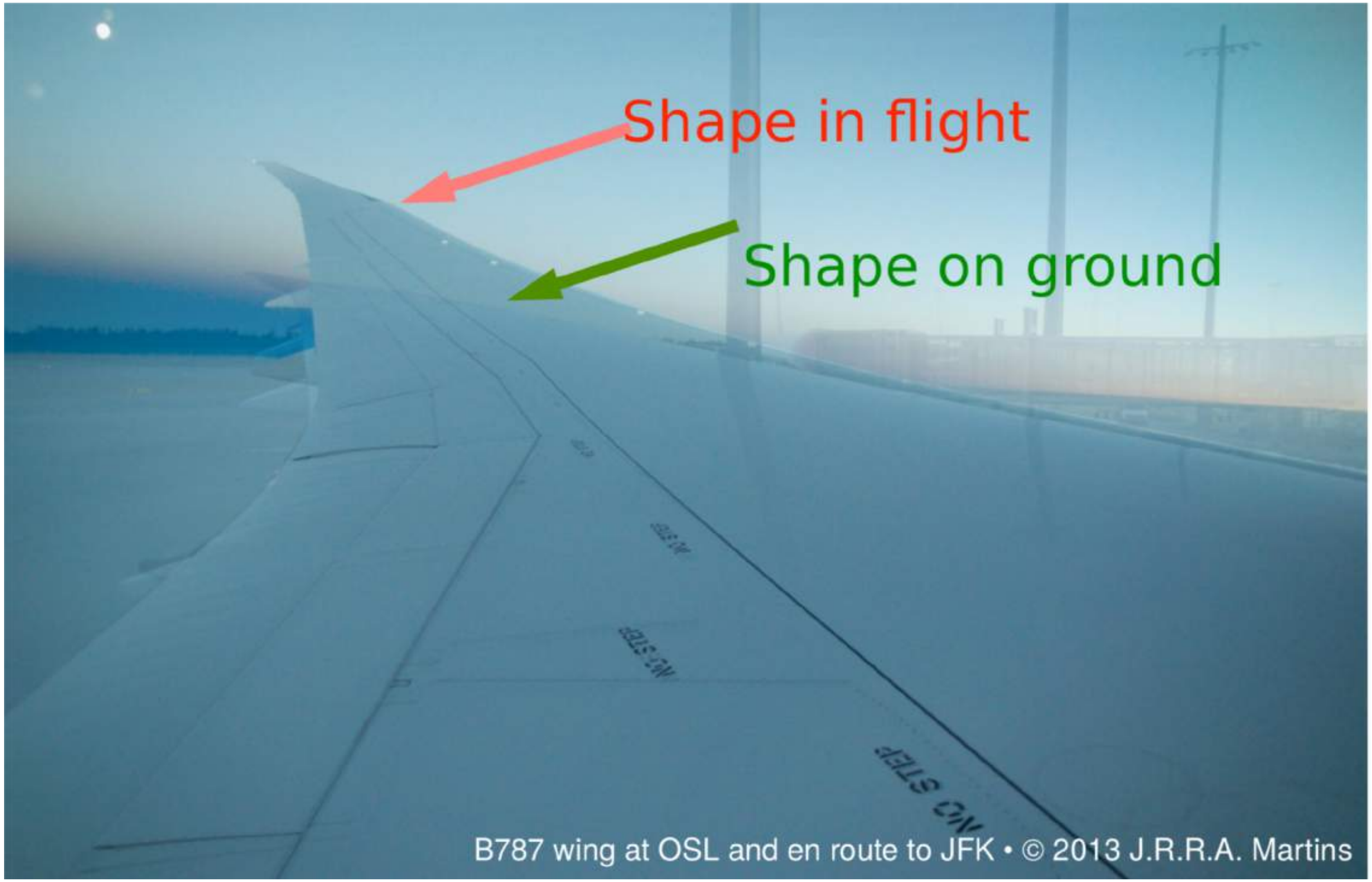
Structural stresses

Design changes

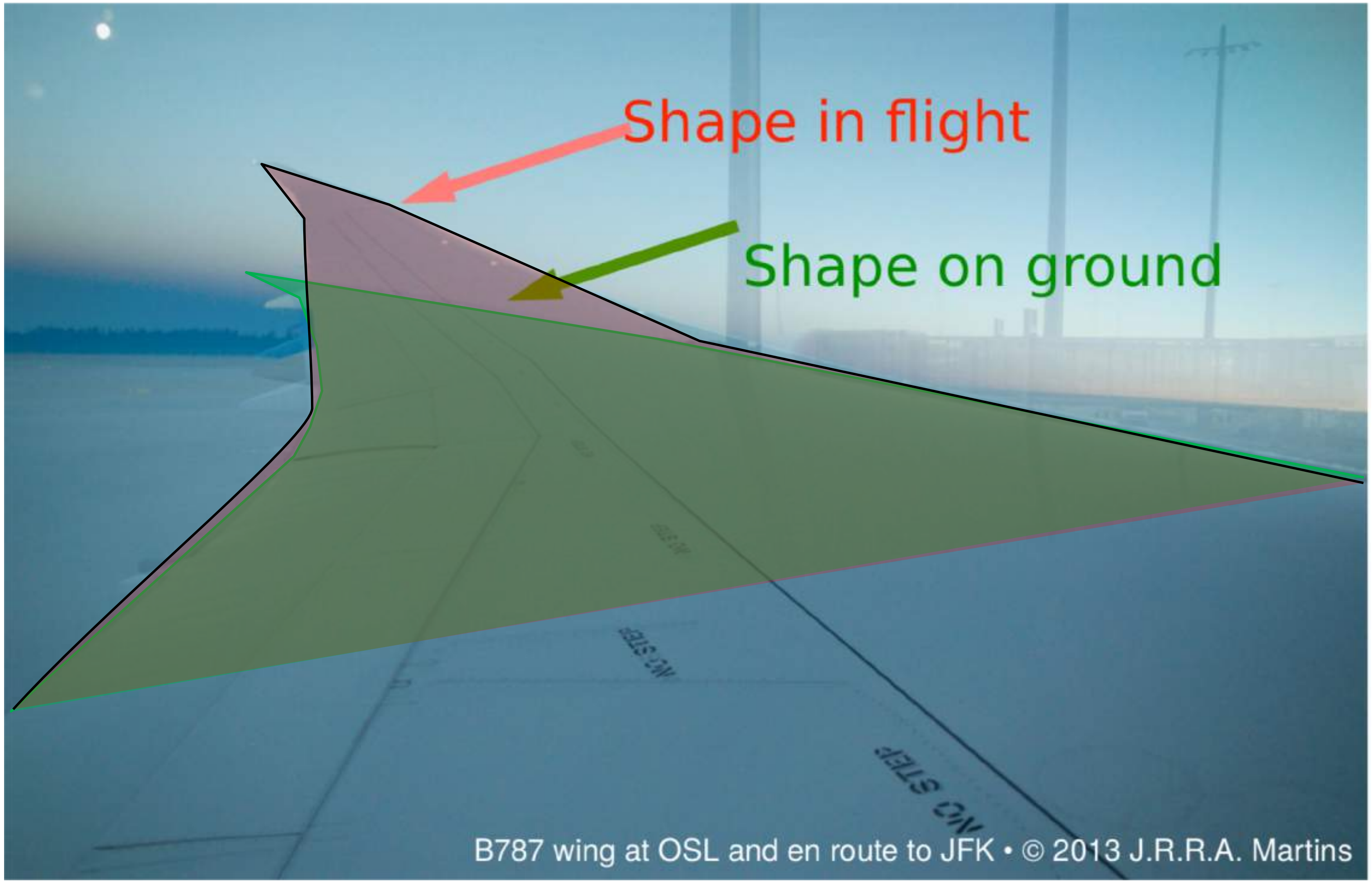
Design optimization problem:

minimize	f(x)	objective
with respect to	x	design variables
subject to	c(x) ≤ 0	constraints

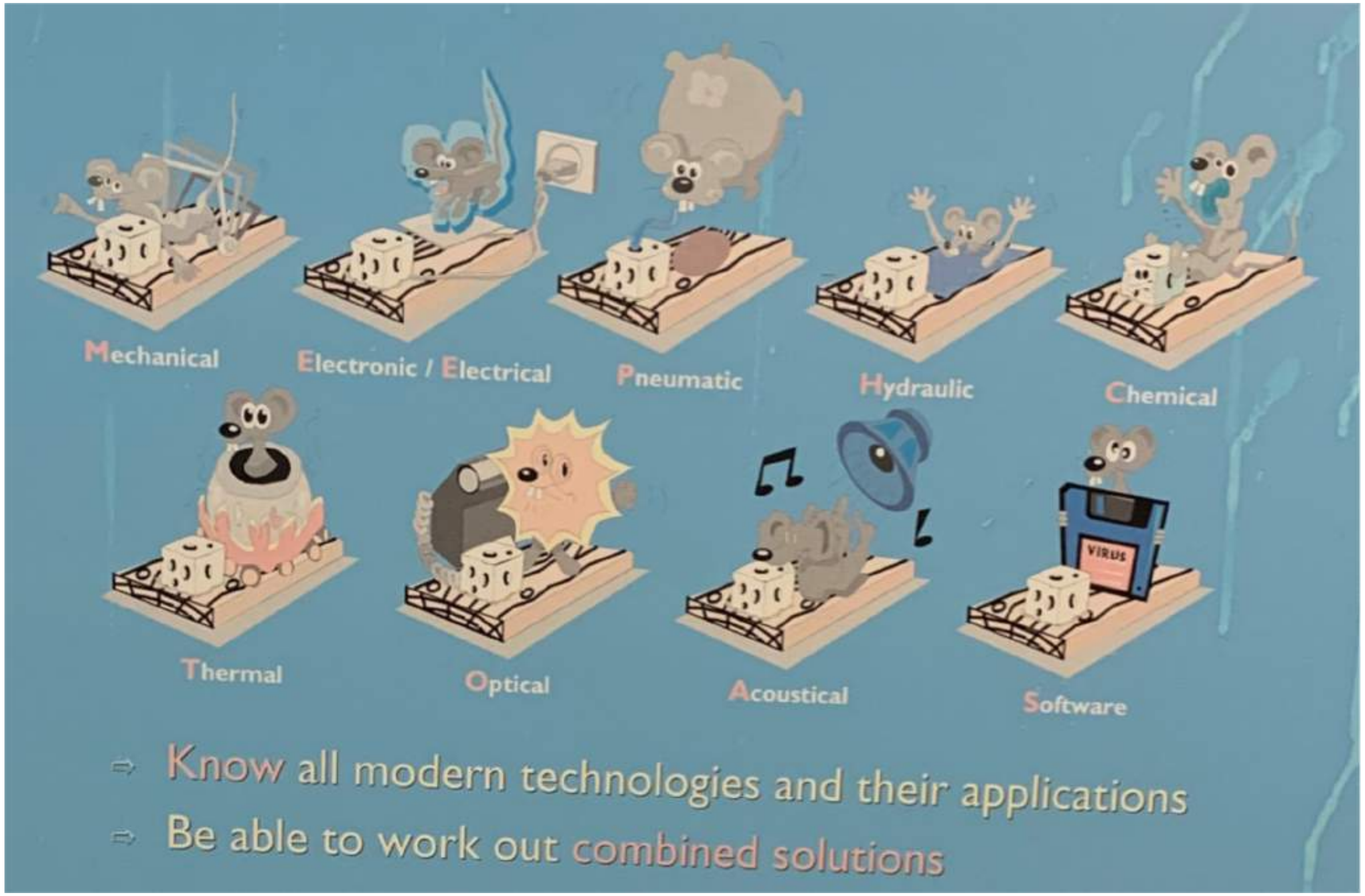
Coupled problem



Coupled problem



@Philips : Combining disciplines provides better solutions



Nowadays' Engineering Design Optimization is MDO {M:Multidisciplinary}

Wing span
Airfoil shapes
Structural sizing

Fuel burn

Structural stresses

Design changes

Reformulate optimization problem

Post-optimality studies

May include large numbers of disciplines, design variables, constraints,

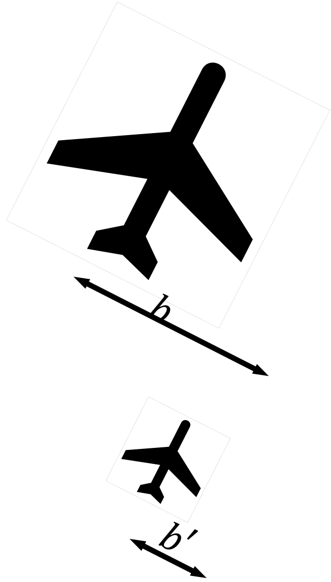
scalability due to gradient based approach

MDO for Scaled aircraft aeroelasticity

[bombardier.com]

$$\lambda_l = \frac{b'}{b}$$

[MSP, uav.com.pl]



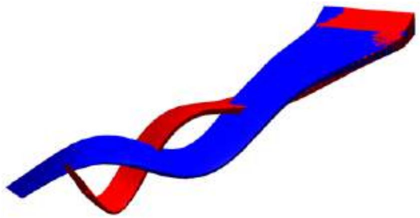
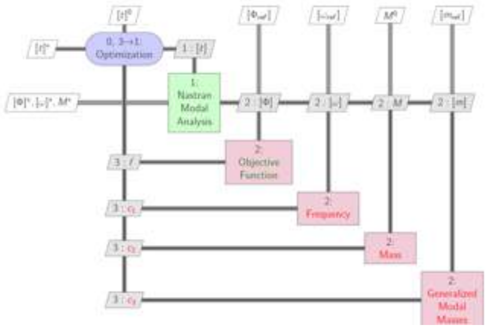
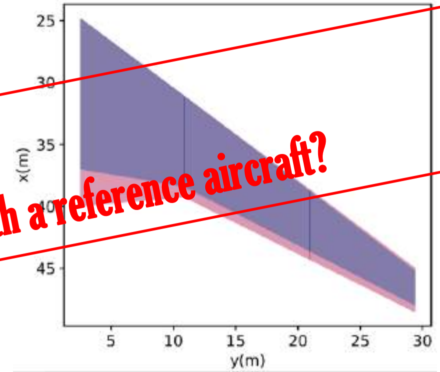
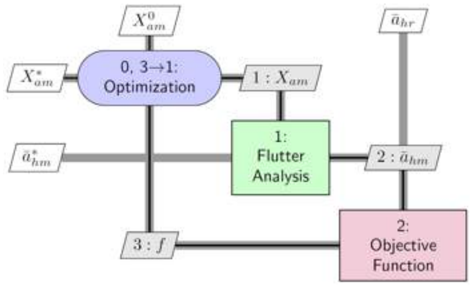
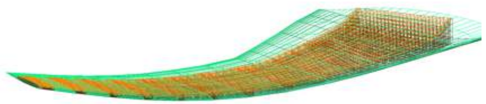
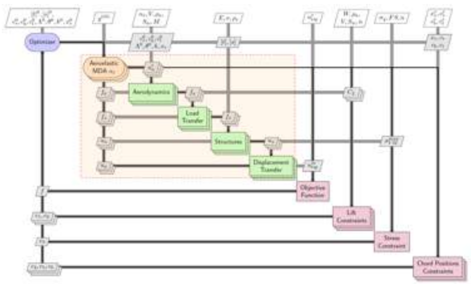
To get experimental data on the **in-flight aeroelastic** behavior of new aircraft concepts while avoiding **costs** and **risks** of **full-scale** aircraft:

- Development and manufacturing cost
- Operational risk of test aircraft

λ_l

[Chambers, Modeling Flight, NASA, 2010]

Joan's thesis

Problem	Model structure	Design variables	Objective	Constraints
Modal optimization for aeroelastic scaling [1] 		Thicknesses, stringer sections	Modal Assurance Criterion	Eigenfrequencies, mass
Wing planform optimization for scaled flutter similarity [2] 		Chord lengths, sweep angle	Norm of the difference between aerodynamic matrices	-
Multidisciplinary optimization for similar static aeroelasticity [3] 		Thicknesses, stringer sections, planform, root twist, thickness-to-chord ratio	Static wing deflection error	Lift, stress, longitudinal position of wing sections

Modal matching

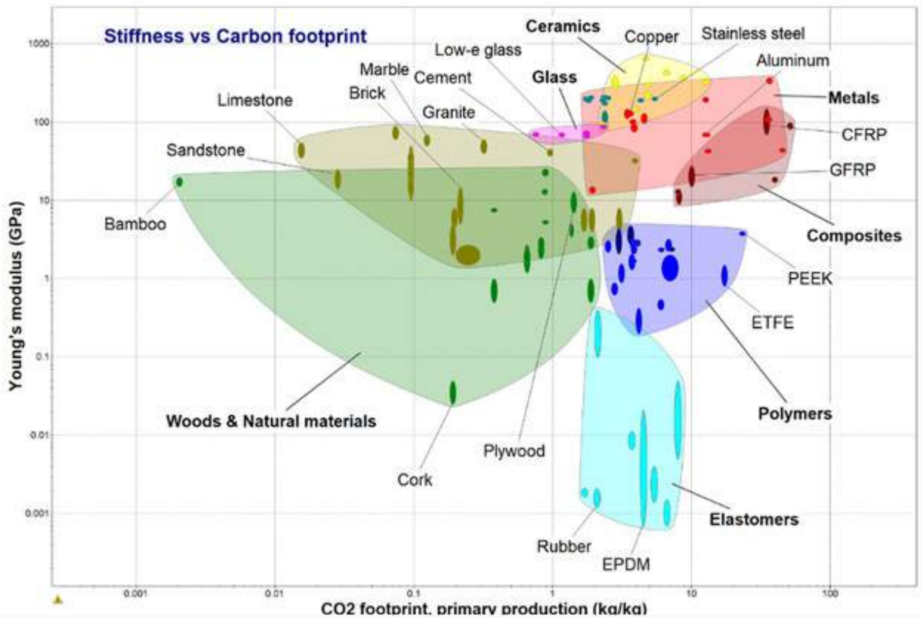
Scaled model's optimal planform that ensure Flutter similarity with a reference aircraft?

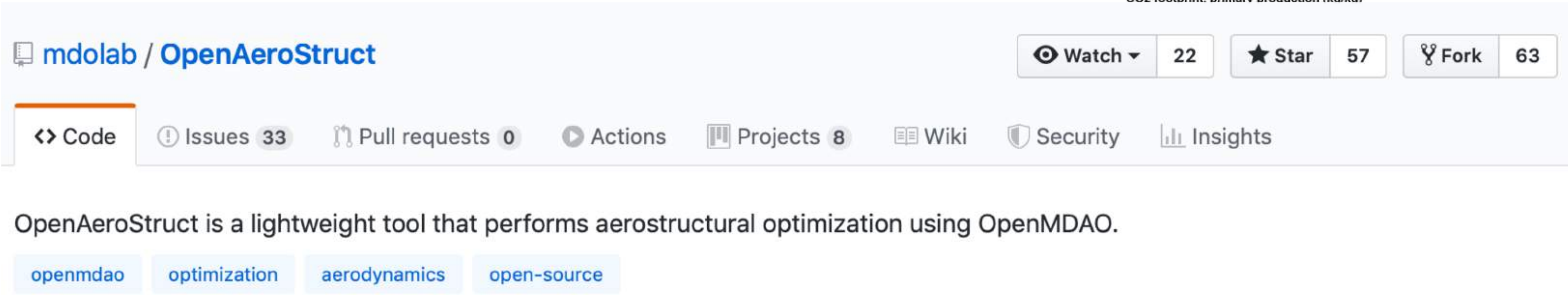
Aeroelastic similarity

https://github.com/mid2SUPAERO/aerostructures

MDO for ECOHALE design

- Trade-off between use phase (young's modulus and density) and production phase (CO2 footprint)

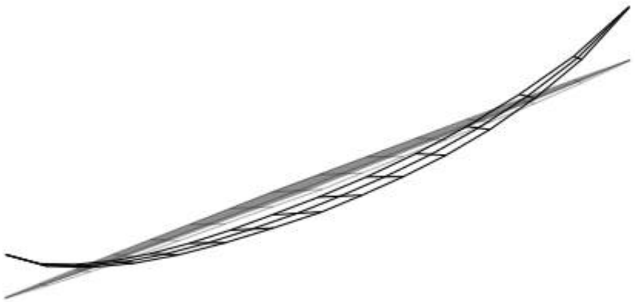
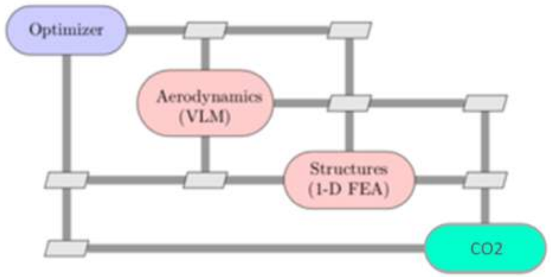




Chauhan, S. S., & Martins, J. R. (2018, September). Low-fidelity aerostructural optimization of aircraft wings with a simplified wingbox model using OpenAeroStruct. In International Conference on Engineering Optimization (pp. 418-431). Springer, Cham.
Jasa, J. P., Hwang, J. T., & Martins, J. R. (2018). Open-source coupled aerostructural optimization using Python. Structural and Multidisciplinary Optimization, 57(4), 1815-1827.

ECO Hale

Derive OAS 2.0 to treat a HALE pseudo sattelite Design problem

HALE ecodesign MDO		Thicknesses, twists, material, geometry	CO2 footprint	Available power, stress, flight
				

<u>Assets:</u> Flexible, repositionable, permanent coverage, cheaper, lower environnemental impact?

Fig. 1: Airbus-built HALE Zephyr

Discrete variables

Minimize CO_2
w.r.t. thicknesses, twist, geometry,
materials database CES EDUPACK *(CFRP-3, GFRP, ALU,…)*
Subject to Available solar power, stress, buckling, flight

From OAS to EcoHale

- Commercial aircraft
- Breguet range equation
- Fuel consumption
- 2.5G manoeuvre
- High Reynolds number
- Fixed structural material

➤ HALE drones

➤ Power equilibrium

➤ Power from batteries and solar panels

➤ Shear gust wall

➤ Low Reynolds number

➤ Material choice optimization

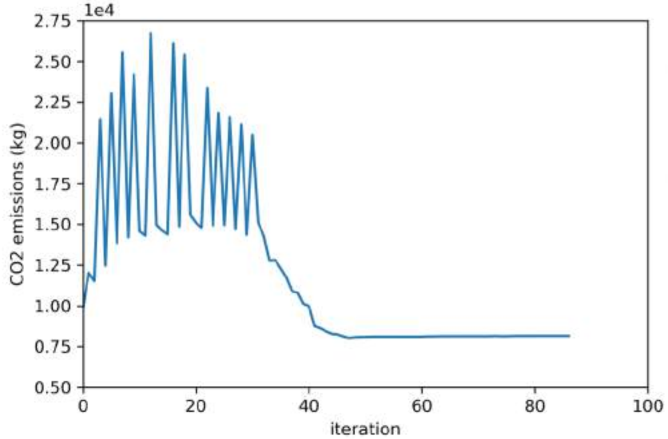
Discipline	Method	Implementation	Reference
Aerodynamics	VLM	OAS	Anderson (1991)
Structure	Wingbox beams	OAS	Chauhan and Martins (2019)
Energy	Simple in-house method	Section 2.1	data from Colas et al. (2018)
Environmental	Proportional to mass	Section 2.3.2	data from Wetzel and Borchers (2015), Hao et al. (2017)

Objective function

- CO2 emitted by the HALE drone during its life cycle
- No fuel ➤ CO2 from materials and processing
  - Structure ➤ $CO2_{struct} = M_{spar} \cdot CO2_{mat1} + M_{skin} \cdot CO2_{mat2}$
  - Solar panels ➤ $CO2_{PV} = P_{needed} \cdot CO2_{/W}$
  - Batteries ➤ $CO2_{bat} = P_{needed} \cdot t_{night} \cdot CO2_{/Wh}$
- $CO2_{total} = CO2_{struct} + CO2_{PV} + CO2_{bat}$

CO2 footprint minimization

(a) Objective function: total CO2 emitted:



(b) Material density for skins and spars:

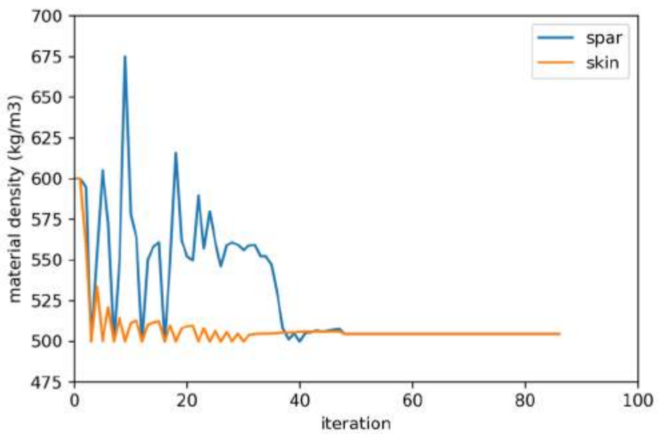


Fig. 8: Convergence graphs

Optimization algorithm ➤ SLSQP

Stopping criteria:

- ➤ Convergence accuracy: 10^{-3}
- ➤ Maximum number of iterations: 250

Objective function	Dimension	Bounds
$CO2_{tot}$	$\mathbb{R}$	
Design variables		
Density	$\mathbb{R}^2$	[400, 8000] kg/m^3
Twist control points	$\mathbb{R}^4$	[-15, 15] deg
Skin thickness (t_{skin}) control points	$\mathbb{R}^4$	[0.001, 0.1] m
Spar thickness control points	$\mathbb{R}^4$	[0.001, 0.1] m
Thickness-to-chord ratio control points	$\mathbb{R}^4$	[0.01, 0.4]
Span	$\mathbb{R}$	[1, 1000] m
Root chord	$\mathbb{R}$	[1.4, 500] m
Taper ratio	$\mathbb{R}$	[0.3, 0.99]
Motor location over semi-span ratio	$\mathbb{R}$	[0, 1]
Constraints		
Mechanical failure $\sigma < \sigma_{max}$	$\mathbb{R}^7$	
Buckling $R_s^2 + R_c < 1$	$\mathbb{R}^7$	
Skin thickness $2t_{skin} < t_{wing}$	$\mathbb{R}^4$	
Power equilibrium $P_{needed}/A_{PV} < S_{wing}$	$\mathbb{R}$	

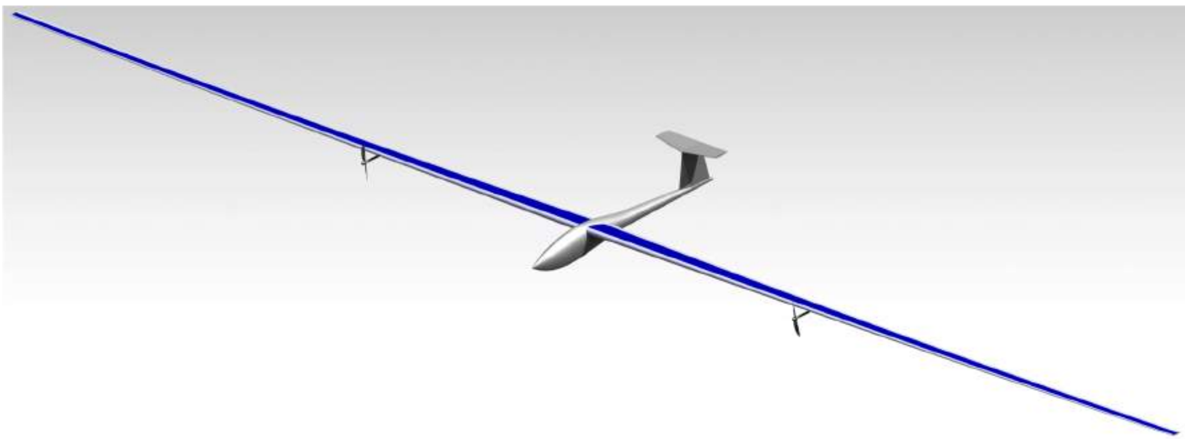


Fig. 9: CAD model of the optimal HALE obtained

Au programme

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Surrogate

ML vs Engineering

Kriging (Pionneer)	Gaussian Processes (link with AI)
Developed by Daniel Krige – 1951; formalized by Georges Mathéron in the 60's (Mines Paris)	Neural network with infinite neurons tend to Gaussian Process 1994

Krige, D. G., 1951, A statistical approach to some basic mine valuation problems on the Witwatersrand: J. Chem. Metal. Min. Soc. South Africa, v. 52, p. 119-139.

Matheron, G., 1963b, Principles of geostatistics: Economic Geol., v. 58, p. 1246-1266.

Neal, R. Priors for infinite networks. Tech. rep., University of Toronto, 1994.

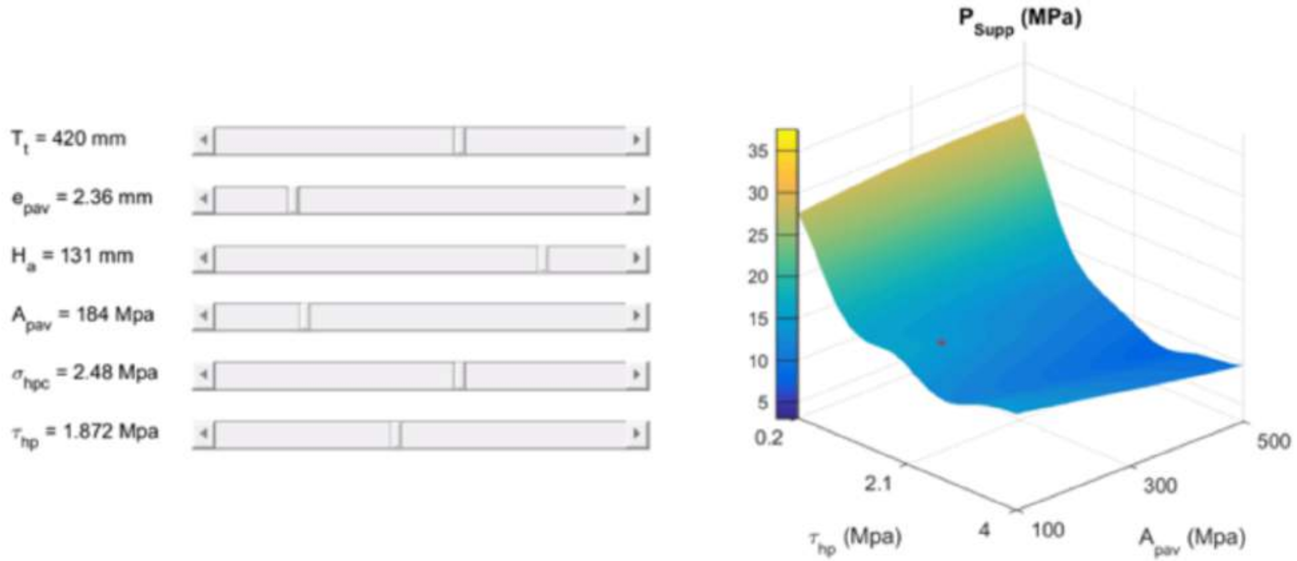
Williams, C. K. I., and Rasmussen, C. E. Gaussian processes for regression. *Advances in Neural Information Processing Systems 8* (1996), 514–520.

Qualitative claims such as "ML works OK for interpolation but doesn't work for extrapolation" are wrong.
https://arxiv.org/abs/2110.09485

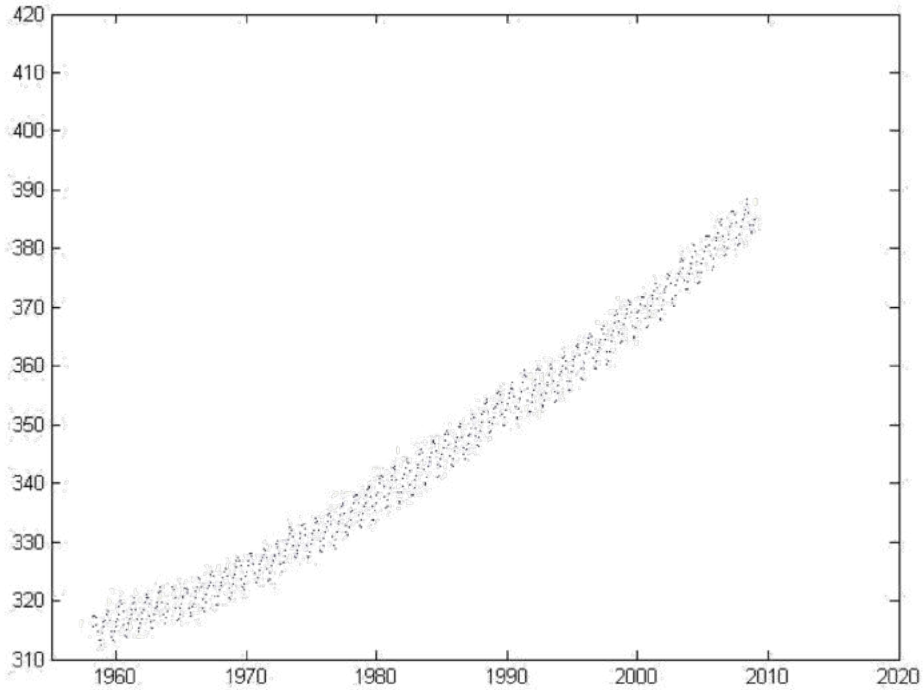
http://extrapolated-art.com

Surrogate Models

- A surrogate model of a function is an approximation of the function that is less costly to evaluate
- The surrogate model can then be used to help direct the search for the optimum of the real objective function



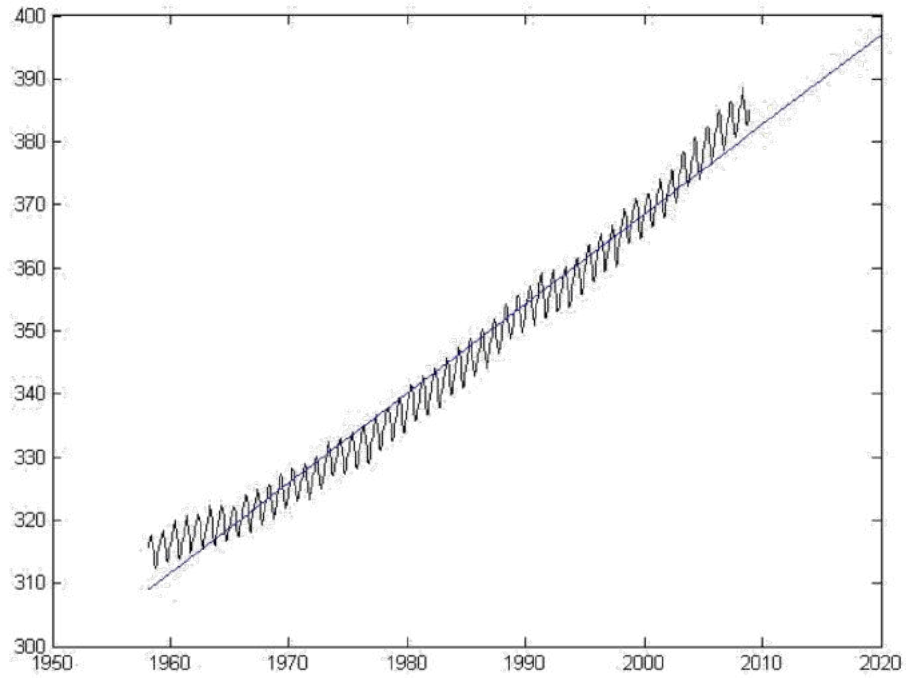
Limit of linear models for prediction



Month-wise data of Co2 concentration in atmosphere at Hawaii

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

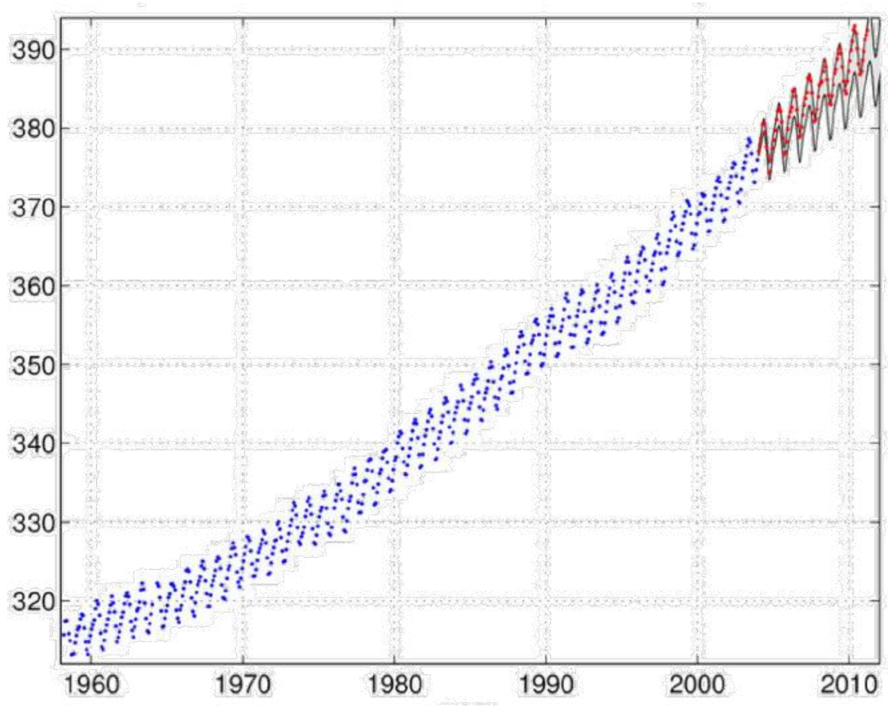
Example – Linear Regression



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/

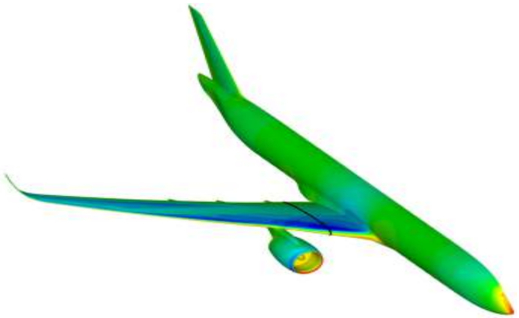
Example – Gaussian Process

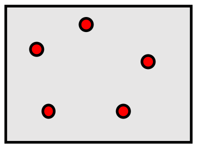


Predicted variance after year 2005 in grey, real data-points in red

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

Surrogate modeling Recipes

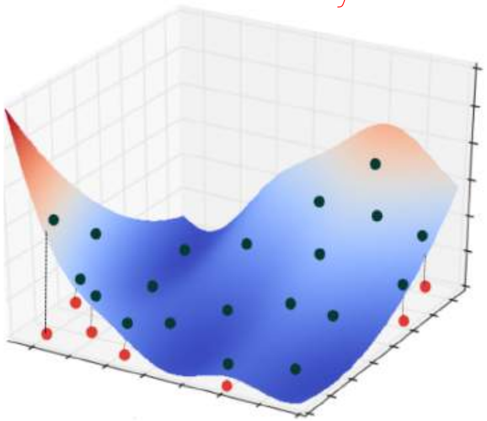


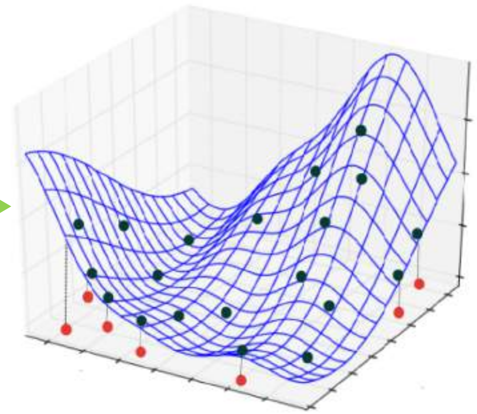


DOE

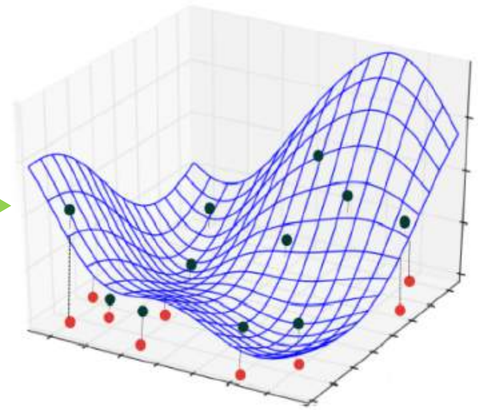
True Function Evaluation

This is costly!





Interpolant model



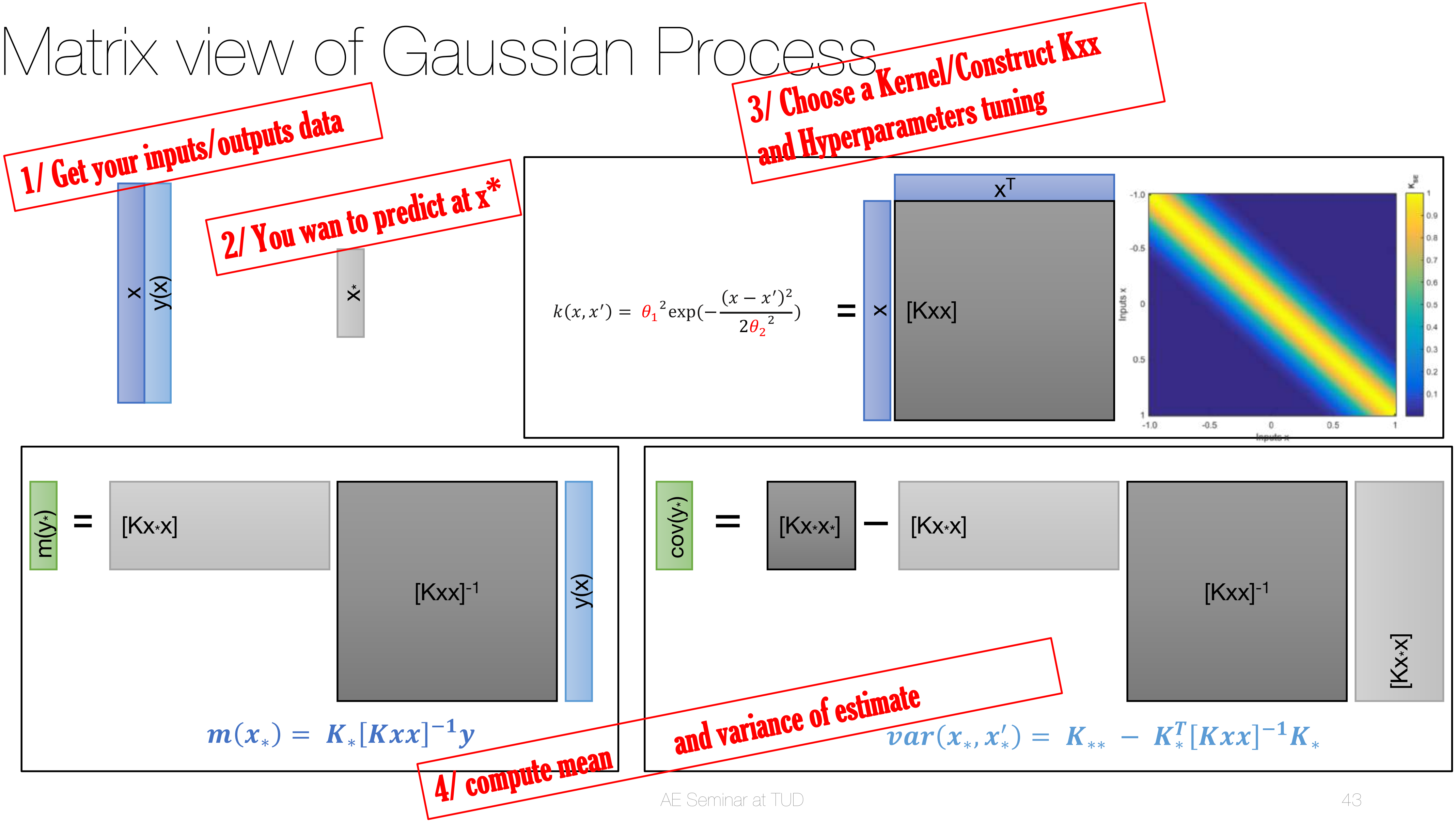
Regression model

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

$$LOF = \frac{MSE}{Var(y)}$$

$\boldsymbol{n}$ is the number of samples
$\hat{\boldsymbol{y}}$ is the predictions of the n samples
$\boldsymbol{y}$ is the true outputs of the n samples

Matrix view of Gaussian Process

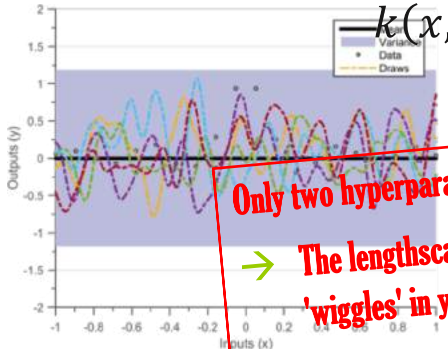


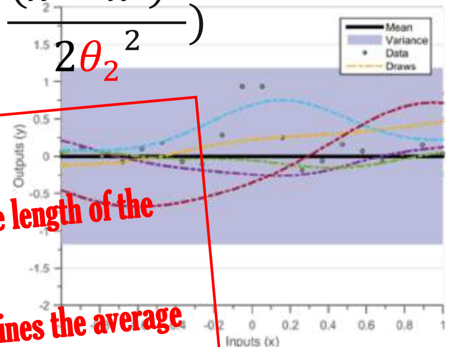
Optimizing Marginal Likelihood (ML)

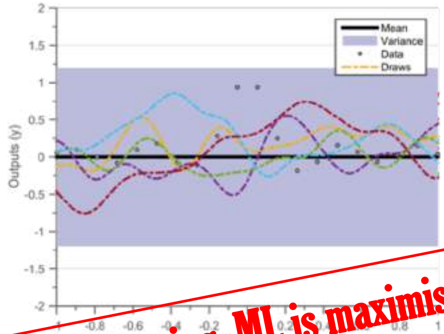
$$\text{ML} = log\big(p(y|X,\theta)\big) = -\frac{1}{2}y^T K^{-1} y - \frac{1}{2}\log|K| - \frac{n}{2}\log(2\pi)$$

- It is a combination of **data-fit term**, a **complexity penalty** term and a **normalization term**

$$k(x,x') = \theta_1{}^2 \exp\left(-\frac{(x-x')^2}{2\theta_2{}^2}\right)$$







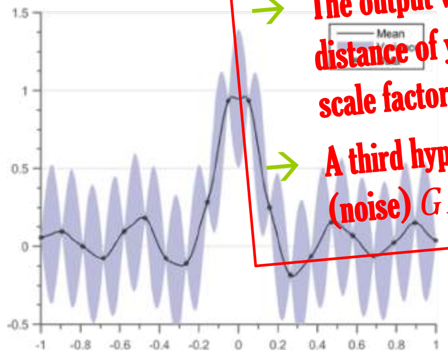
Only two hyperparameters:

→ **The lengthscale θ_2 or ℓ determines the length of the 'wiggles' in your function.**

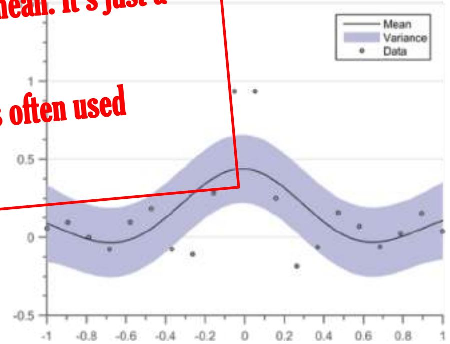
→ **The output variance $\theta_1{}^2$ or σ^2 determines the average distance of your function away from its mean. It's just a scale factor.**

→ **A third hyperparameter θ_3 or σ_n^2 is often used (noise) $GP(0, K + \sigma_n^2 I)$**

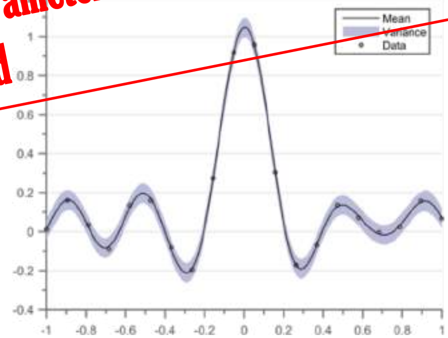
3/ Hyperparameters tuning. ML is maximised, θ^* is found



ML = -8.2



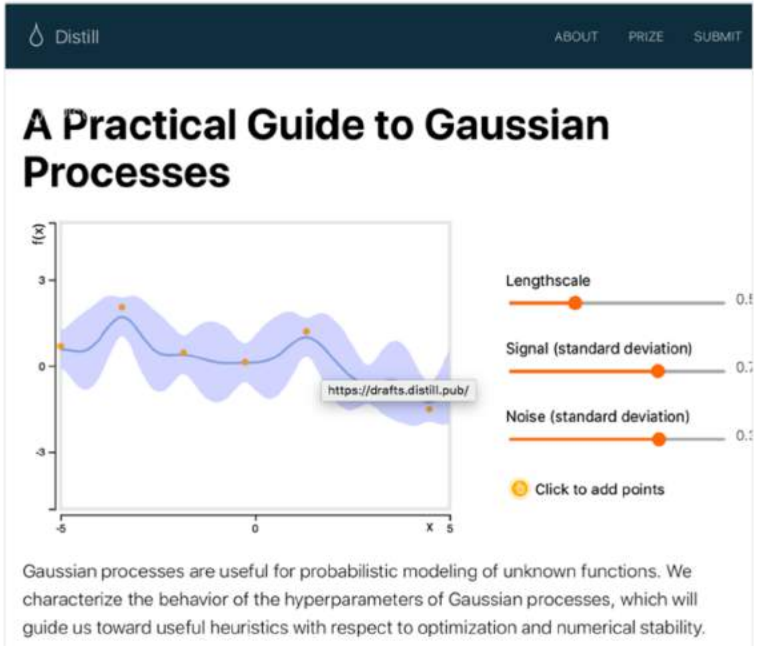
ML = -35.3



ML = 6,04

A good starting point x_0=Rasmussen's book

- https://drafts.distill.pub/gp/



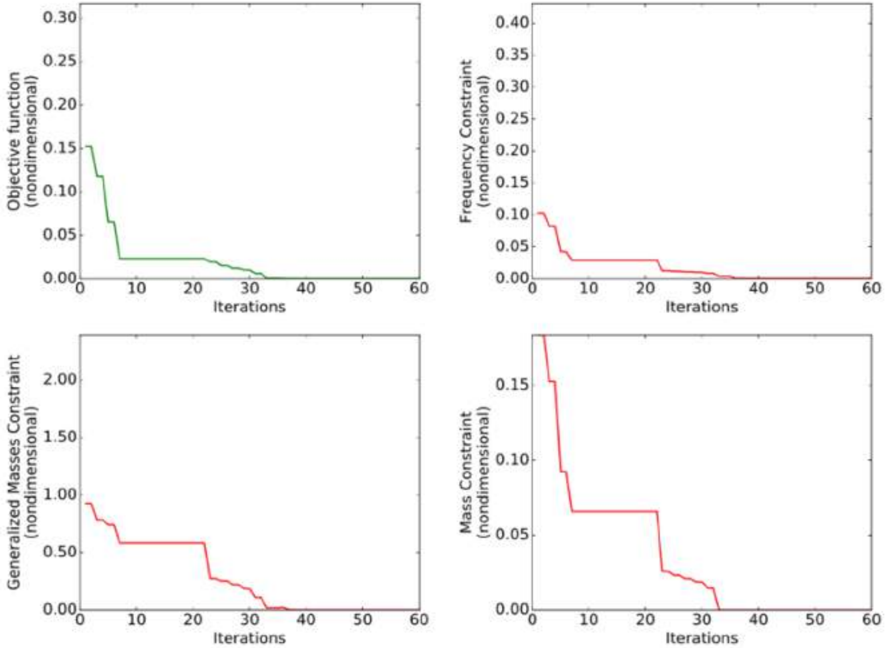
C. E. Rasmussen & C. K. I. Williams, Gaussian Processes for Machine Learning, the MIT Press, 2006, ISBN 026218253X. © 2006 Massachusetts Institute of Technology. www.GaussianProcess.org/gpml

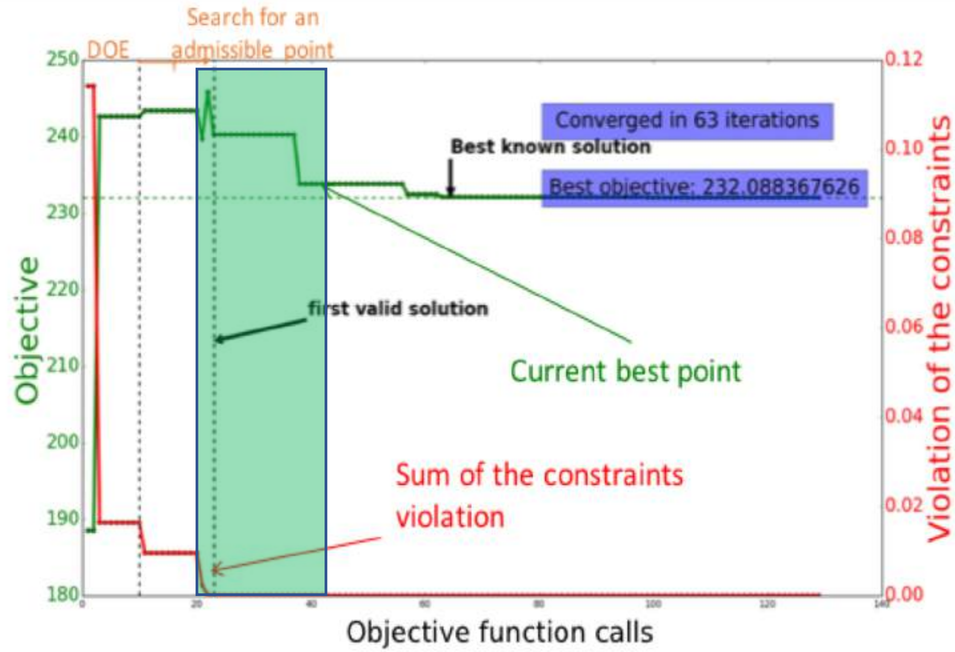
Gaussian Processes for Machine Learning

Convergency graphs

Gradient based Optimality, Feasibility

SBO Exploration, Exploitation





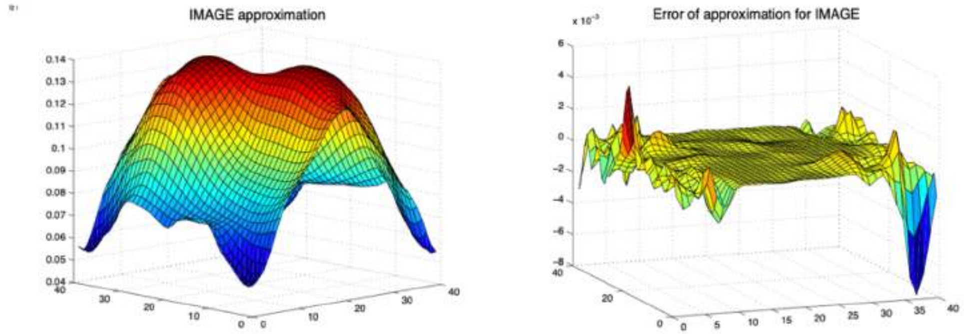
Stopping criteria: tolfun, tolx, maxiter

Stopping criteria: Max Budget (Function calls)

...A long time ago far away

in Onera/Supaero Toulouse

- 2008-2011 D. Bettebghor's PhD first works on Mixture of Experts → How to assemble local surrogates in a global one? IMAGE in matlab



(a) IMAGE approximation (b) Error for IMAGE approximation

- Results of The PhD of M. Boulhel (2013-2016) → KPLS trick → treat HD engineer's problem

Ordinary Kriging $k(x,x') = \sigma^2 \exp\left(-\sum_{i=1}^{d} \theta_i |x_i - x_i'|^{p_i}\right)$ d parameters θ_i to evaluate

Covariance kernel ⬇

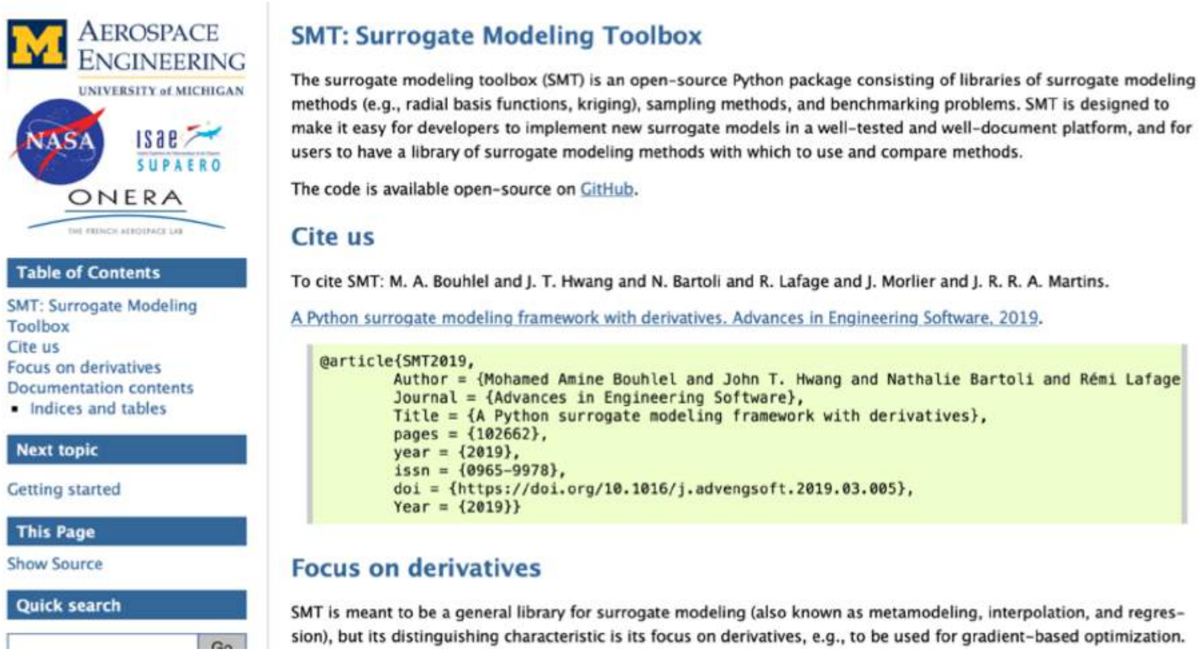
KPLS $k_{PLS}(x,x') = \sigma^2 \exp\left(-\sum_{i=1}^{d} \eta_i |x_i - x_i'|^{p_i}\right)$ with $\eta_i = \sum_{j=1}^{h} \theta_j \left|w_{i,j}\right|^{p_i}$

h parameters θ_j to evaluate

- M. Bouhlel left to Michigan as postdoc.We decide to unify our forces with UoM, Nasa Glenn, Supaero/Onera → spirit of reproducible research **RR** developed at the MDOlab (Prof Martins)

- $\left|w_{i,j}\right|_{i=1,\cdots,d}$ describes how sensitive the j-th principal component is to each design variable i ➔ PLS
- θ_j describes how sensitive the function is to each principal component (max $h \approx 4$) ➔ MLE
- If $h = d$ ➔ classical kriging (exponential kernels)

...in 2017 the first SMT version was released



AEROSPACE ENGINEERING
UNIVERSITY of MICHIGAN
NASA
isae SUPAERO
ONERA

Table of Contents

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

Next topic

Getting started

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SMT: Surrogate Modeling Toolbox

The surrogate modeling 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.

Cite us

To cite SMT: M. A. Bouhlel and J. T. Hwang and N. Bartoli and R. Lafage and J. Morlier and J. R. R. A. Martins.

A Python surrogate modeling framework with derivatives. Advances in Engineering Software, 2019.

```
@article{SMT2019,
        Author = {Mohamed Amine Bouhlel and John T. Hwang and Nathalie Bartoli and Rémi Lafage
        Journal = {Advances in Engineering Software},
        Title = {A Python surrogate modeling framework with derivatives},
        pages = {102662},
        year = {2019},
        issn = {0965-9978},
        doi = {https://doi.org/10.1016/j.advengsoft.2019.03.005},
        Year = {2019}}
```

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.

The paper had to wait until 2019...

Bouhlel, M. A., Hwang, J. T., Bartoli, N., Lafage, R., Morlier, J., & Martins, J. R. (2019). A Python surrogate modeling framework with derivatives. *Advances in Engineering Software*, *135*, 102662.

SMT structure – Surrogate

1.1.0 Latest Compare

relf released this 1 hour ago v1.1.0 651df91

- Mixed integer surrogate enhancements (thanks **@Paul-Saves**)
  - Add number of components estimation in KPLS surrogate models (#325)
  - Add `propagate_uncertainty` option in MFK method (#320) : when True the variance of lower fidelity levels are taken into account.
  - Add ordered variables management in mixed integer surrogates (#326, #327). Deprecation warning: INT type is deprecated and superseded by ORD type.
  - Update version for the GOWER distance model. (#330)
  - Implement generalization of the homoscedastic hypersphere kernel from Pelamatti et al. (#330)

Svante Wold (1978) Cross-Validatory Estimation of the Number of Components in Factor and Principal Components Models, Technometrics, 20:4, 397-405, DOI: 10.1080/00401706.1978.10489693

- Radial basis functions
- Inverse-distance weighting
- Regularized minimal-energy tensor-product splines
- Least-squares approximation
- Second order polynomial approximation
- Kriging
- Kriging with partial least square (KPLS)
- KPLSK
- Gradient-enhanced KPLS
- Gradient-enhanced neural networks
- Marginal Gaussian process

Useful for low dimensional problem

useful for kriging in high dimension

Focus on derivatives

Bouhlel, M. A., Hwang, J. T., Bartoli, N., Lafage, R., Morlier, J., & Martins, J. R. (2019). A Python surrogate modeling framework with derivatives. Advances in Engineering Software, 135, 102662.

Focus on derivatives

Method	Advantages (+) and disadvantages (−)	Derivatives		
		Train.	Pred.	Out.
Kriging	+ Prediction variance, flexible − Costly if number of inputs or training points is large − Numerical issues when points are too close to each other	No	Yes	No
KPLS	+ Prediction variance, fast construction + Suitable for high-dimensional problems − Numerical issues when points are too close to each other	No	Yes	No
KPLSK	+ Prediction variance, fast construction + Suitable for high-dimensional problems − Numerical issues when points are too close to each other	No	Yes	No
GE-KPLS	+ Prediction variance, fast construction + Suitable for high-dimensional problems + Control of the correlation matrix size − Numerical issues when points are too close to each other − Choice of step parameter is not intuitive	Yes	Yes	No
RMTS	+ Fast prediction + Training scales well up to 10^5 training points + No issues with points that are too close to each other − Poor scaling with number of inputs above 4 − Slow training overall	Yes	Yes	Yes
RBF	+ Simple, only a single tuning parameter + Fast training for small number of training points − Susceptible to oscillations − Numerical issues when points are too close to each other	No	Yes	Yes

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

$(\boldsymbol{xt}, \boldsymbol{yt})$ Training data
$(\boldsymbol{x}, \boldsymbol{y})$ Prediction data

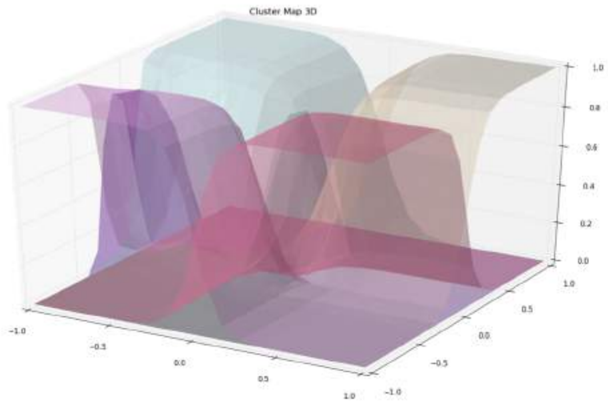
$(\boldsymbol{dyt}/\boldsymbol{dxt})$: training derivatives used for gradient-enhanced modeling

$(\boldsymbol{dy}/\boldsymbol{dx})$: prediction derivatives

$(\boldsymbol{dy}/\boldsymbol{dyt})$: derivatives with respect to the training data

AI4E

- Mixture of experts (MOE) - if 1 expert , comparison of all experts
- Variable-fidelity modeling (VFM)
- Multi-Fidelity Kriging (MFK)
- Multi-Fidelity Kriging KPLS (MFKPLS)
- Multi-Fidelity Kriging KPLSK (MFKPLSK)
- Efficient Global Optimization (EGO)
- Mixed-Integer Sampling and Surrogate (Continuous Relaxation)
- Mixed-Integer Surrogate with Gower Distance



How to approximate highly non linear function?

•Handle heterogeneity and non linearity (all phases in the flight mission, buckling factor for composite fuselage)

•Combine multiple surrogate models divide-and- conquer strategy

AI4E

- Mixture of experts (MOE)
- Variable-fidelity modeling (VFM)
- Multi-Fidelity Kriging (MFK)
- Multi-Fidelity Kriging KPLS (MFKPLS)
- Multi-Fidelity Kriging KPLSK (MFKPLSK)
- Efficient Global Optimization (EGO)
- Mixed-Integer Sampling and Surrogate (Continuous Relaxation)
- Mixed-Integer Surrogate with Gower Distance

How to handle multi-information sources?

- Access to different information sources that approximate $y(x)$ with varying accuracy and cost

Hierarchical relationships among information sources: low-fidelity / high-fidelity

Why multifidelity?

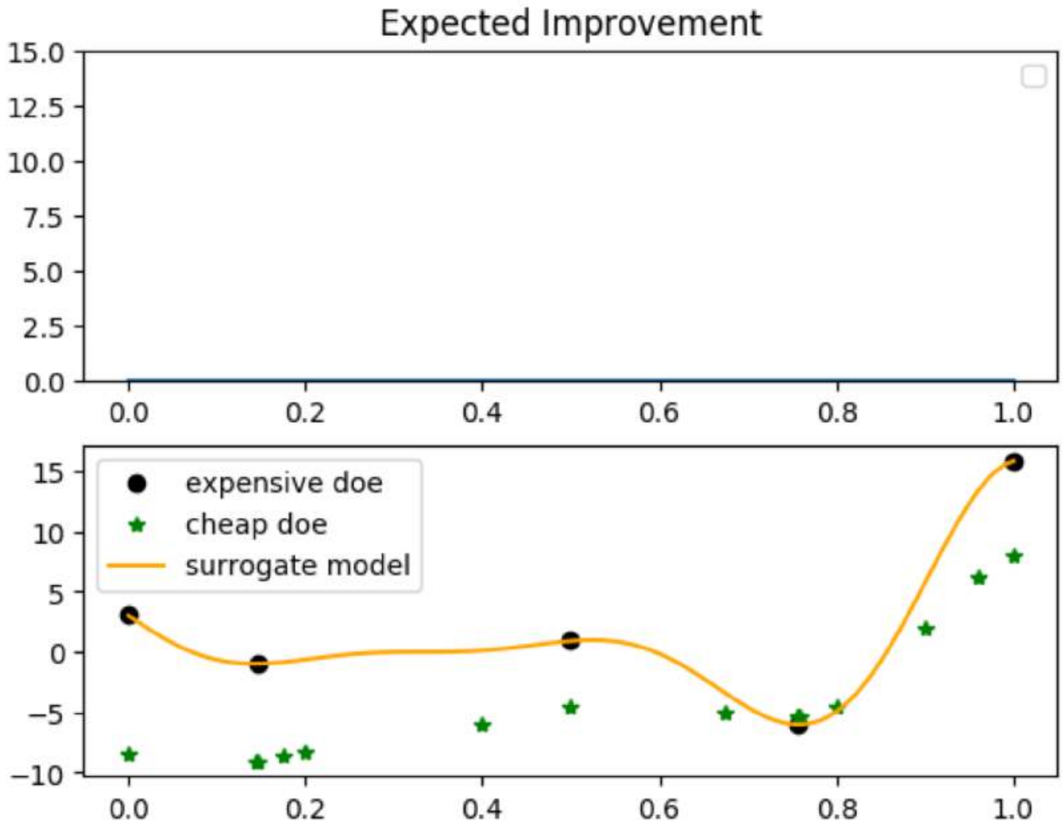
Artificial Intelligence for Engineers, means learning for optimizing a computational design.

Given a surrogate model with both prediction and confidence parameters, an optimization procedure must balance the search for the expected optimal point and decreasing uncertainty **(Bayesian Optimization)**

What if Several levels of fidelity of the same simulation are available?
(in aerodynamics **multifidelity** means: Lifting line theory, Vortex lattice method, and RANS CFD simulation tools available)

Raw approach luse ow fidelity for exploration and high fidelity for exploitation

Our approach combine Bayesian optimization with multifidelity



AI4E

- [Mixture of experts (MOE]
- [Variable-fidelity modeling (VFM)]
- [Multi-Fidelity Kriging (MFK)]
- [Multi-Fidelity Kriging KPLS (MFKPLS)]
- [Multi-Fidelity Kriging KPLSK (MFKPLSK)]
- [Efficient Global Optimization (EGO)]
- [Mixed-Integer Sampling and Surrogate (Continuous Relaxation)]
- [Mixed-Integer Surrogate with Gower Distance]

Bayesian optimization (EGO without constraint) for continuous and mixed variables

Included some dedicated Jupyter Notebooks

..
SMT_EGO_application.ipynb
SMT_MixedInteger_application.ipynb
SMT_Noise.ipynb
SMT_Tutorial.ipynb

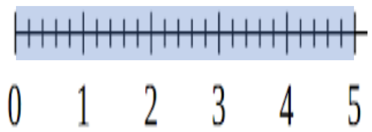
AI4E

- Mixture of experts (MOE
- Variable-fidelity modeling (VFM)
- Multi-Fidelity Kriging (MFK)
- Multi-Fidelity Kriging KPLS (MFKPLS)
- Multi-Fidelity Kriging KPLSK (MFKPLSK)
- Efficient Global Optimization (EGO)
- Mixed-Integer Sampling and Surrogate (Continuous Relaxation)
- Mixed-Integer Surrogate with Gower Distance

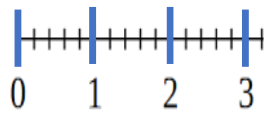
Focus on mixed integer

Variables types :

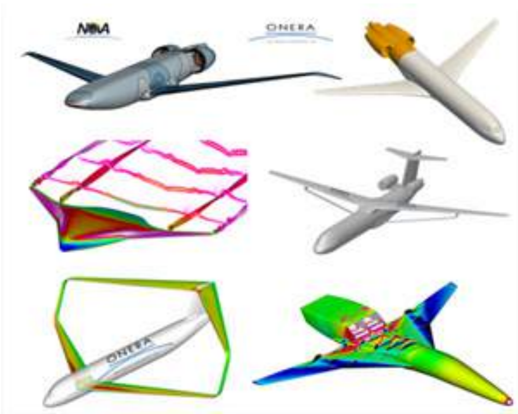
Continuous (x) Ex: wing length



Integer (z) Ex: winglet number



Categorical (u) Ex: Plane shape



Categorical variables: n variables,
n=2
u1= shape
u2= color

Levels: L_i levels for I in 1,..,n,
L_1=3, L_2=2.
Levels(u1)= square, circle, rhombus
Levels(u2)= blue, green

Categories: $\prod_{i=1}^{n} L_i$, 2*3=6
- Blue square
- Blue circle
- Blue rhombus
- Green square
- Green circle
- Green rhombus

Focus on mixed integer

Continuous relaxation

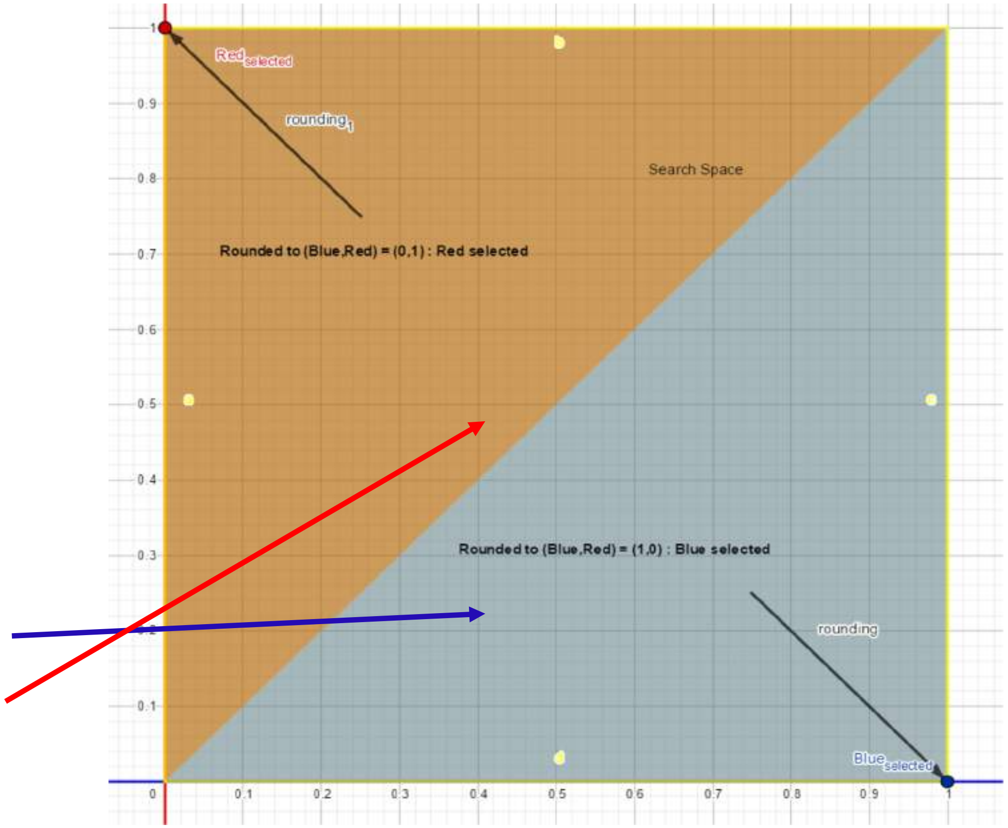
E. C. Garrido-Merchán, and D. Hernández-Lobato. "Dealing with categorical and integer-valued variables in Bayesian Optimization with Gaussian processes". Neurocomputing, vol. 380 (2020), pages 20-35

Example with 1 categorical variable and two levels

- Red color
- Blue color

➔Categorical variable replaced by two continuous variables denoted by X_1 and X_2

- If $X_1>X_2$ => (1., 0.) => Blue color
- If $X_1<X_2$ => (0.,1.) => Red color

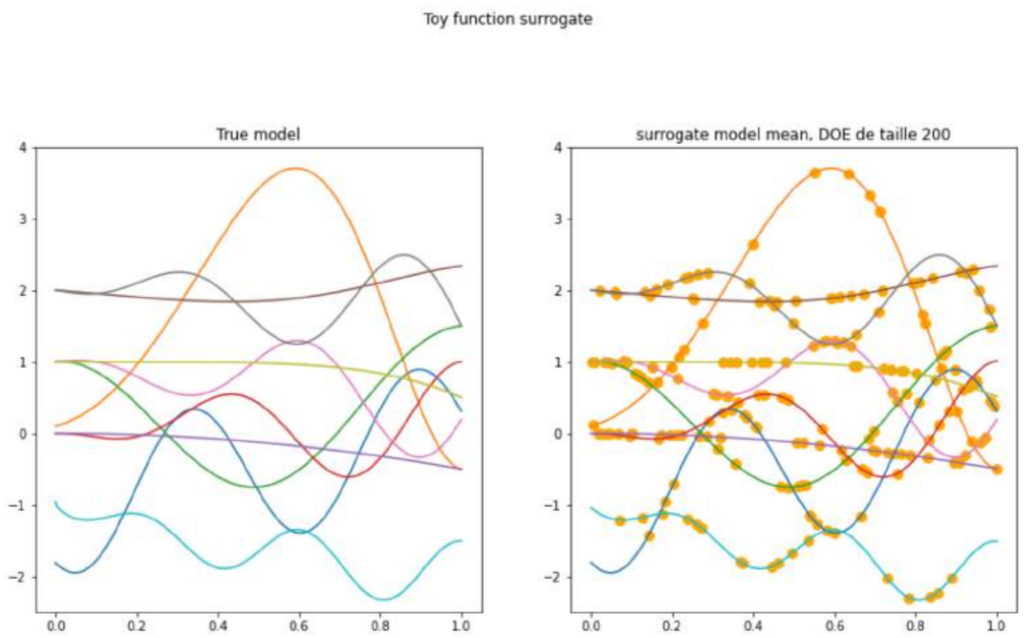


Focus on mixed integer

Continuous relaxation

Validation problem $n_{var} = 2$
Variable types: continuous and categorical with 10 levels. $n_{var,relaxed} = 11$

$$f(x,z) = \begin{cases} \cos(3.6\pi(x-2)) + x - 1 & \text{if} \quad z = 1, \\ 2\cos(1.1\pi\exp(x)) - \frac{x}{2} + 2 & \text{if} \quad z = 2, \\ \cos(2\pi x) + \frac{1}{2}x & \text{if} \quad z = 3, \\ x\left(\cos(3.4\pi(x-1)) - \frac{x-1}{2}\right) & \text{if} \quad z = 4, \\ -\frac{x^2}{2} & \text{if} \quad z = 5, \\ 2\cos(\frac{\pi}{4}\exp(-x^4))^2 - \frac{x}{2} + 1 & \text{if} \quad z = 6, \\ x\cos(3.4\pi x) - \frac{x}{2} + 1 & \text{if} \quad z = 7, \\ x(-\cos\left(7\frac{\pi}{2}x\right) - \frac{x}{2}) + 2 & \text{if} \quad z = 8, \\ -\frac{x^5}{2} + 1 & \text{if} \quad z = 9, \\ -\cos(5\frac{\pi}{2}x)^2\sqrt{x} - \frac{\ln(x+0.5)}{2} - 1.3 & \text{if} \quad z = 10. \end{cases}$$



SMT installation

On the github website, some instructions are given

- to perform the installation
- to have access to the documentation
- to find some examples

Documentation

http://smt.readthedocs.io

Required packages

SMT depends on the following modules: numpy, scipy, scikit-learn, pyDOE2 and Cython.

Installation

If you want to install the latest release

```
pip install smt
```

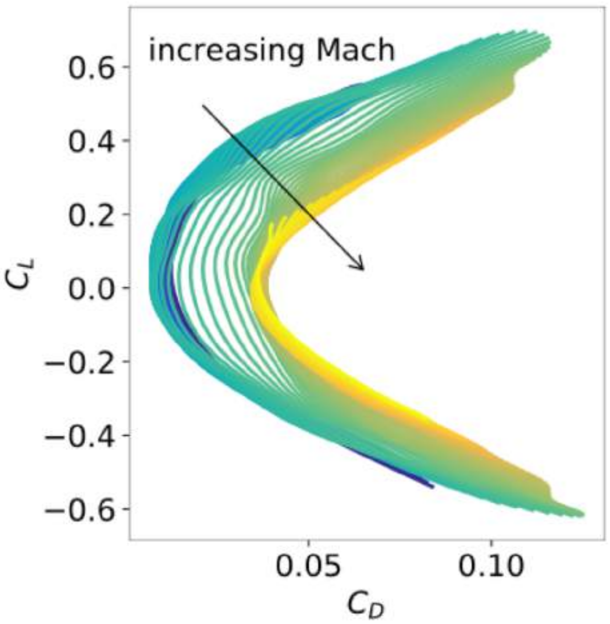
or else if you want to install from the current master branch

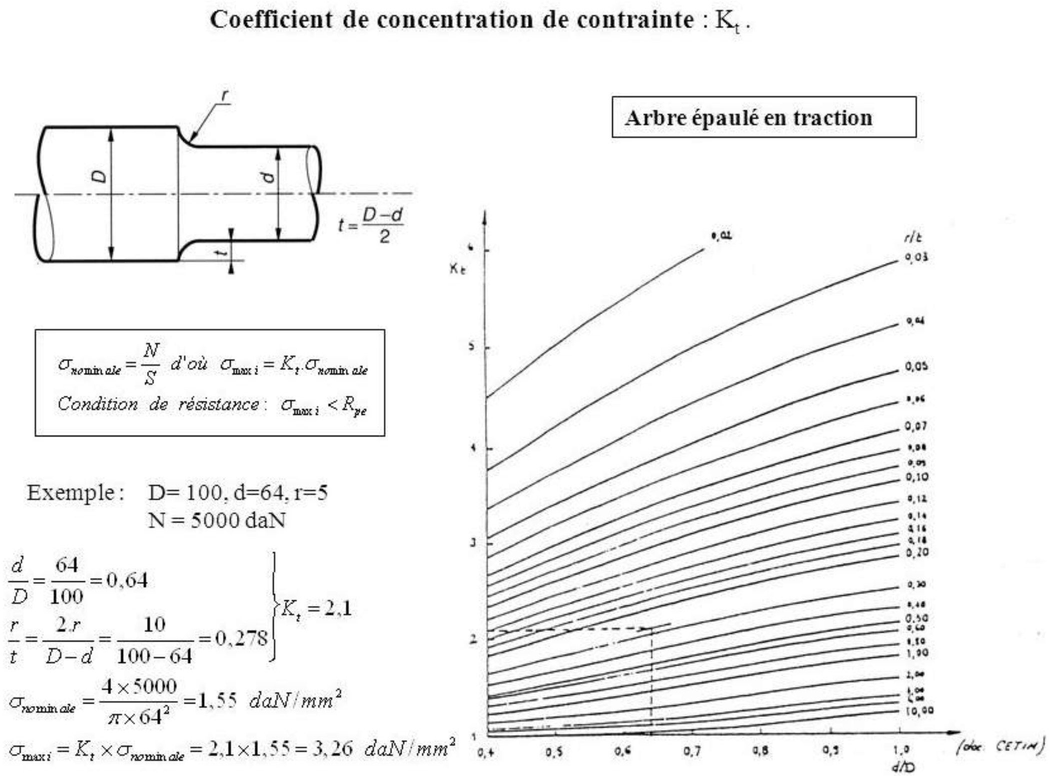
```
pip install git+https://github.com/SMTOrg/smt.git@master
```

Usage

For examples demonstrating how to use SMT, you can take a look at the tutorial notebook or go to the 'smt/examples' folder.

Surrogate is the new abacus





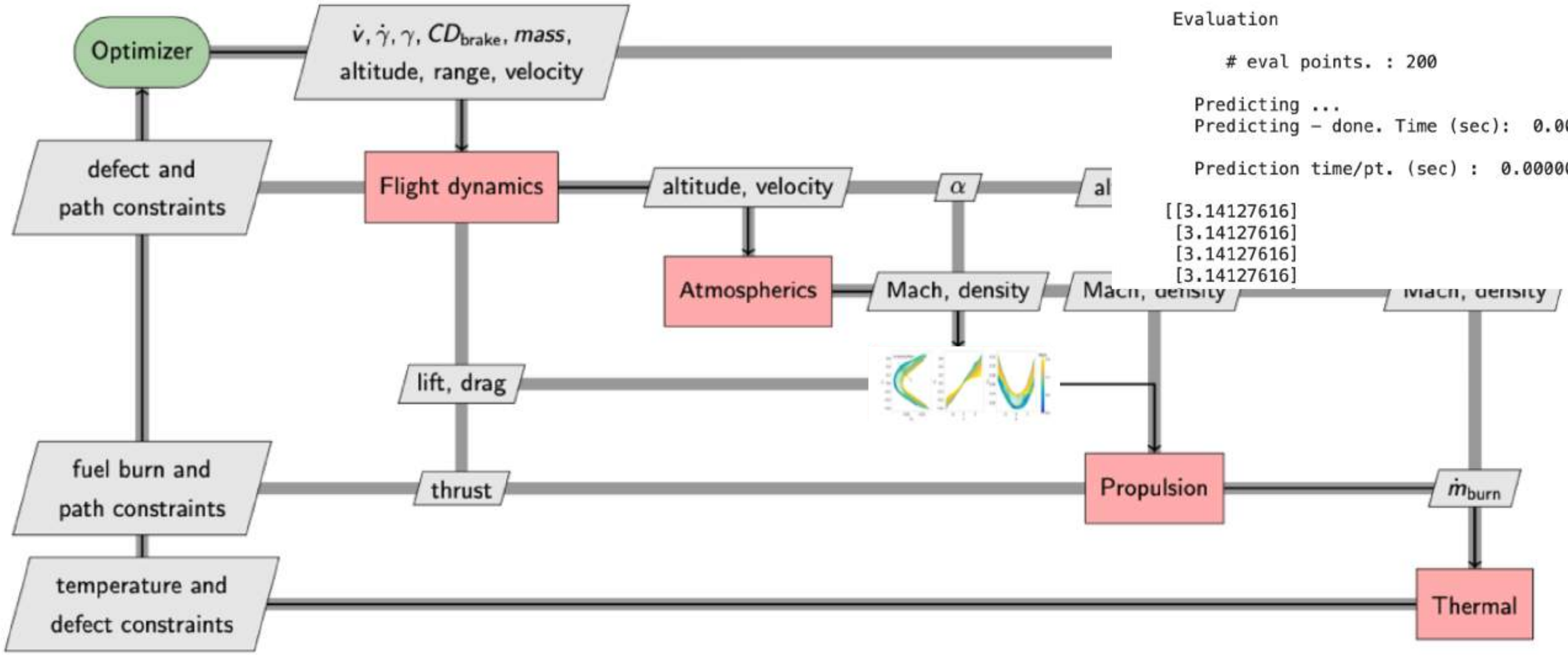
Benefits of Opensource

Coupling with OpenMDAO

Jasa, J. P., Brelje, B. J., Gray, J. S., Mader, C. A., & Martins, J. R. (2020). Large-Scale Path-Dependent Optimization of Supersonic Aircraft. Aerospace, 7(10), 152.

```
[ ] import pickle
    #For saving models written in Python
    filename = "sm.pkl"
    with open(filename, "wb") as f:
       pickle.dump(sm, f)
    #For loading the model
    sm_load = None
    with open(filename, "rb") as f:
        sm_load= pickle.load(f)

    #to use the surrogate model
    y_load = sm_load.predict_values(xtest)
    print(y[1:10])
    print(y_load[1:10])
```

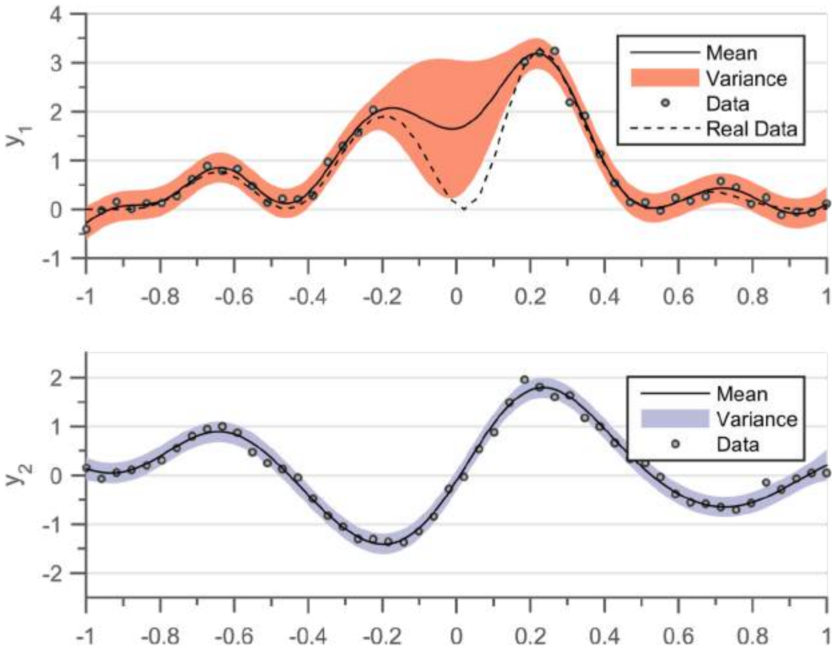
```
Evaluation

     # eval points. : 200

   Predicting ...
   Predicting - done. Time (sec):  0.0008404

   Prediction time/pt. (sec) :  0.0000042

[[3.14127616]
 [3.14127616]
 [3.14127616]
 [3.14127616]
```



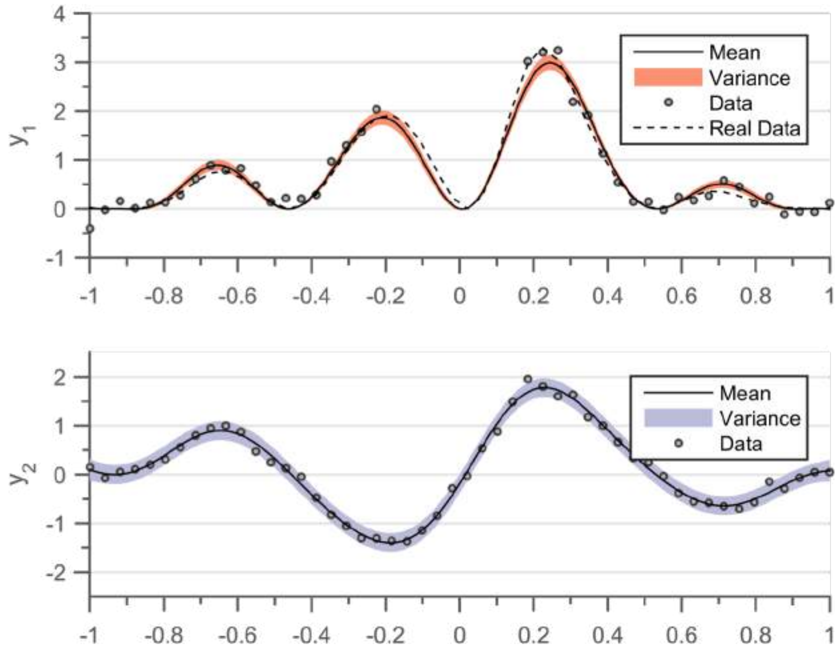
What we did few years ago before PINN and SciML…

https://github.com/ankitchiplunkar/thesis_isae

Faulty sensor



Independent GPs

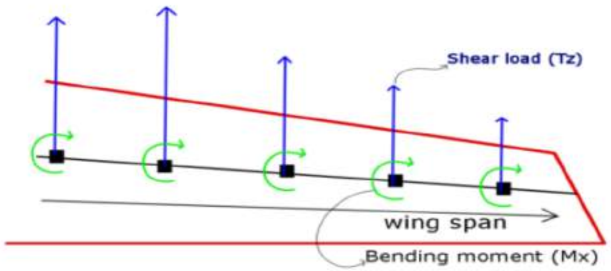


Related GPs

What we did few years ago before PINN and SciML…

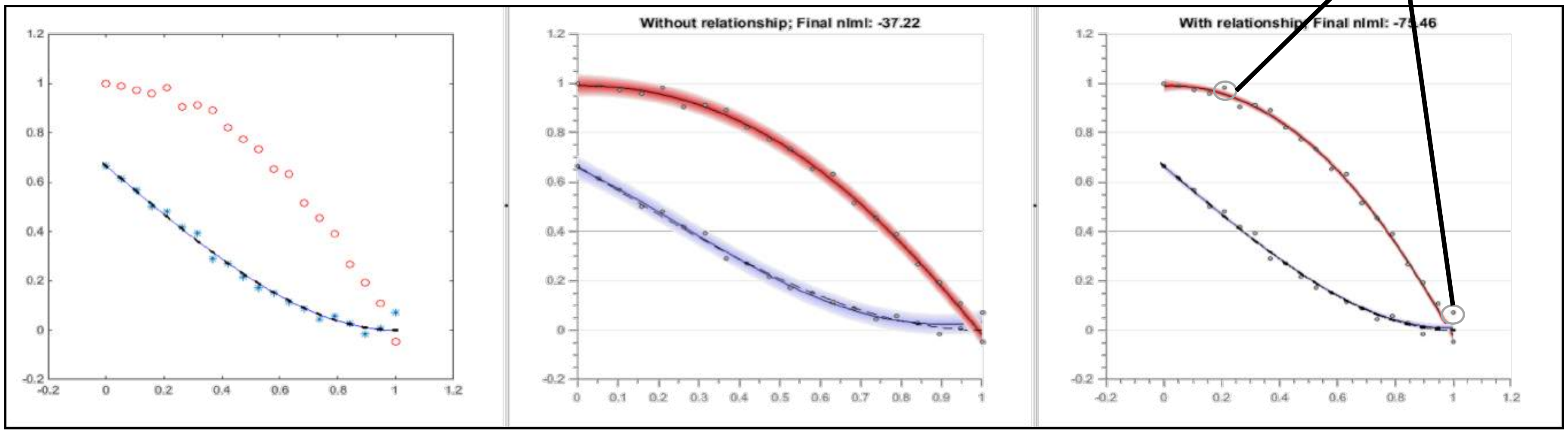
https://github.com/ankitchiplunkar/thesis_isae

Flight test - Relationship between Tz and Mx



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

Wrong data point



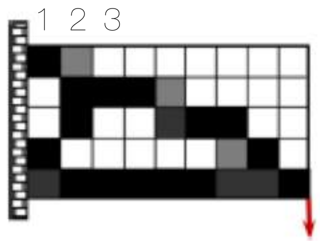
Au programme

Duration	Description	Agenda
10’	MDO	Examples
10’	Surrogate	SMT
10’	Ecodesign	Lighter and Greener
2’	Conclusions	And future works?

Ecodesign

Intuitive Problem? Quadratic Form

$x_1 = 1$
$x_2 = 0.5$
$x_3 = 0$
$\dots$



- Objective function; Strain energy

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

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

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

Scalar

- Contraints: mass target

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

Scalar

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

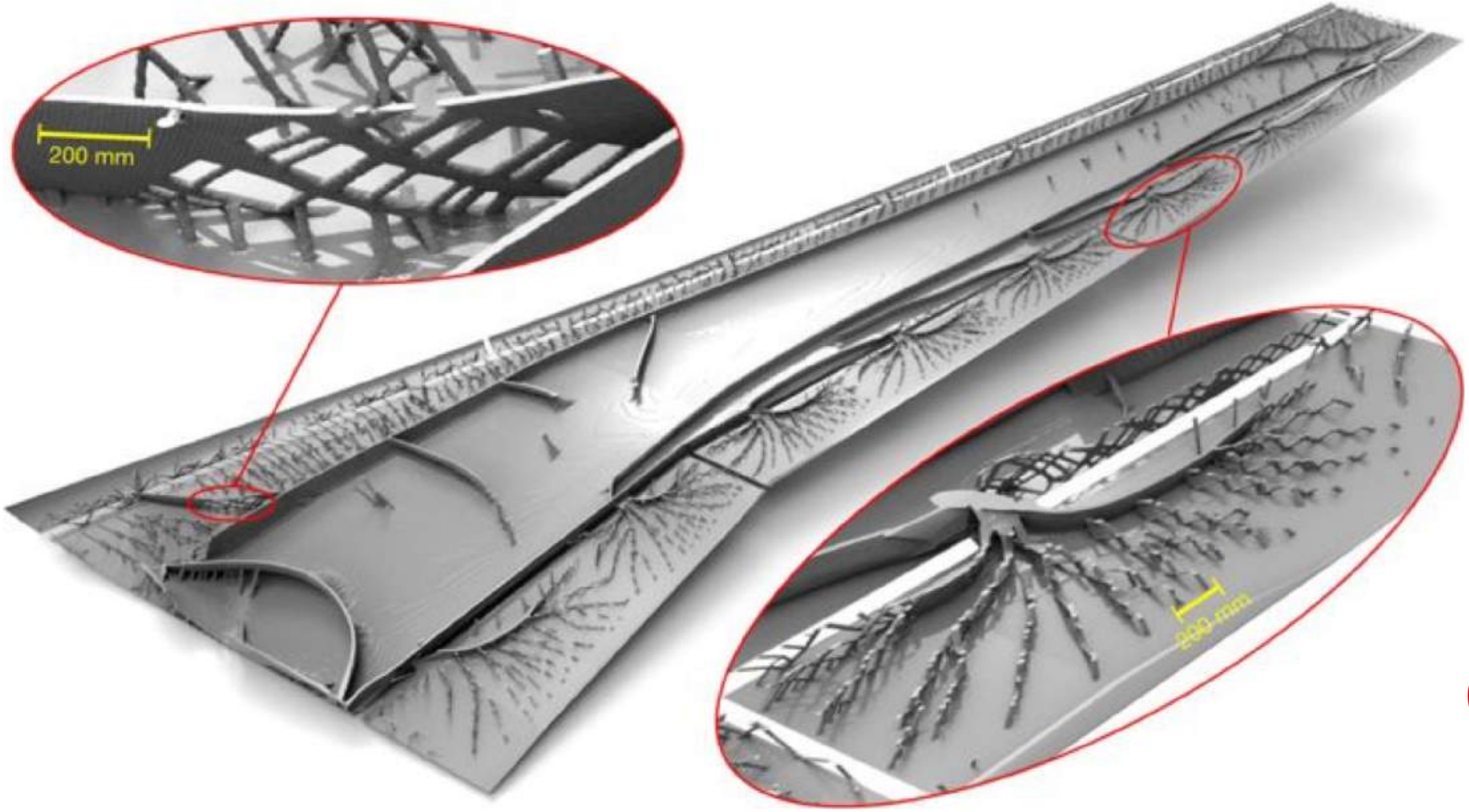
Pixels?

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

Chris Columbus et al, Pixels, movie 2015

Use HPC and lot of time

Niels Aage, Erik Andreassen, Boyan S Lazarov, and Ole Sigmund. Giga-voxel computational morphogenesis for structural design. Nature, 550(7674):84, 2017.

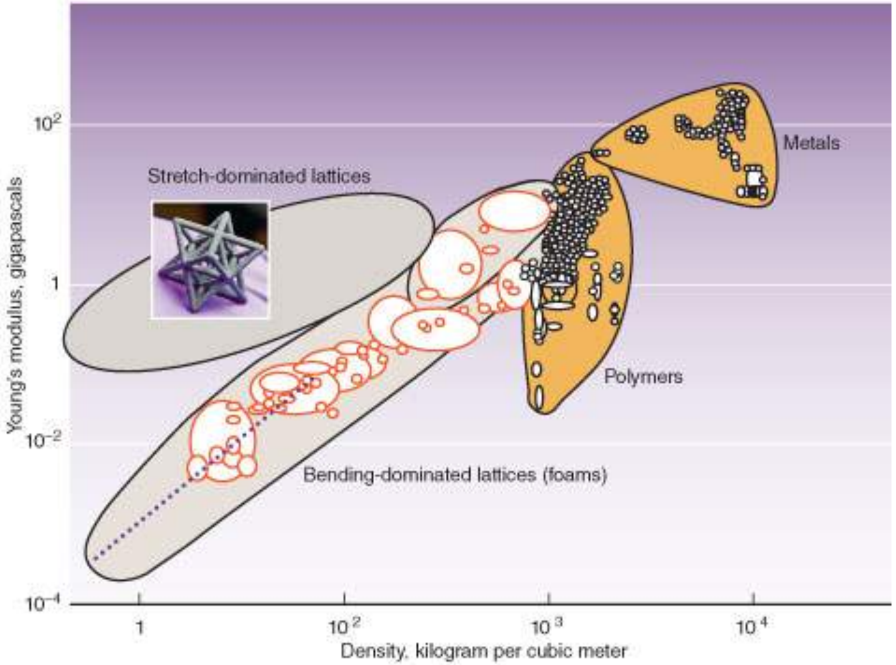


or

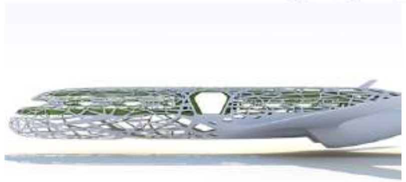
Reproducible Research

- https://www.topopt.mek.dtu.dk
- https://www.top3d.app

The ERA of DIGITAL MATERIALS



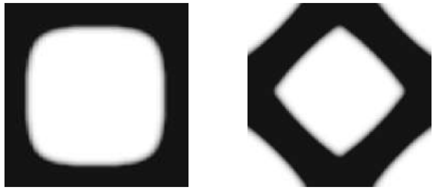
(a) (b)



Chris Spadaccini (llnl,USA) "By controlling the architecture of a microstructure, we can create materials with previously unobtainable properties in the bulk form."

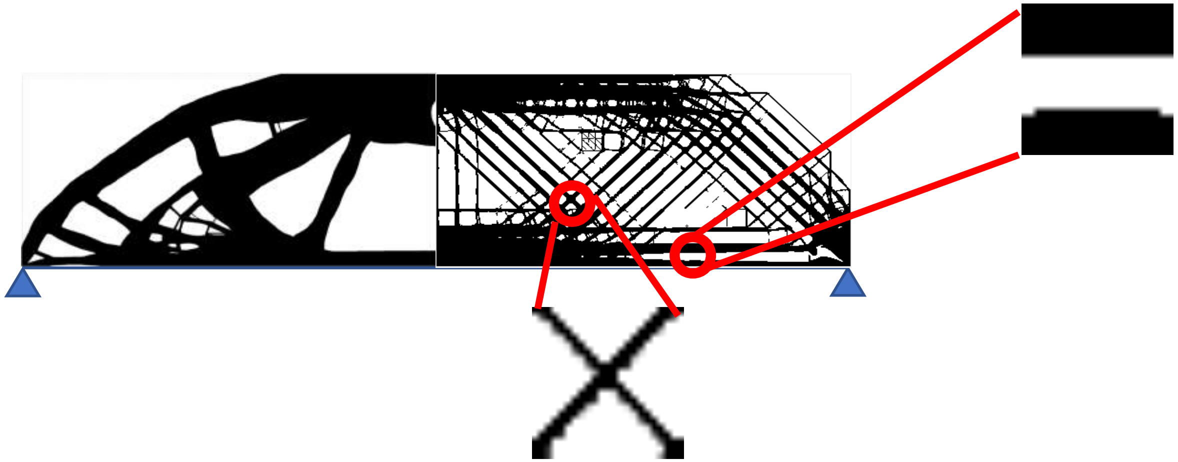
Multi-scale TO

A two level optimization that combines Unit cell design & Topology Optimization



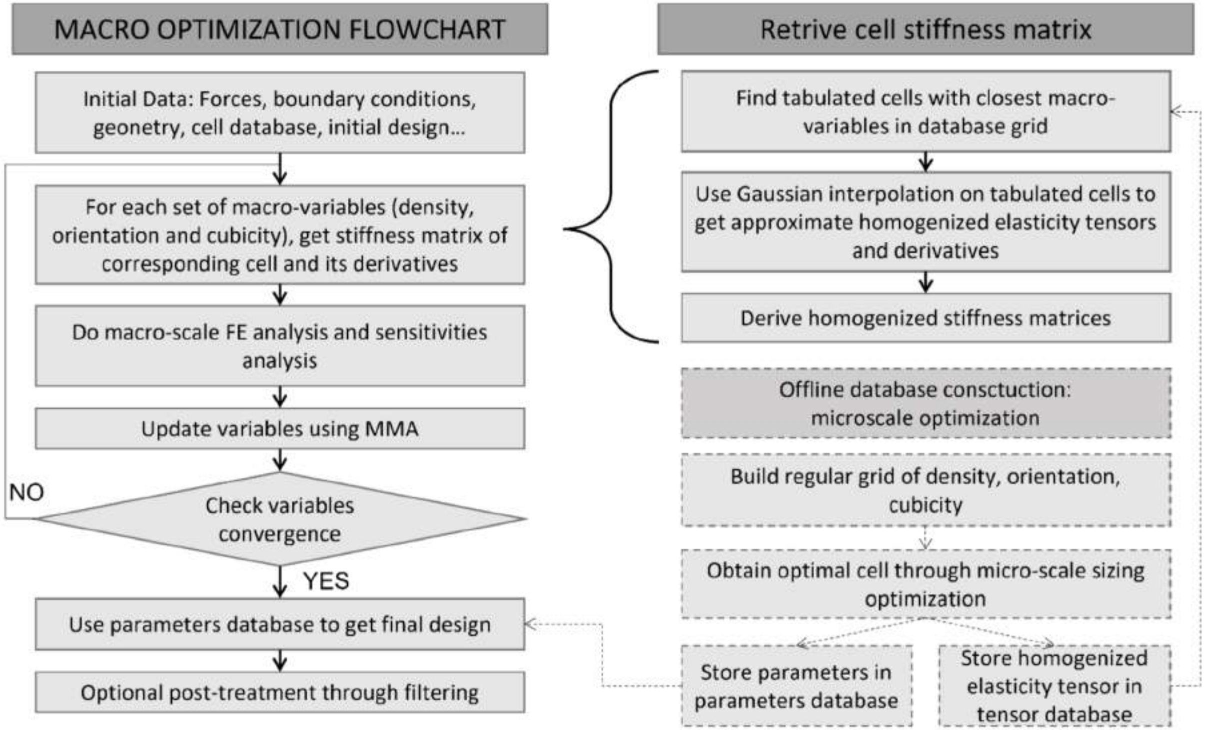
+

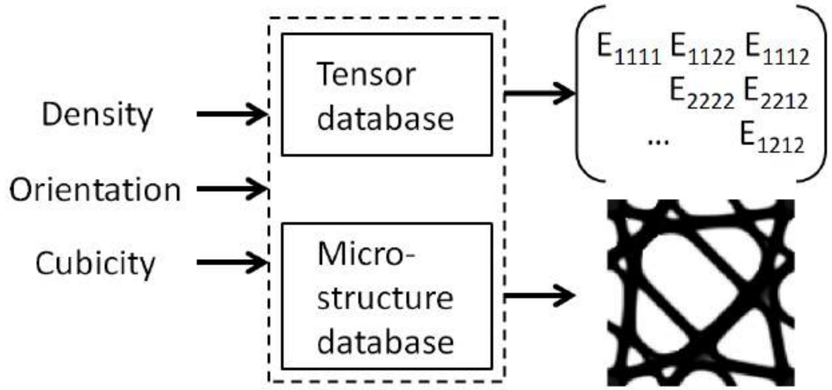
+



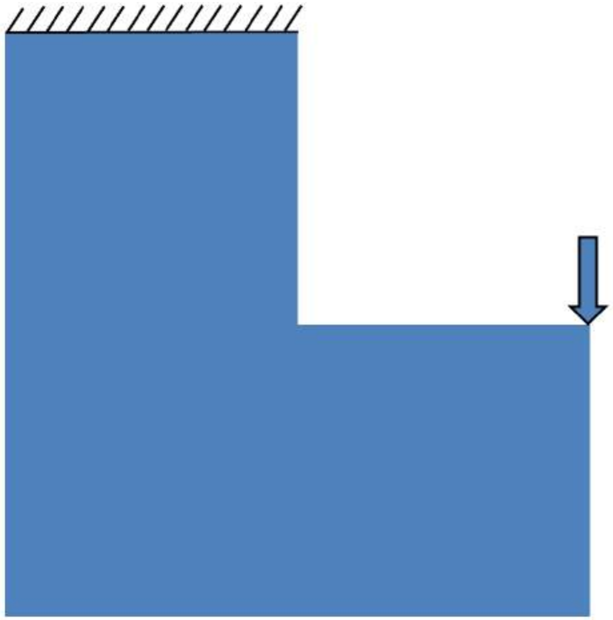
Xia L, Breitkopf P (2015) Design of materials using topology optimization and energy-based homogenization approach in Matlab. Struct Multidisc Optim 52(6):1229–1241. https://doi.org/10.1007/s00158-015-1294-0

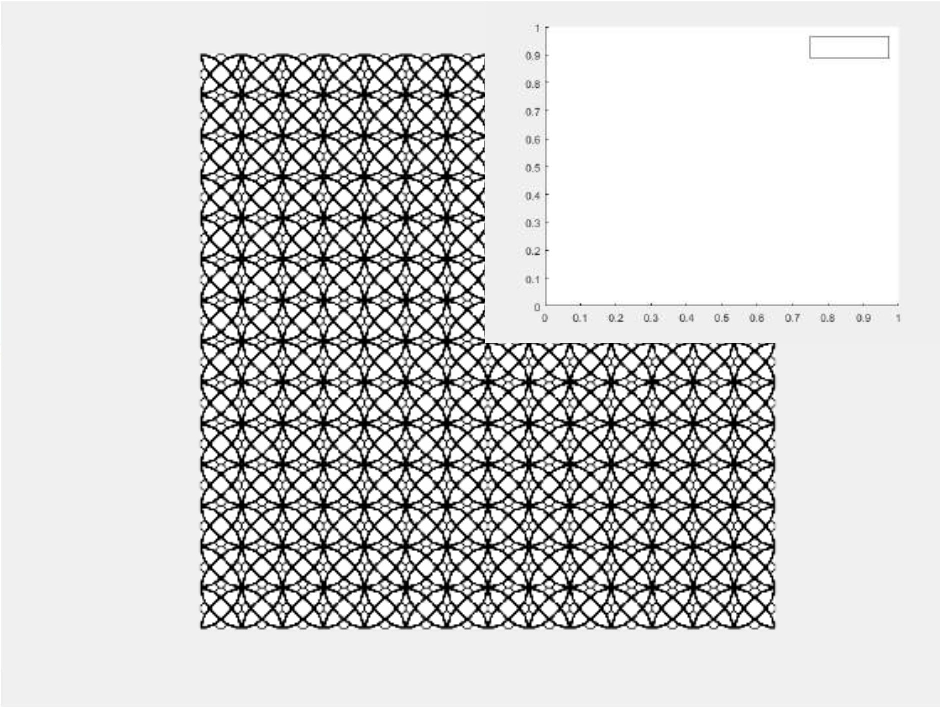
Acceleration through AI





EMTO on L-shape (cellular /digital materials)





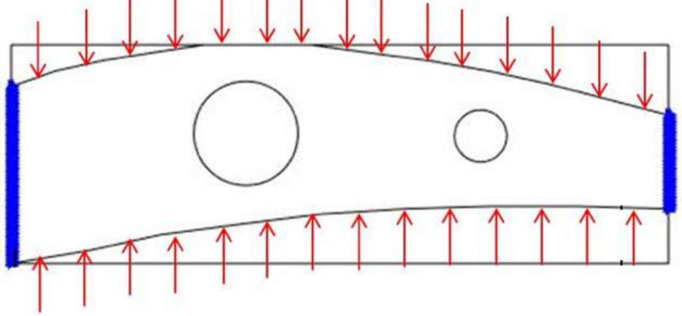
https://github.com/mid2SUPAERO/EMTO

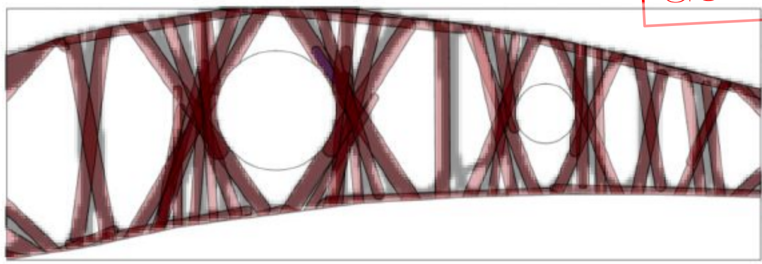
Aircraft rib design

GGP := EASY EXPLORATION of POTENTIAL DESIGN OF STRUCTURES

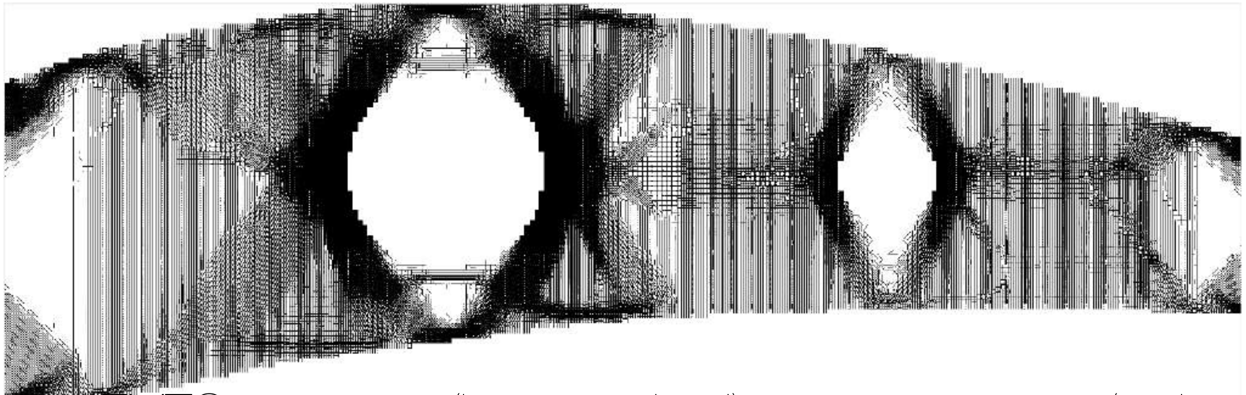
GGP-MNA: C=0.194

- Again Only pressure loads



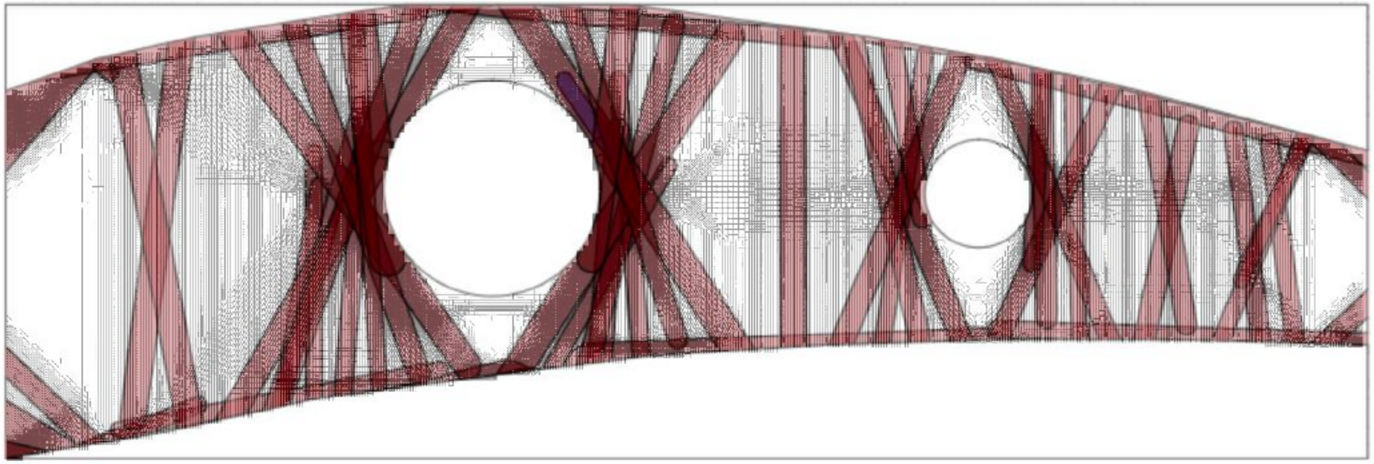


SIMP : c=0.198

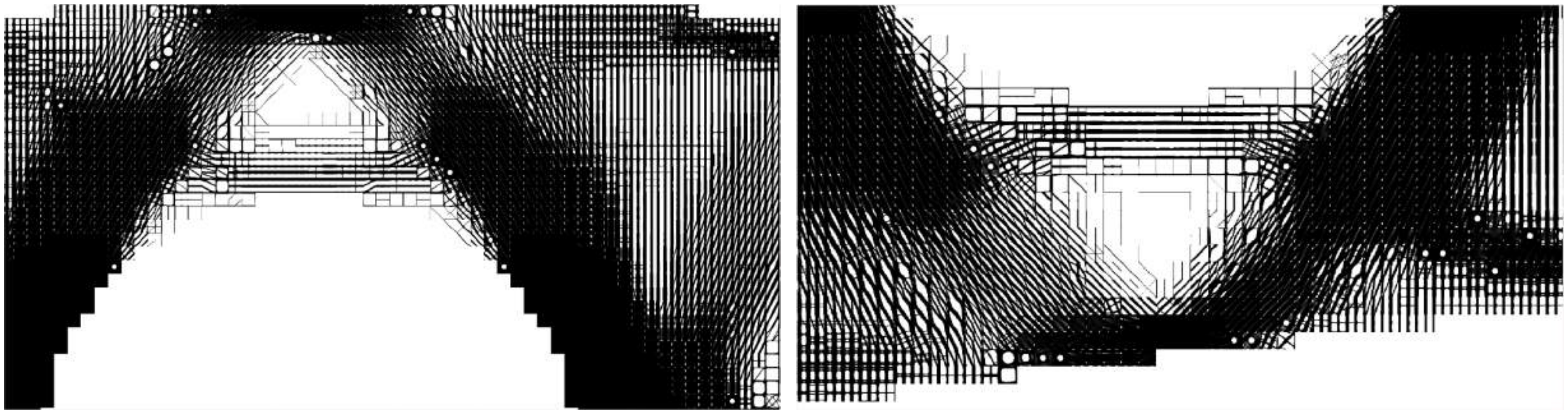


EMTO : c=0.172(homogenized) c=0.178-0.206(estimate)

EMTO vs GGP



Multiscale approach is a complete REDESIGN: Creation of multiple paths for internal forces



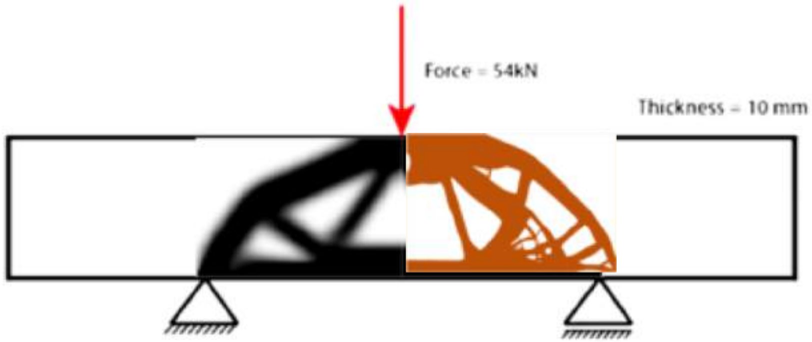
It should be manufactured by machine

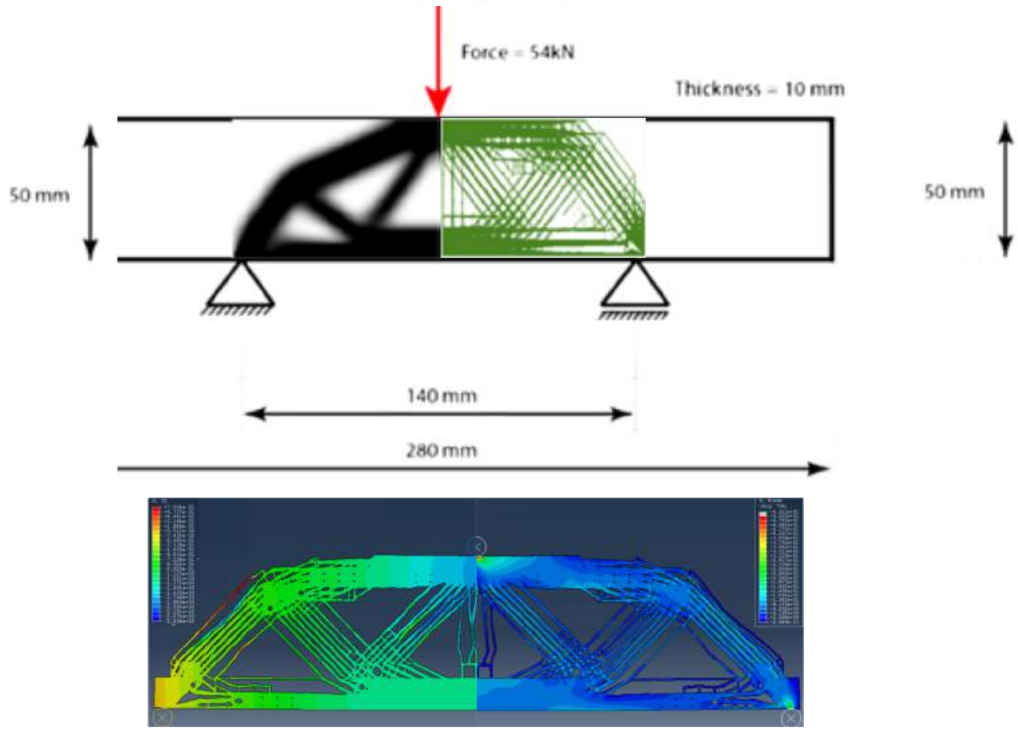
How to **ECO**design tomorrow's structures?

Prof. Joseph Morlier, Edouard Duriez, Miguel Charlotte, Catherine Azzaro-Pantel

Print it , Test it

EXP +ABAQUS REANALYSE

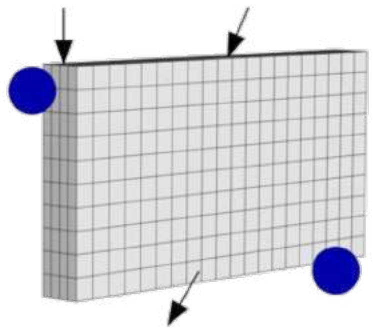




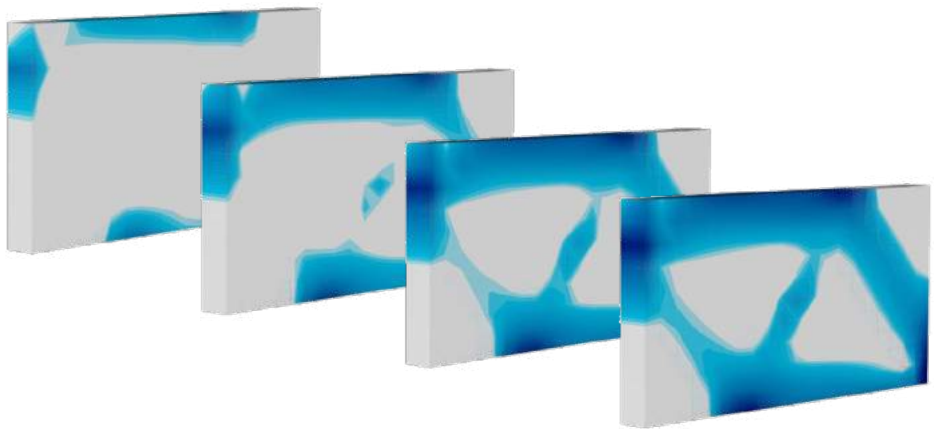
PLA or Selective Laser Melting (SLM)

A simple way to do Ecodesign with Topology Optimization?

Start with Topology Optimization



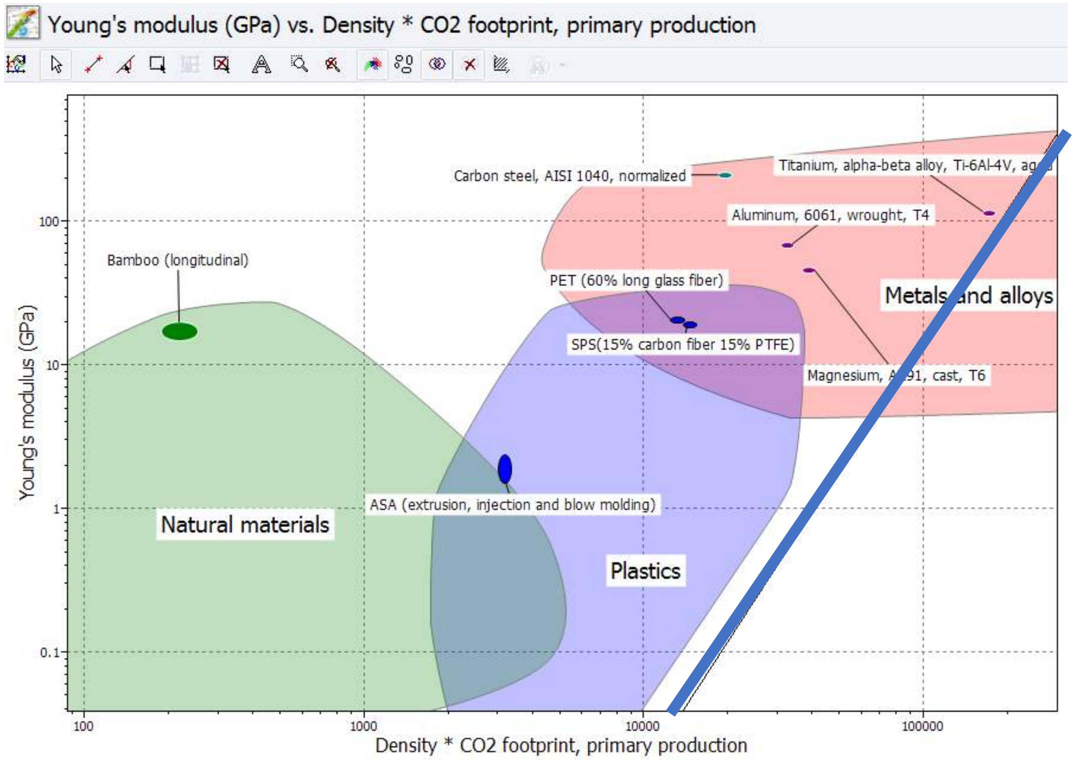
Inputs: Material, BCs and Loading



Outputs: design of a „stiff" bicycle frame

CO2 footprint minimization (Ashby's method)

Inputs: Type of Structures, default materials



Outputs: Optimal material (bamboo) with optimal Design

MDO

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32nd CIRP Design Conference

Ecodesign with topology optimization

Edouard Duriez*[a], Joseph Morlier[a], Catherine Azzaro-Pantel[b], Miguel Charlotte[a]

#Generalized Ashby's theory compatible with TopOpt
#All In One problem is a MDO problem !!!

$$
\begin{aligned}
\underset{mat,\mathcal{D},t}{\arg\min} \quad & CO_2^{tot}(mat,\mathcal{D},t) \\
s.t. \quad & \delta \leq \delta_{max} \\
& mat = \{E, \rho, CO_{2mat}^{i}\} \in \Phi \\
& 0 < v_f(\mathcal{D}) \leq 1
\end{aligned}
$$

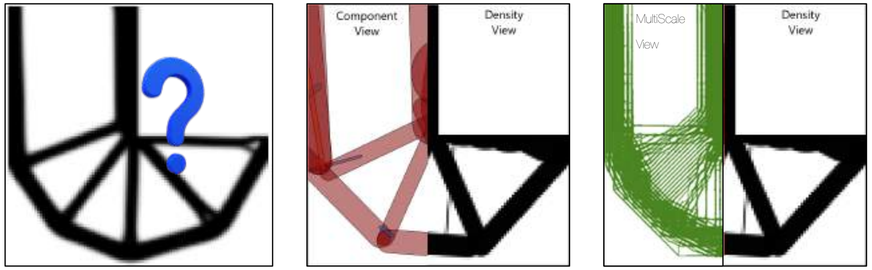
Time to conclude

Duration	Description	Agenda
10’	MDO	Examples
10’	Surrogate	SMT
10’	Ecodesign	Lighter and Greener
4’	Conclusions	And future works?

Researcher view (Reproducible Research)

- https://www.topopt.mek.dtu.dk
- https://www.top3d.app

- https://github.com/topggp/blog
- Crystal clear and preliminary ALM
- https://github.com/mid2SUPAERO/EMTO
- Redesign for ALM
- https://smt.readthedocs.io/en/latest/
- Design Acceleration



on SMT

« Learning » an industrial (**&costly**) simulation code is interesting to easilly exchange data only (without having access to the code in a collaborative project)

Given its focus on **derivatives**, SMT is synergistic with the OpenMDAO framework. **It can provide the derivatives that OpenMDAO requires from its components to compute the coupled derivatives of the multidisciplinary model.**

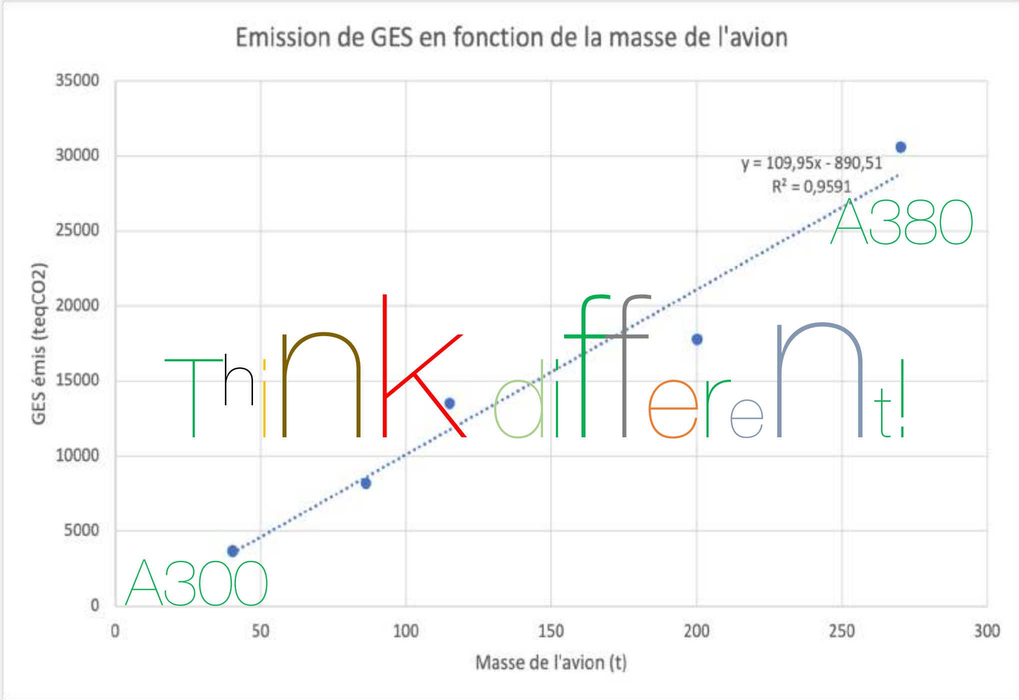
SMT is a natural framework for Bayesian Optimization (**DV<100 through KPLS**)

SMT core capabilities has been adapted for efficient **mixed variables / multifidelity / multiObjectives**

Rank1 on actual aircraft

At the first order

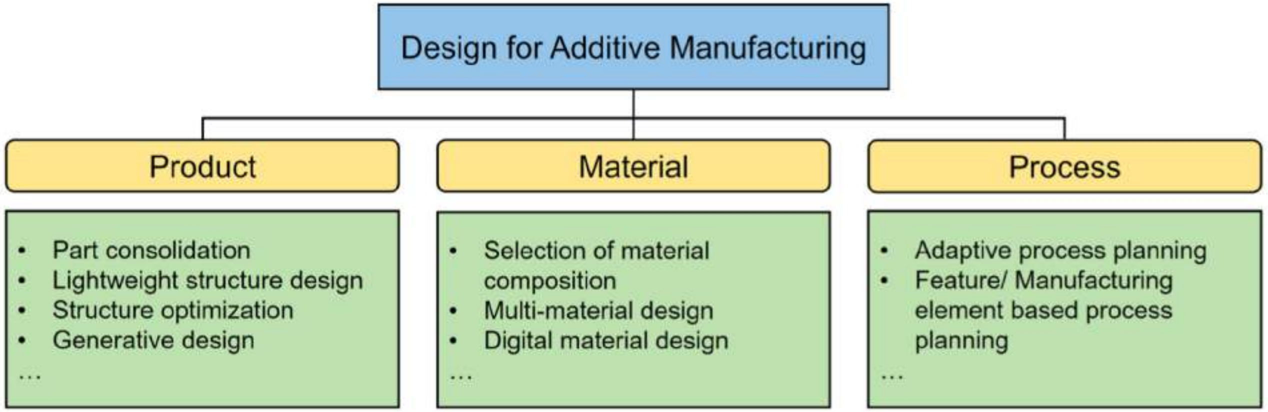
min {mass} is
proportional to
min {CO2}



Stiffer, Lighter, Greener **=**

TOPOLOGY OPTIMIZATION + ARCHITECTED MATERIALS + DIGITAL FABRICATION + ECODESIGN

MDO approach for EcoDFAM



Architected Materials

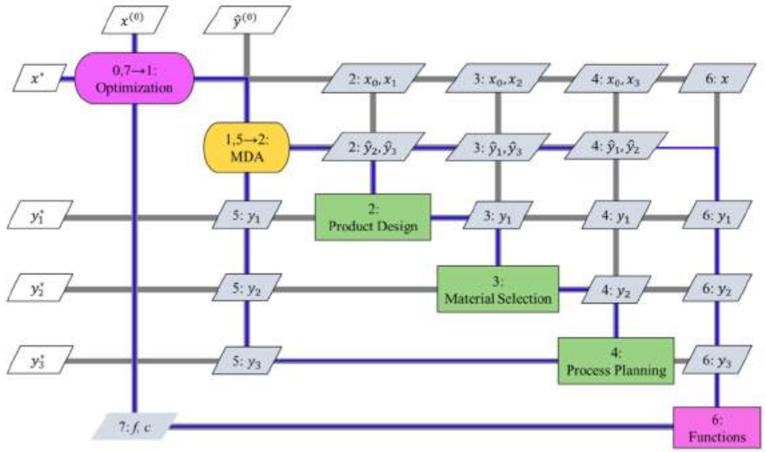
Eco Material & Process selection *(LCA)*

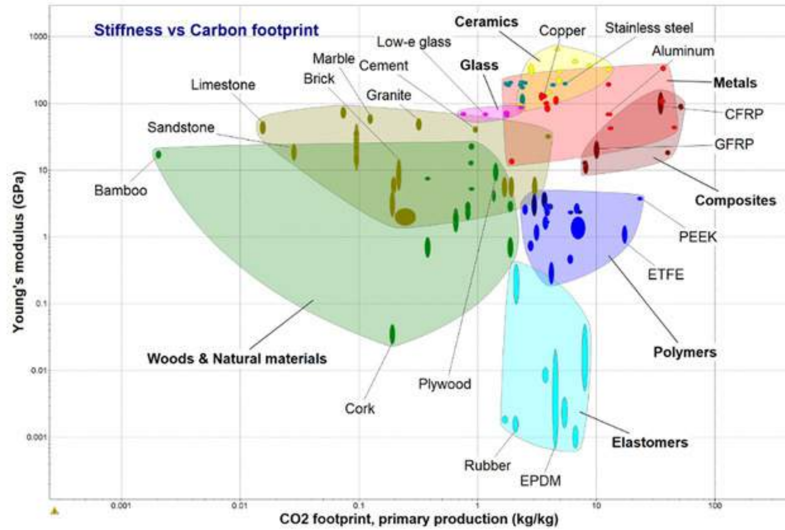
Carbon Footprint

Energy requirement

Water withdrawal

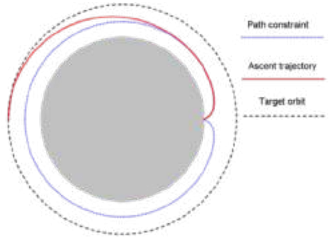
Generation of waste

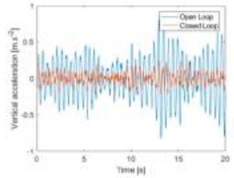




https://ica.cnrs.fr/author/jmorlier/

INSTITUT CLÉMENT ADER

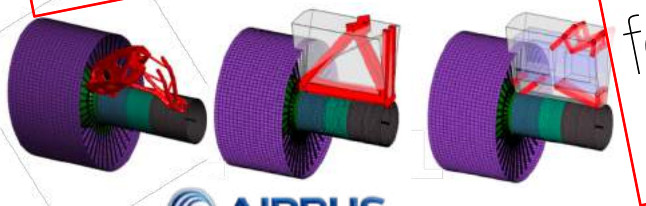




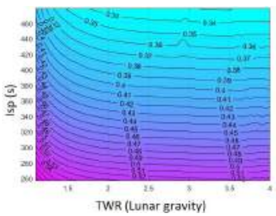
Structural Optimization & Ecodesign

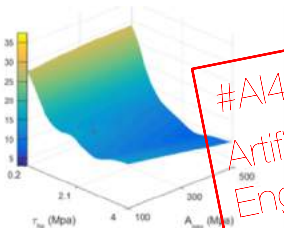
THANK YOU for Your ATTENTION

Multidisciplinary Design Optimization



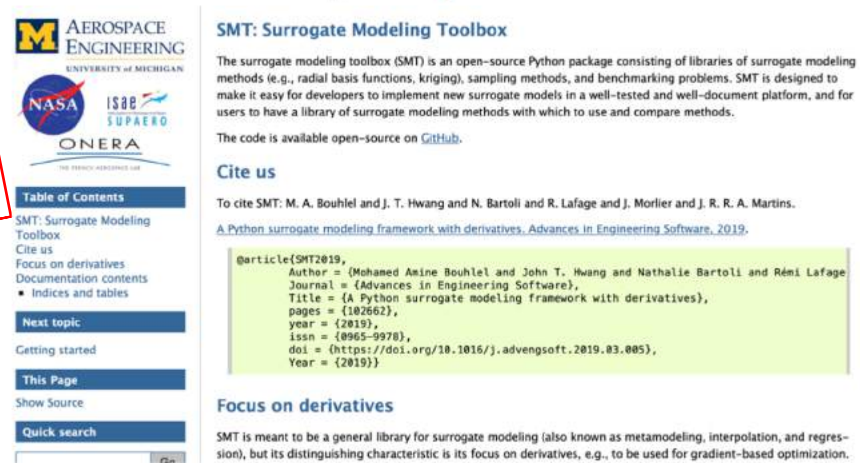
AIRBUS





#AI4E
Artificial Intelligence For Engineers

https://github.com/SMTorg/smt



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UNIVERSITY of MICHIGAN

NASA ISAE SUPAERO ONERA

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SMT: Surrogate Modeling Toolbox

The surrogate modeling 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.

Cite us

To cite SMT: M. A. Bouhlel and J. T. Hwang and N. Bartoli and R. Lafage and J. Morlier and J. R. R. A. Martins.

A Python surrogate modeling framework with derivatives. Advances in Engineering Software, 2019.

```
@article{SMT2019,
        Author = {Mohamed Amine Bouhlel and John T. Hwang and Nathalie Bartoli and Rémi Lafage
        Journal = {Advances in Engineering Software},
        Title = {A Python surrogate modeling framework with derivatives},
        pages = {102662},
        year = {2019},
        issn = {0965-9978},
        doi = {https://doi.org/10.1016/j.advengsoft.2019.03.005},
        Year = {2019}}
```

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.