

A new recipe in EcoDesign for Additive Manufacturing
(EDfAM)

Prof. Joseph Morlier



Research Experiences

- PhD graduated from Univ. Bordeaux in SHM of civil engineering structures in 2005
- Visiting Postdoc in Beijing (China), LIAMA : Sino French lab on Applied Mathematics (summer 2006)
- 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 University of Michigan @MDOLab (summer 2017)
- in TU Delft (May 2022) with **ANR Grant 2021** (French Science Foundation) → Also the Purpose of My actual visit at MDOLab

Key Figures at a Glance

1909

200

PhD students

30%

Foreign
Students

130

Professors &
Researchers

60 M€

Budget

> 130

Academic
Agreements

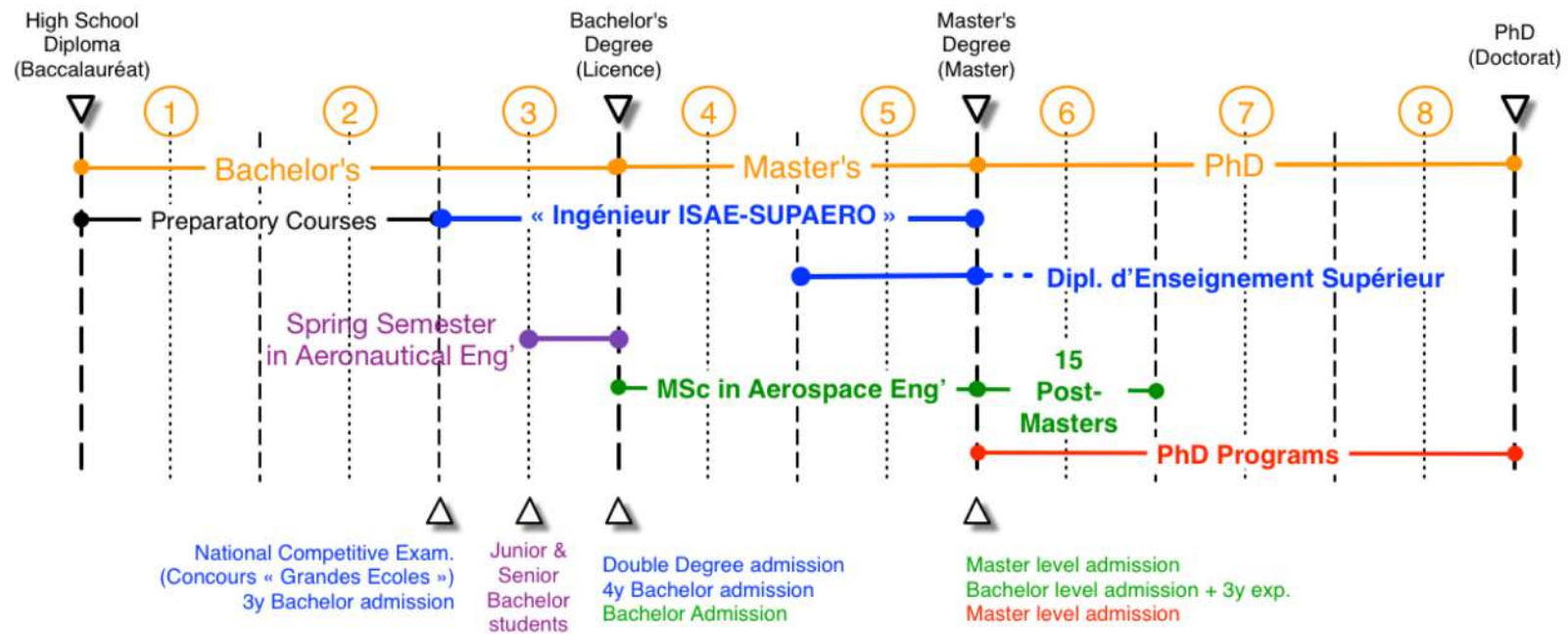
1 700

Students on
campus

650

students graduated
a year

ISAE-SUPAERO Programs & Bologna Process



Toulouse: Aerospace Activities



Actual PHD students in my group:

Ecodesign and topology optimization of architected materials and structures, PhD Edouard Duriez, X fund

Fast nonlinear aeroelasticity, PhD Oriol Chandre-Villa - AIRBUS fund

Multifidelity aeroelastic modeling for Ultra High Aspect Ratio Wing, PhD Yoann Le Lamer – EU/ONERA fund

Co-design and MDO for Military UAV design, PhD Remy Charayron –DGA/ONERA fund

Discrete optimization for topology optimization of architected materials with variable linking, PhD Enrico Stragiotti – ONERA fund

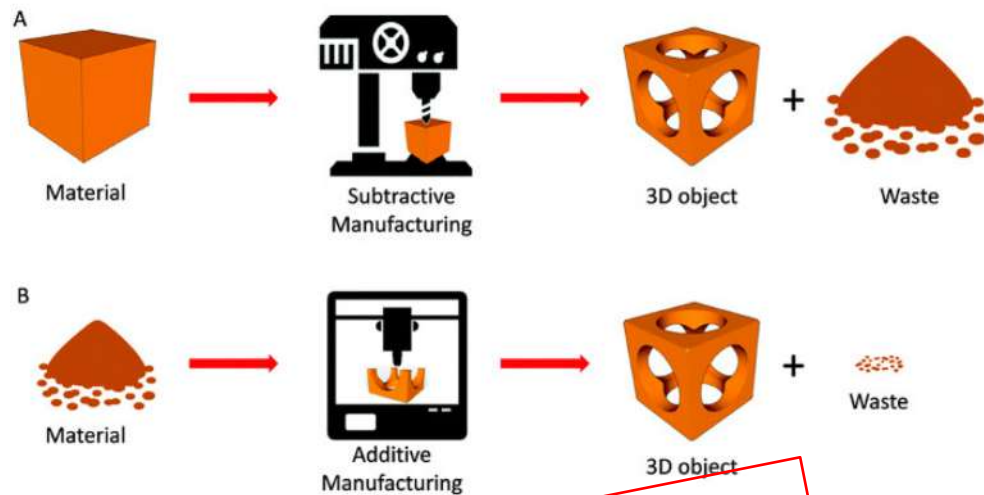
Eco-optimization of space launchers, PhD of Thomas Bellier - ANR&RMIT fund

Graph Neural Networks for aerospace dynamic systems Michele Colombo – Airbus fund

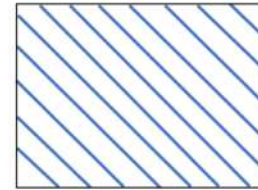
ECODESIGN/ARCHITECTED MATERIALS & MDO

Why DfAM?

<https://dfam.substack.com/p/dfam-education-in-2022>

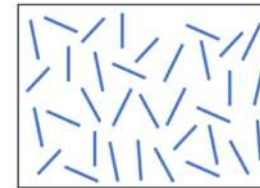


Regular and periodic



Natural
(optimal?)

Random



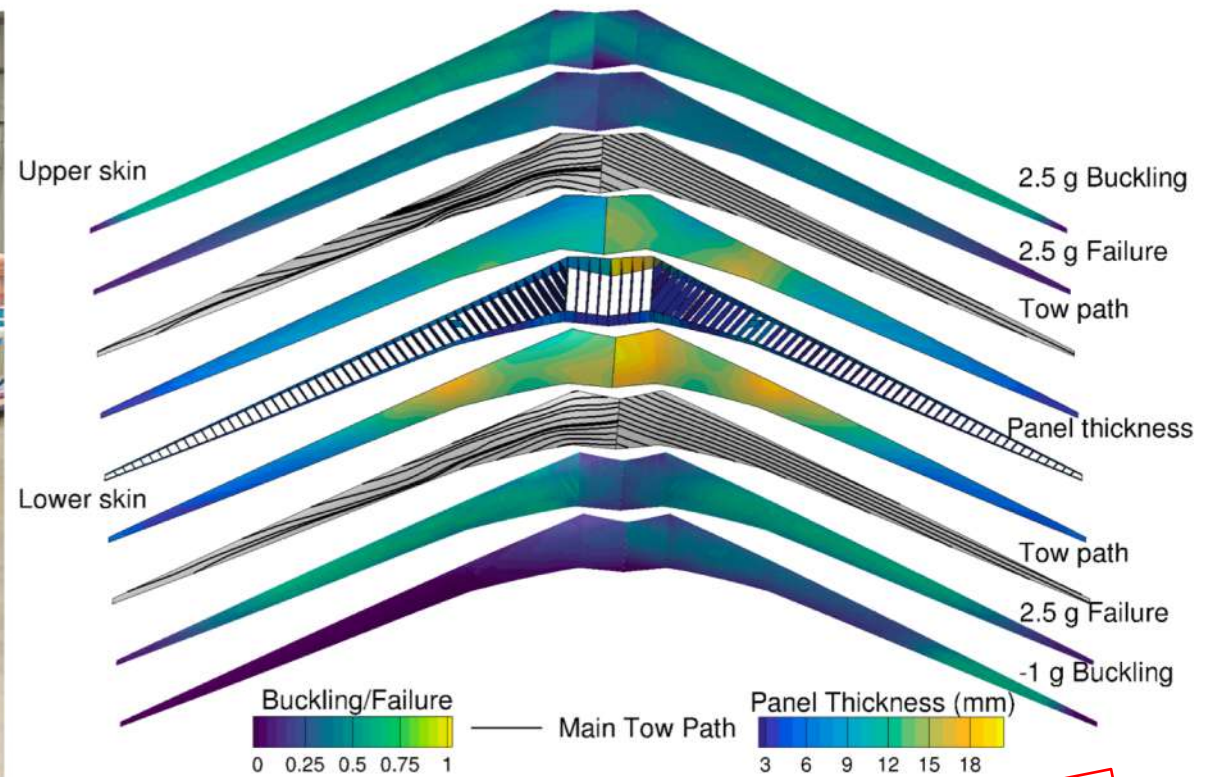
Non-periodic and
specific (optimal)

+Near 100% material utilization
+Recyclability, Buy to fly ratio
+LCA of 3D printing machine
+Monitoring

**+ Automatic Fiber
Placement + eco-
fiber/resin selection**
+Monitoring

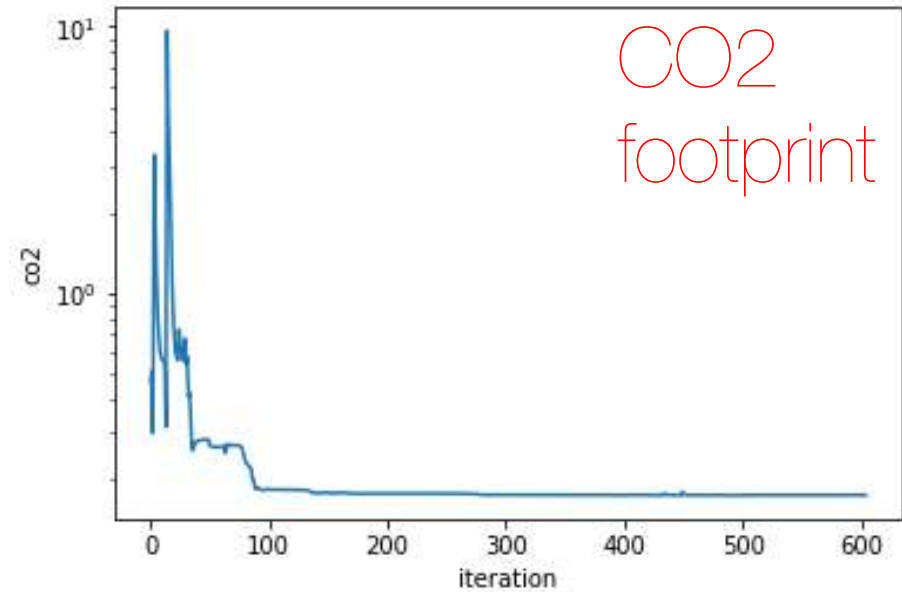
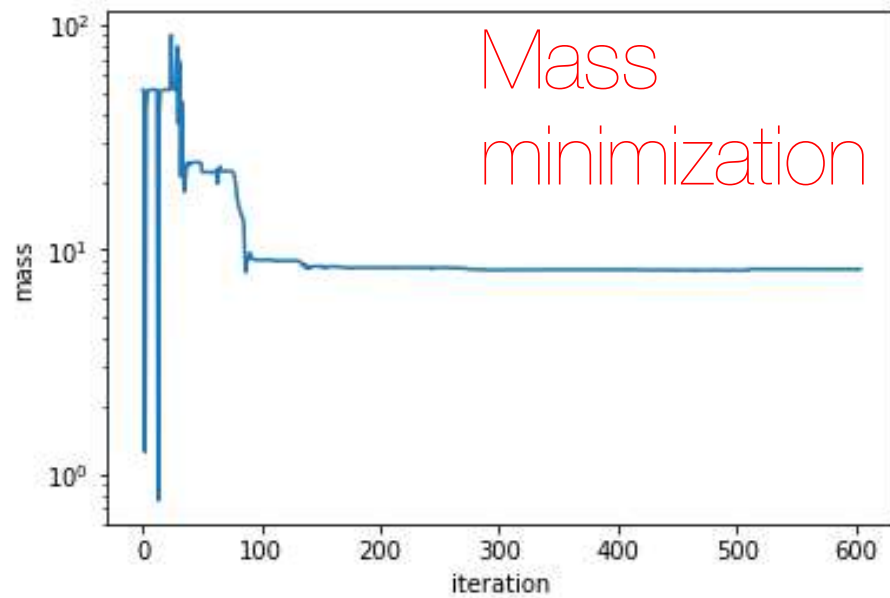
Composites as a new DV

<https://www.compositesworld.com/articles/leveraging-motorsports-composites-for-next-gen-rotorcraft>



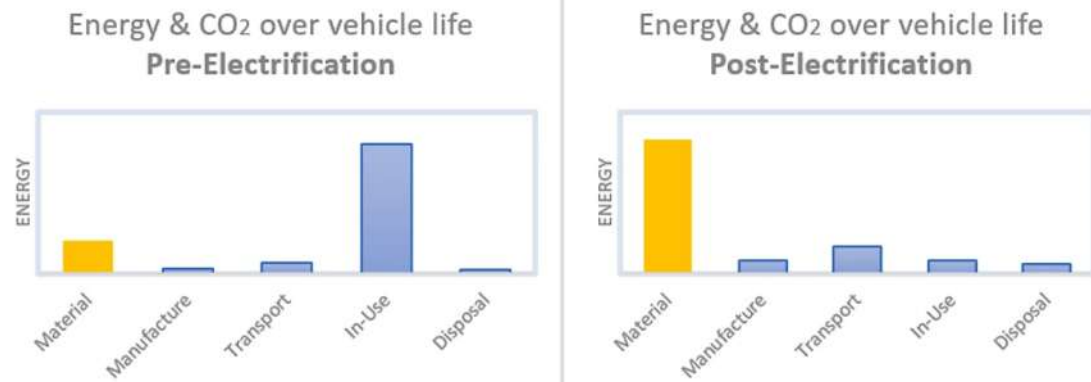
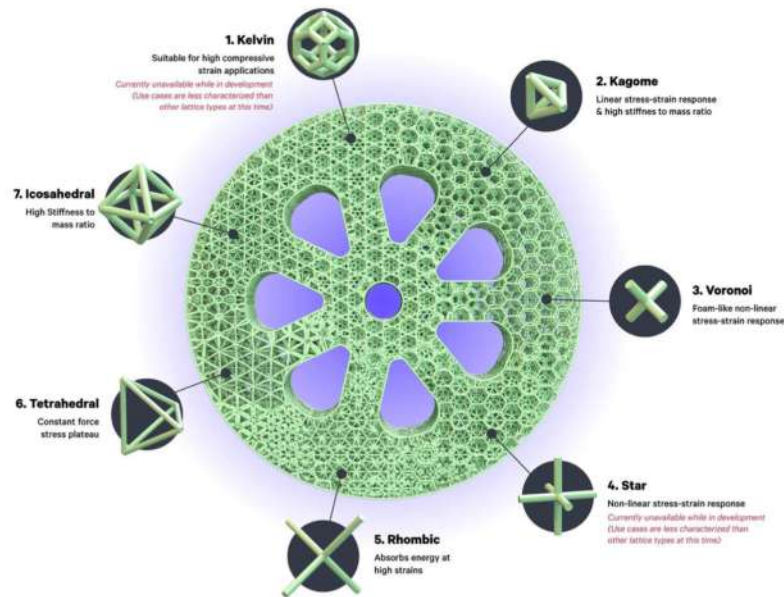
Less fuel burn, lower wing mass

Why EcoDfam



Material/Process as new design variables in MDO

Eco Material selection
Eco Process selection



<https://www.ansys.com/blog/the-impact-of-materials-on-sustainability-part-2>

Unit cell design (anisotropy)
Digital materials

Material/Process as new design variables

Eco Process selection

Additive manufacturing (AM) energy consumption

- Consumption depend on material, technology, machine and parameters

=> very high standard deviation

Technology		Material	Energy consumption – Mean and std dev (kWh/kg)
Metals	SLM	stainless steel	30 ± 6 ^{[24](a)(b)}
		aluminium	130 ± 32 ^{[24](c)(d)}
	DMLS	stainless steel	44 ± 17 ^{[24](e)}
	EBM	Titanium alloy	27 ± 19 ^{[24](f)}
Polymers	FDM	ABS	174 ± 109 ^{[24](g)(h)(i)}
	SLS	PA (nylon)	38 ± 18 ^{[24](g)(j)(k)(l)(m)}
	SLA	epoxy resin	32 ± 10 ^{[24](g)}

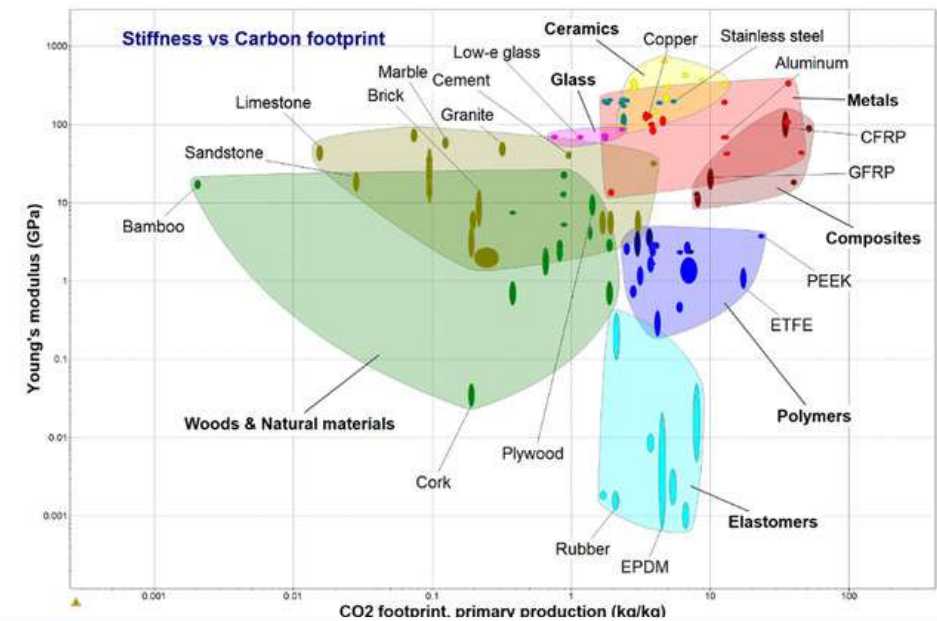
- (a) M. Baumers, C. Tuck, R. Hague, R. Wildman, I. Ashcroft, "Energy inputs to additive manufacturing : does capacity utilization matter ?", *22nd Annual International Solid Freeform Fabrication Symposium - An Additive Manufacturing Conference, SFF*, **2011**, 30-38.
- (b) M. Baumers, C. Tuck, R. Hague, R. Wildman, I. Ashcroft, "A comparative study of metallic additive manufacturing power consumption". *21st Annual International Solid Freeform Fabrication Symposium - An Additive Manufacturing Conference, SFF*, **2010**, 278-288.
- (c) K. Kellens, R. Mertens, D. Paraskevas, W. Dewulf, J.R. Duflou, "Environmental, Impact of Additive Manufacturing Processes: Does AM Contribute to a More Sustainable Way of Part Manufacturing?", *Procedia CIRP*, **61**, **2017**, 582-587.
- (d) J. Faludi, M. Baumers, I. Maskery, et al., "Environmental Impacts of Selective Laser Melting: Do Printer, Powder, Or Power Dominate?", *Journal of Industrial Ecology*, **21(S1)**, **2017**, S144-S156.
- (e) P. Mognol, D. Lepicart, N. Perry, "Rapid prototyping: energy and environment in the spotlight", *Rapid Prototyping Journal*, **12**, **2006**, 26-34.
- (f) M. Baumers, C. Tuck, R. Wildman, I. Ashcroft, R. Hague, "Shape complexity and process energy consumption in electron beam melting: a case of something for nothing in additive manufacturing?", *Journal of Industrial Ecology*, **21(S1)**, **2017**, S157-S167.
- (g) Y. Luo et al., "Environmental Performance Analysis of Solid Freedom Fabrication Processes", *Proceedings of the 1999 IEEE International Symposium on Electronics and the Environment*, 1999, 1-6.
- (h) S.Junk et S.Coté, "A Practical Approach To Comparing Energy Effectiveness Of Rapid Prototyping Technologies", *Proceedings of AEPR'12, 17th European Forum on Rapid Prototyping and Manufacturing*, Paris, France, 12-14 Juin 2012.
- (i) H-S. Yoon, J-Y. Lee, H-S. Kim, M-S. Kim and al., "A comparison of energy consumption in bulk forming, subtractive, and additive processes: Review and case study". *Int J Precis Eng and Manuf-Green Technol*, **1(3)**, **2015**, 261-279.
- (j) K. Kellens, W. Dewulf, J. Duflou, « The CO2PE!-Initiative (Cooperative Effort on Process Emissions in Manufacturing)", *Conference: 14th ERSF and 6th EMSU conference*, 2010.
- (k) Sreenivasan, R., Bourell, D. et al., "Sustainability Study in Selective Laser Sintering - An Energy Perspective", *Proceedings of the 20th International Solid FreeForm Fabrication Symposium*, 2009.
- (l) Baumers, M., Tuck, C., Bourell, D., Sreenivasan, R., and Hague, R., "Sustainability of Additive Manufacturing: Measuring the Energy Consumption of the Laser Sintering Process," *Proc. of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, **225 (12)**, **2011**, 2228-2239.
- (m) C. Telenko, & C. C. Seepersad, "A comparative evaluation of energy consumption of Selective Laser Sintering and Injection Molding of Nylon parts", *Rapid Prototyping Journal*, **18(6)**, **2012**, 1-31.

Material/Process as new design variables

Eco Material selection

ECOHALE design

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



mdolab / OpenAeroStruct

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Code

Issues 33

Pull requests 0

Actions

Projects 8

Wiki

Security

Insights

OpenAeroStruct is a lightweight tool that performs aerostructural optimization using OpenMDAO.

openmdao

optimization

aerodynamics

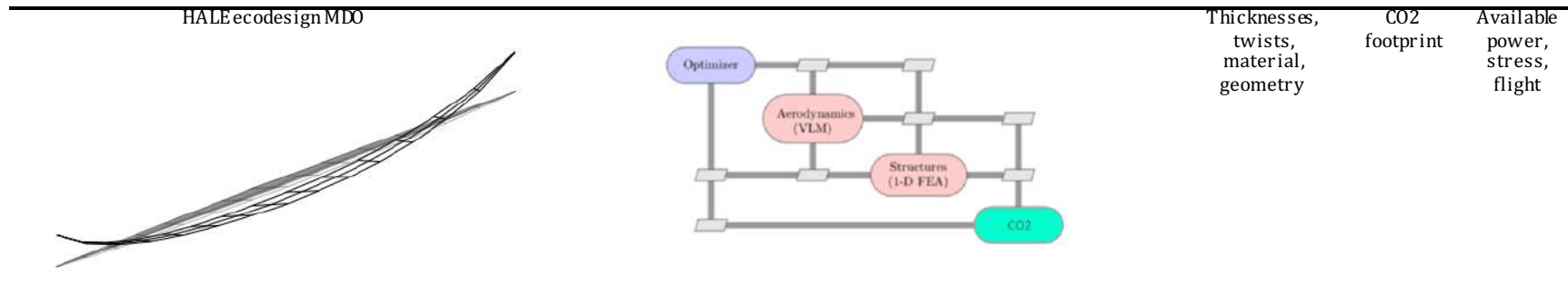
open-source

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 satellite Design problem



Assets: Flexible, repositionable, permanent coverage, cheaper, lower environmental impact?



Airbus-built HALE Zephyr

Discrete variables

Minimize CO2

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

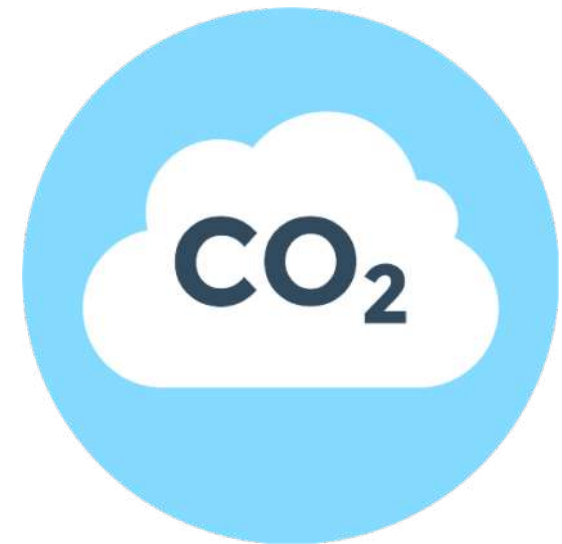
- Commercial aircraft
 - Breguet range equation
 - Fuel consumption
 - 2.5G manoeuvre
 - High Reynolds number
 - Fixed structural material
- HALE drones
 - Power equilibrium
 - Power from batteries and solar panels
 - Shear gust wall
 - Low Reynolds number
 - Material choice optimization



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)

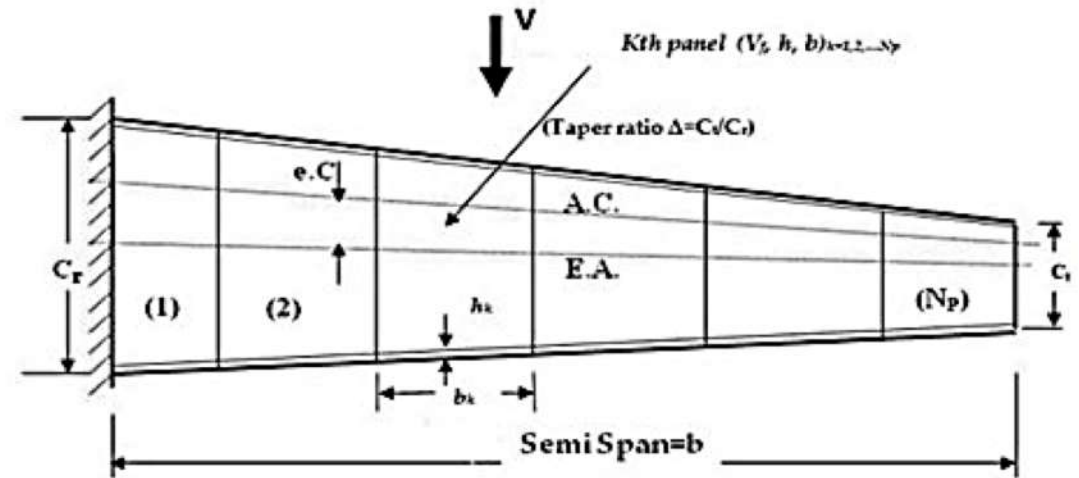
Objective function

- 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 ➤ $CO2_{bat} = P_{needed} \cdot t_{night} \cdot CO2_{/Wh}$
- $CO2_{total} = CO2_{struct} + CO2_{PV} + CO2_{bat}$

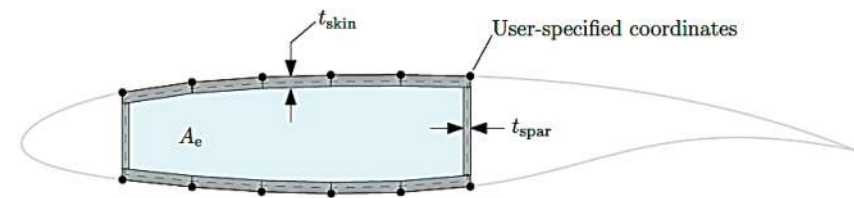


DV

- 8 geometric design variables:
 - Twist + Angle of attack control points
 - Skin thickness control points
 - Spar thickness control points
 - Thickness-to-chord ratio control points
 - Span
 - Root chord
 - Taper ratio
 - Motor spanwise location



Trapezoidal wing planform

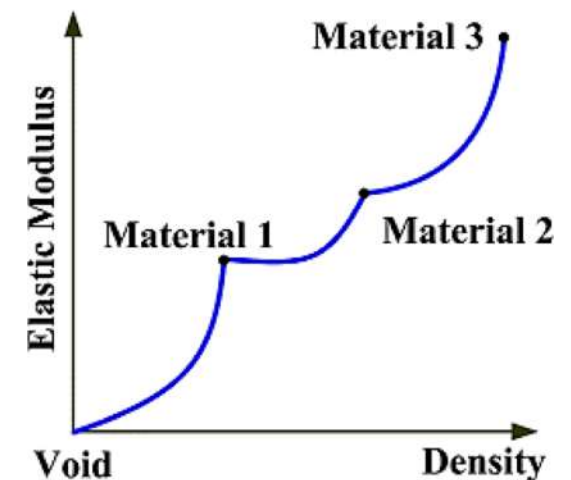


: Wingbox cross-section model [1]

S. S. Chauhan and J. R. Martins, "Low-fidelity aerostructural optimization of aircraft wings with a simplified wingbox model using OpenAeroStruct," in International Conference on Engineering Optimization, pp. 418-431, Springer, 2018.

Discrete Material Choice inspired from SIMP

- 1 material design variable with 2 components:
 - Density of the material used for the spars
 - Density of the material used for the skins
- Material properties as a function of the density:
 - Young's modulus
 - Shear modulus
- Continuous variable by interpolating each material property in the space between real materials from a discrete catalogue



Young's modulus example of penalized interpolation of materials [1]

$$E(\rho) = A \cdot \rho^p + B \quad \text{with} \quad A = \frac{E_{i+1} - E_i}{\rho_{i+1}^p - \rho_i^p} \quad \text{and} \quad B = E_i - A \cdot \rho_i^p$$

Zuo, Wenjie, and Kazuhiro Saitou. "Multi-material topology optimization using ordered SIMP interpolation." Structural and Multidisciplinary Optimization 55.2 (2017): 477-491.

CO2 footprint minimization

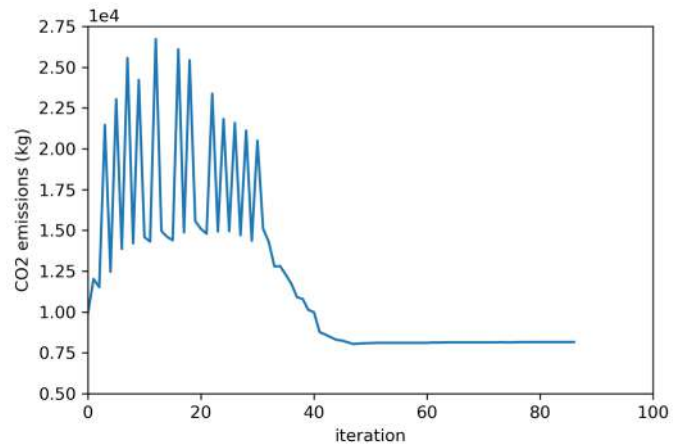
- Optimization algorithm ➤ SLSQP
- Stopping criteria:
 - Convergence accuracy: 10^{-3}
 - Maximum number of iterations: 250

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}	

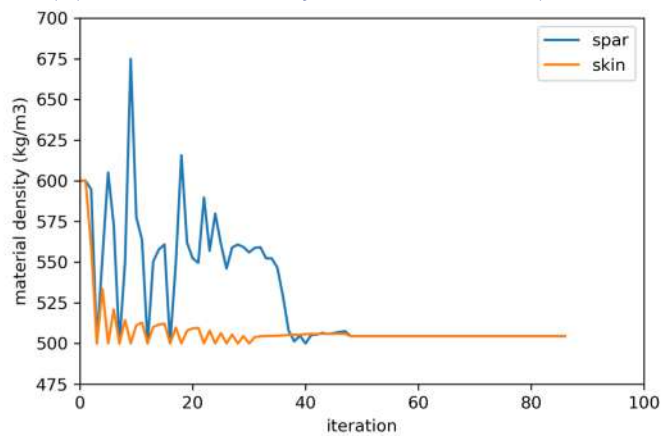
Property	Material 1	Material 2	Material 3	CFRP	GFRP	Aluminum	Steel	Unit
Density	504.5	529	560.5	1565	1860	2800	7750	kg/m ³
CO2 emissions	44.9	42.8	40.3	48.1	6.18	8.66	3.28	kg _{CO2} /kg
Young's modulus	42.5	42.5	42.5	54.9	21.4	72.5	200	GPa
Shear modulus	16.3	16.3	16.3	21	8.14	27	78.5	GPa
Failure strength	587	237	587	670	255	445	562	MPa
Buckling index	0.1539	0.1543	0.1544	0.05049	0.24153	0.1720	0.2302	N ^{$\frac{1}{3}$} ·m ^{$\frac{7}{3}$} /kg _{CO2}
Strength index	25885	10484	25959	8901	22184	18331	22119	N·m·kg _{CO2}

CO2 footprint minimization

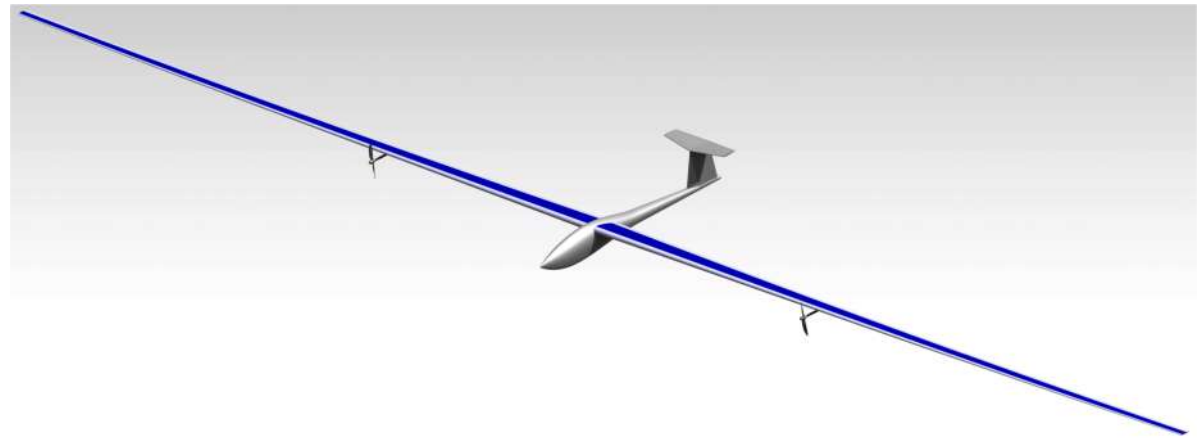
(a) Objective function: total CO2 emitted:



(b) Material density for skins and spars:



Convergence graphs

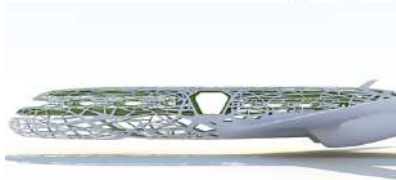
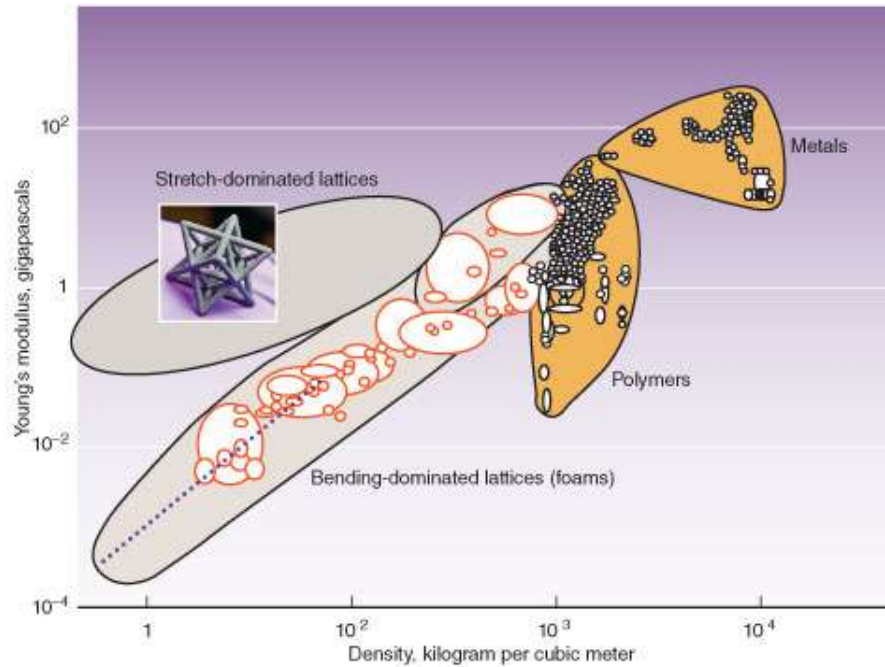


CAD model of the optimal HALE obtained

Material/Process as new design variables

Unit cell design (anisotropy)
Digital materials

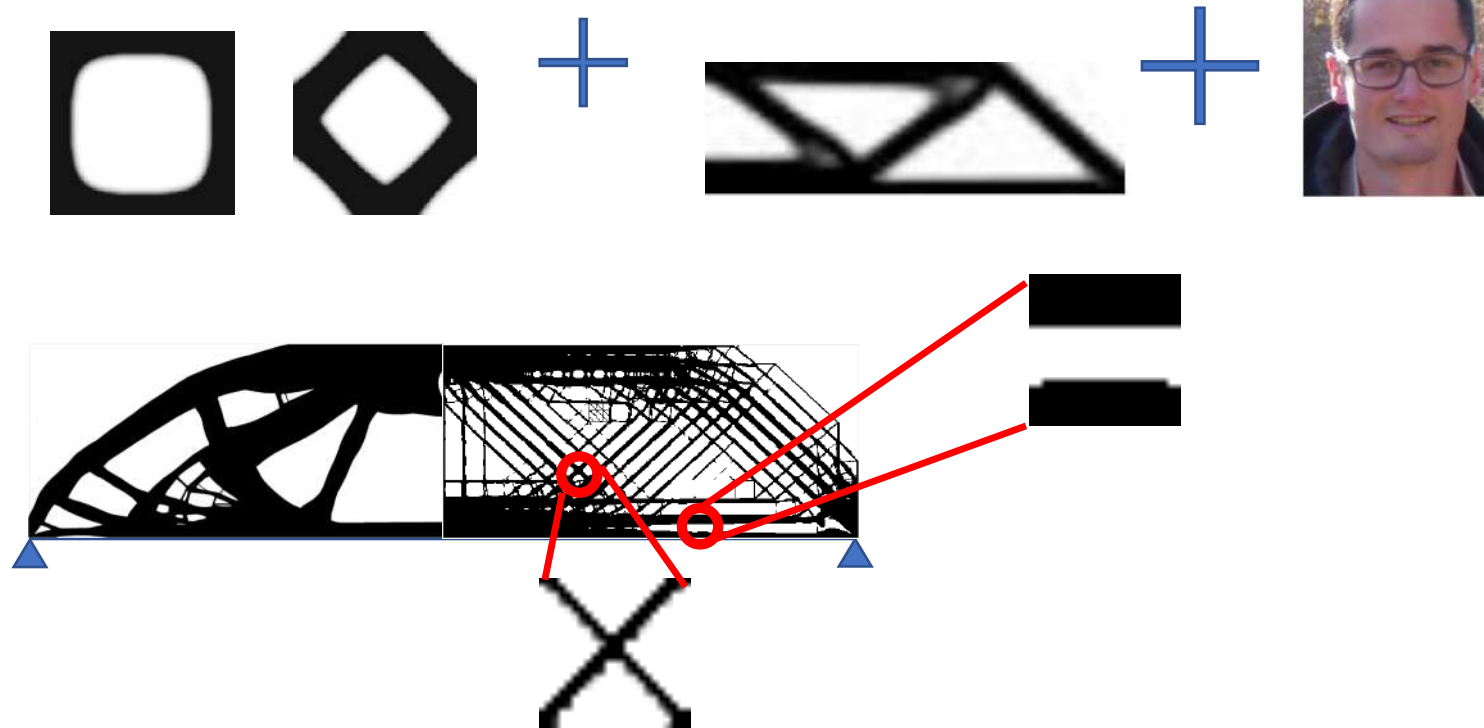
The ERA of DIGITAL MATERIALS



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

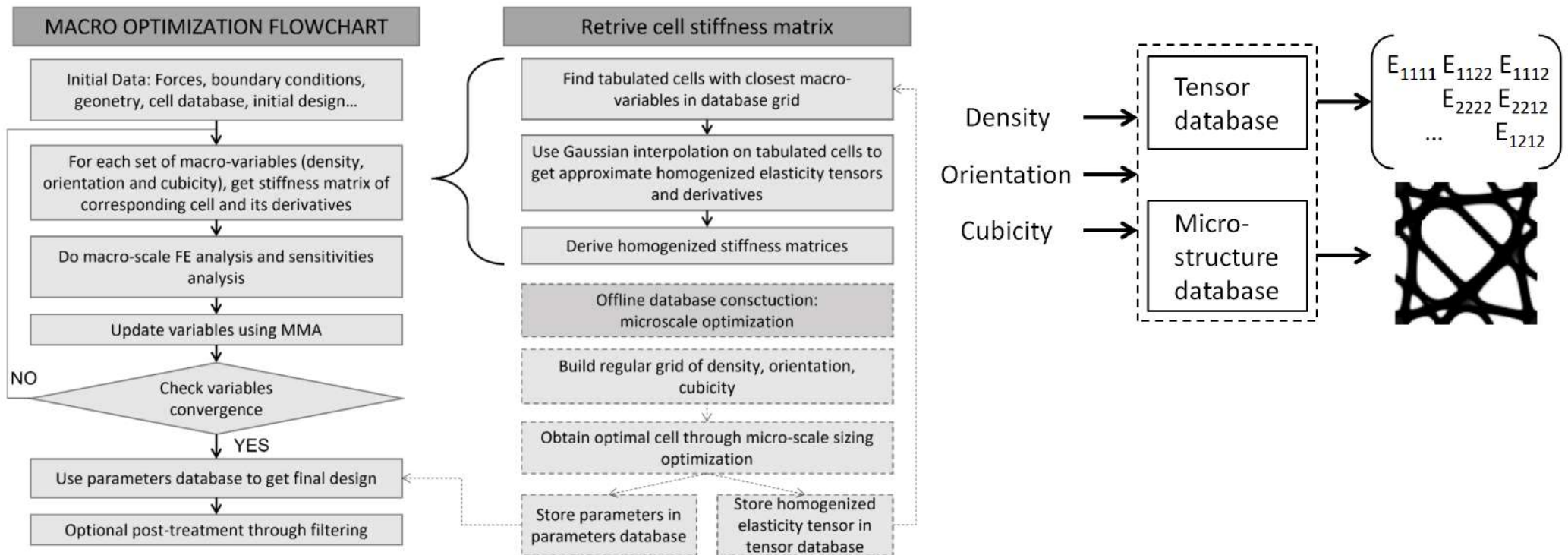
Multi-scale TO

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



Efficient Multiscale Topology Optimization

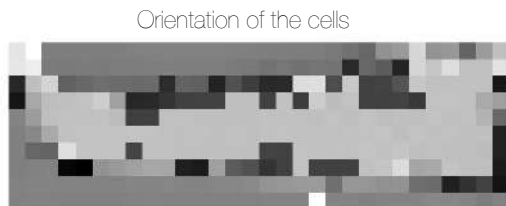
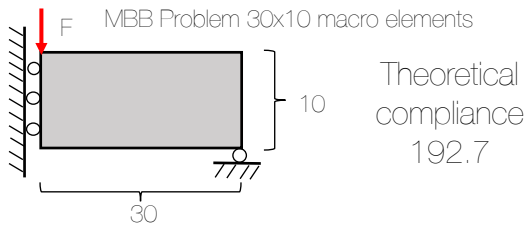
Macroscale Problem

$$\underset{x_{\text{dens}}^i, x_a^i, x_b^i, \dots}{\text{minimize}} \quad c = u^T K u$$

$$\text{subject to} \quad K u = f$$

$$\sum_{i=1}^n \sum_{j=1}^m \rho_{ij} \leq n \times m \times v_f$$

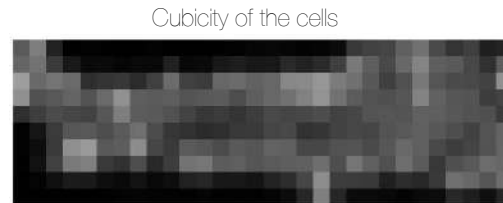
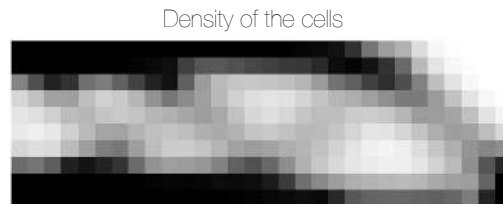
$$\epsilon < \rho_{ij} < 1$$



$$x^i = [x_{\text{dens}}^i, x_{\text{or}}^i, x_{\text{cub}}^i]$$

Optimal

$$x^i = [x_{\text{dens}}^i, x_{\text{or}}^i, x_{\text{cub}}^i]$$



Gaussian regression in the Tensor Database

$$\mathbf{E}_{\text{pred}}(x^i) = \frac{\sum_{l=1}^k G(x^i, x_l) \mathbf{E}_{\text{db}}(x_l)}{\sum_{l=1}^k G(x^i, x_l)}$$

$$G(x^i, x_l) = \exp\left(\frac{-d_{\text{eucl}}(x^i, x_l)^2}{2b^2}\right)$$

$$x^{i'} = [x_{\text{dens}}^i + \Delta, x_{\text{or}}^i, x_{\text{cub}}^i] \quad \Delta = 0.01$$

$$\frac{\partial \mathbf{E}_{\text{pred}}}{\partial x_{\text{dens}}}(x^i) \approx \frac{\mathbf{E}_{\text{pred}}(x^{i'}) - \mathbf{E}_{\text{pred}}(x^i)}{\Delta}$$

EMTO MBB solution

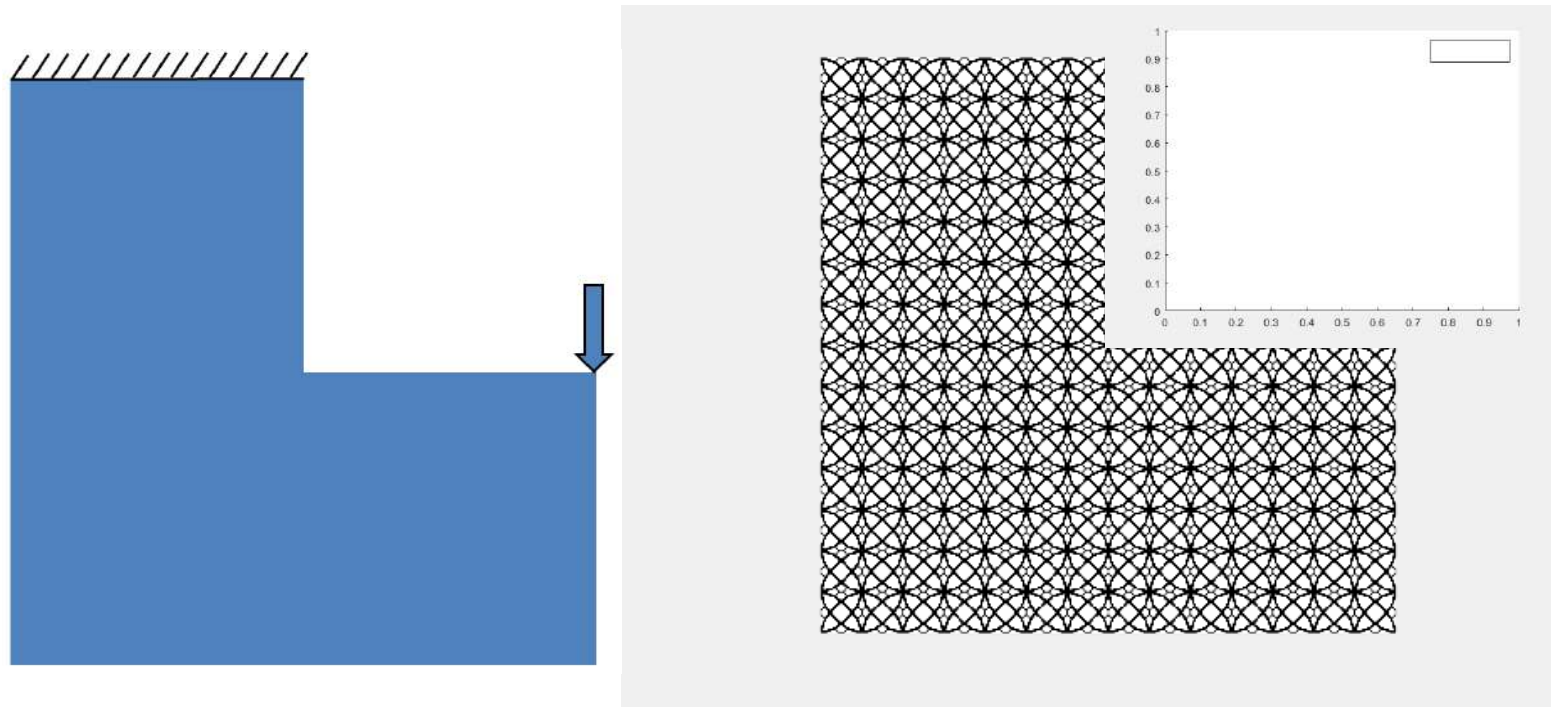


Structure Database and post-treatment

top88 MBB solution



EMTO on L-shape (cellular /digital materials)



<https://github.com/mid2SUPAERO/EMTO>

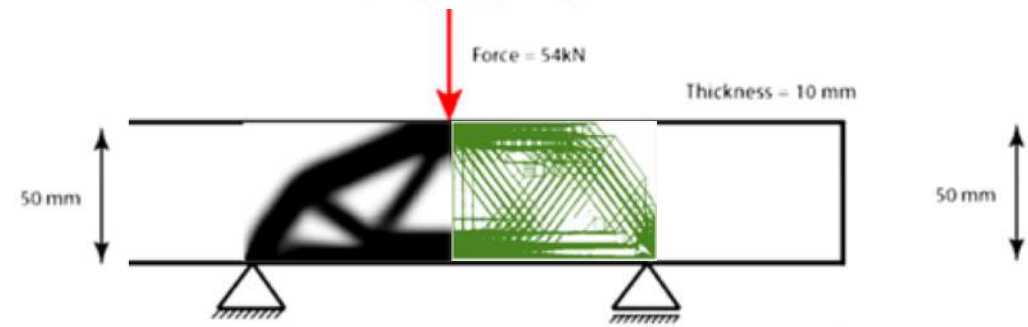
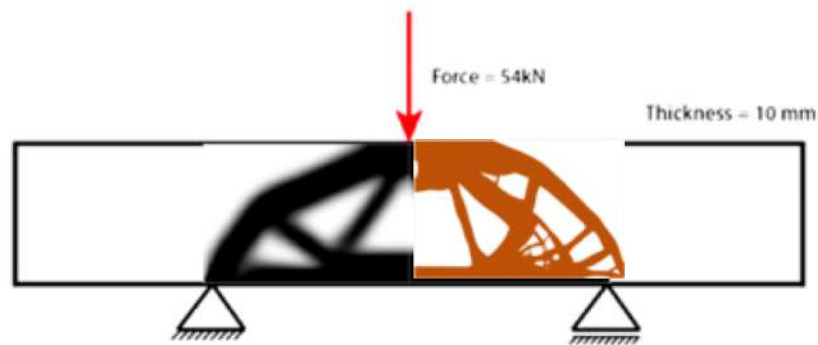
How to **ECO**design tomorrow's structures?

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

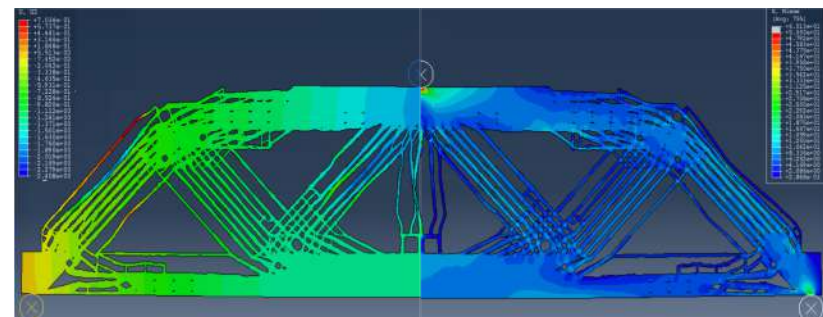
Print it , Test it



EXP + ABAQUS
REANALYSE

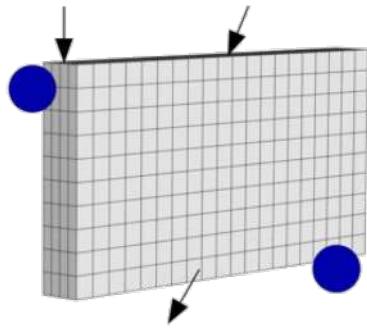


PLA or Selective Laser Melting (SLM)

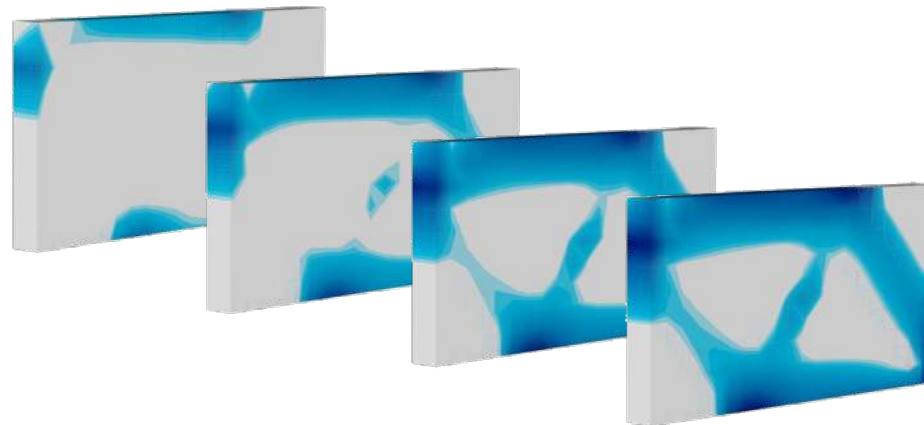


**A simple way to do Ecodesign
with Topology Optimization ?**

Start with Topology Optimization



Inputs: Material, BCs and Loading

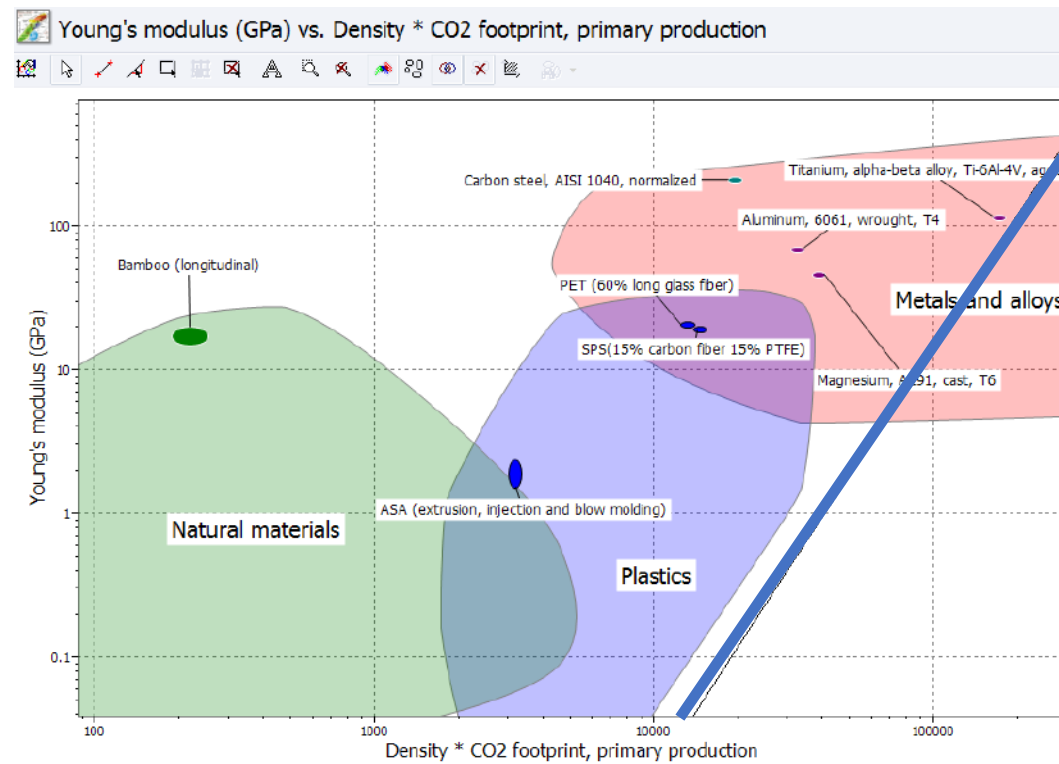


Outputs: design of a „stiff“ bicycle frame



CO2 footprint minimization (Ashby's method)

Inputs: Type of Structures, default materials



Outputs: Optimal material (bamboo) with optimal Design



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 !!!**

$$\arg \min_{mat, \mathcal{D}, t} CO_2^{tot}(mat, \mathcal{D}, t)$$

$$s.t. \quad \delta \leq \delta_{max}$$

$$mat = \{E, \rho, CO_{2mat}^i\} \in \Phi$$

$$0 < v_f(\mathcal{D}) \leq 1$$

BONUS

What's new in SMT ? [the Surrogate Modeling Toolbox]

OpenSource code:
github.com/SMTorg/smt
Documentation:
smt.readthedocs.io



SMT structure – Surrogate

1.1.0 Latest

Compare

reIf 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](https://doi.org/10.1080/00401706.1978.10489693)

Useful for low dimensional problem

- 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

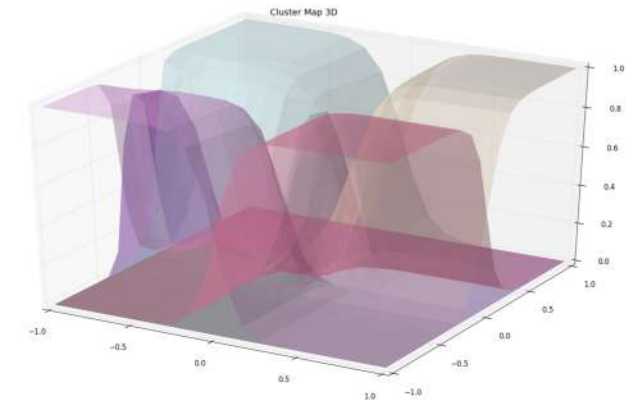
useful for kriging in high dimension

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.

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

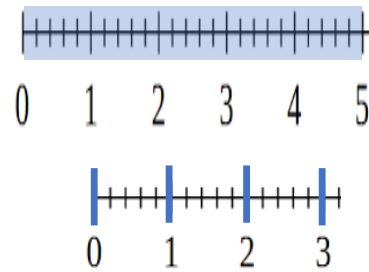
Focus on mixed integer

Variables types :

Continuous (x) Ex: wing length

Integer (z) Ex: winglet number

Categorical (u) Ex: Plane shape



Categorical variables: n variables,
 $n=2$

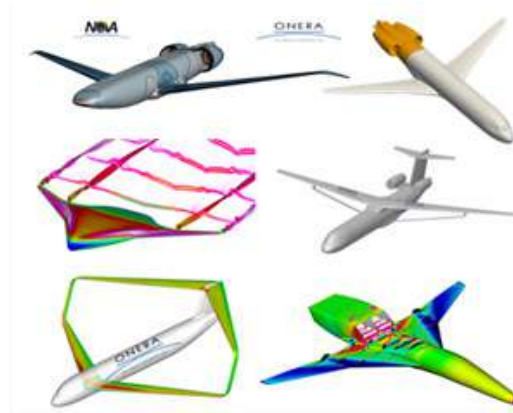
$u1 = \text{shape}$

$u2 = \text{color}$

Levels: L_i levels for i in $1, \dots, n$,
 $L_1=3, L_2=2$.

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

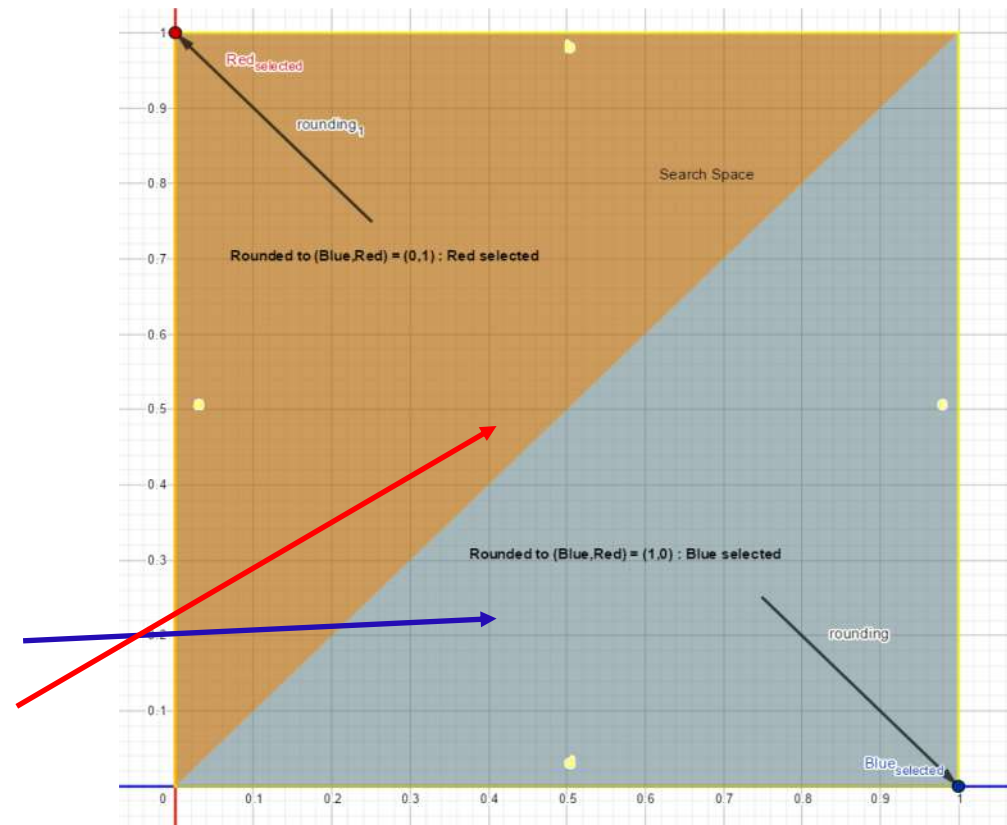
E. C. Garrido-Merchán, and D. Hernández-Lobato. "Dealing with categorical and integer-valued variables in Bayesian Optimization with Gaussian processes". Neurocomputing, vol. 380 (2020), pages 20-35

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



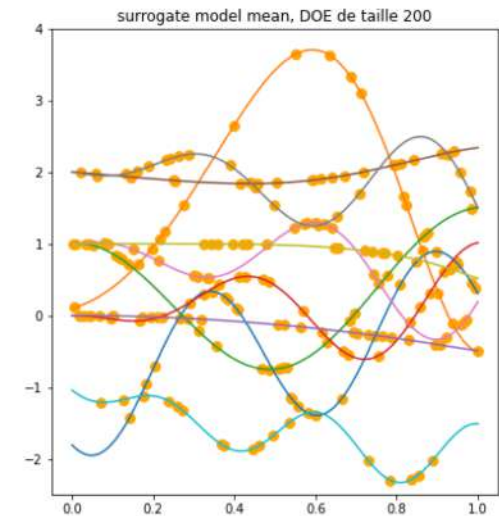
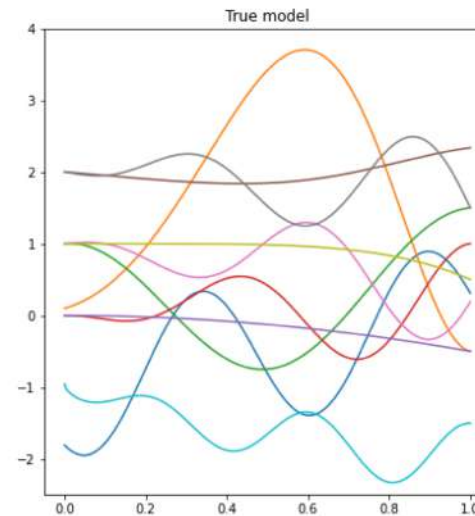
Focus on mixed integer

Continuous relaxation

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

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

Toy function surrogate



Practice online:

<https://github.com/SMTorg/smt/blob/master/tutorial/README.md>

These tutorials introduce to use the opensource Surrogate Modeling Toolbox where different surrogate models are available

SMT Tutorial (linear, quadratic, gaussian process, ...)

 [Open in Colab](#)

Noisy Gaussian process

 [Open in Colab](#)

Multi-Fidelity Gaussian Process

 [Open in Colab](#)

Bayesian Optimization - Efficient Global Optimization to solve unconstrained problems

 [Open in Colab](#)

Mixed-Integer Gaussian Process and Bayesian Optimization to solve unconstrained problems with mixed variables (continuous, discrete, categorical)

 [Open in Colab](#)

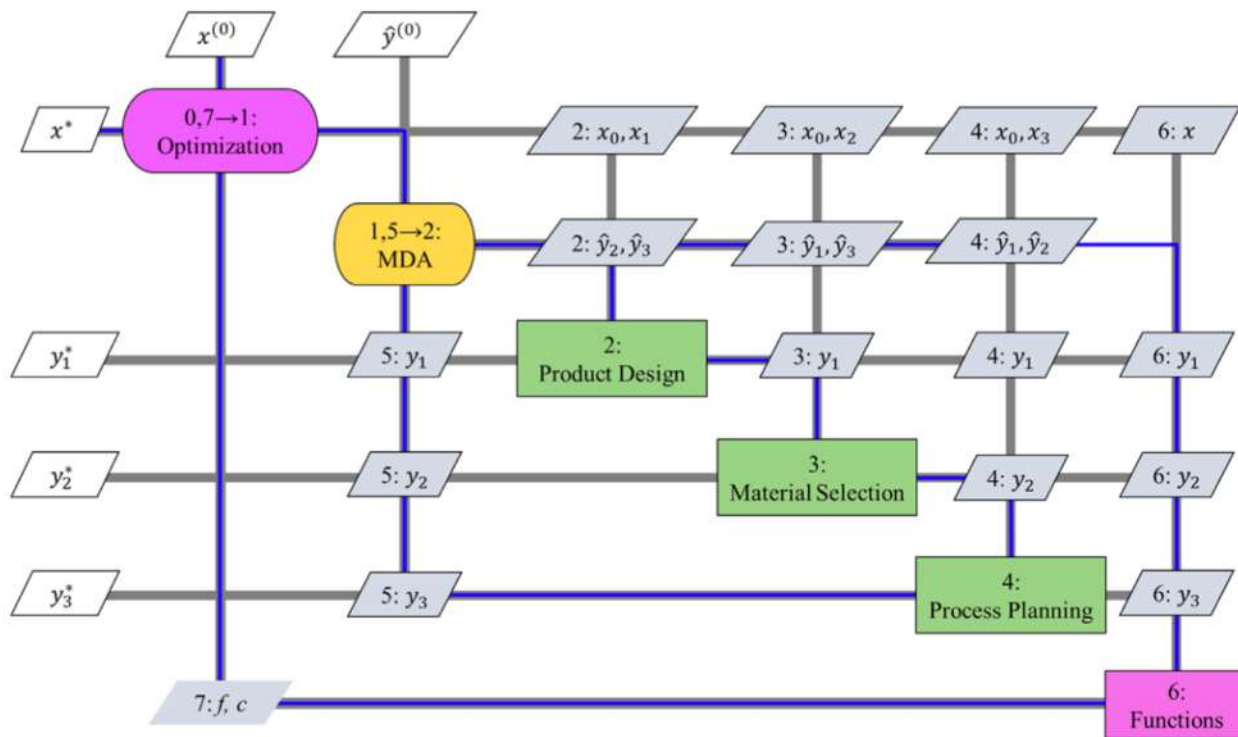
AIAA AVIATION 2022 Forum

- "A general square exponential kernel to handle mixed-categorical variables for Gaussian process" <https://arc.aiaa.org/doi/10.2514/6.2022-3870>.
- "A mixed-categorical data-driven approach for prediction and optimization of hybrid discontinuous composites performance" <https://arc.aiaa.org/doi/10.2514/6.2022-4037>.

Time

To conclude !!

LCA & Eco Selection as a MDO discipline



LCA & eco selection

- Material
- Process
- from cradle to grave
- ...

Water withdrawal



Generation of waste



Use recycled:
Fibers
Resin
Metals
Reuse & Repair

Carbon Footprint

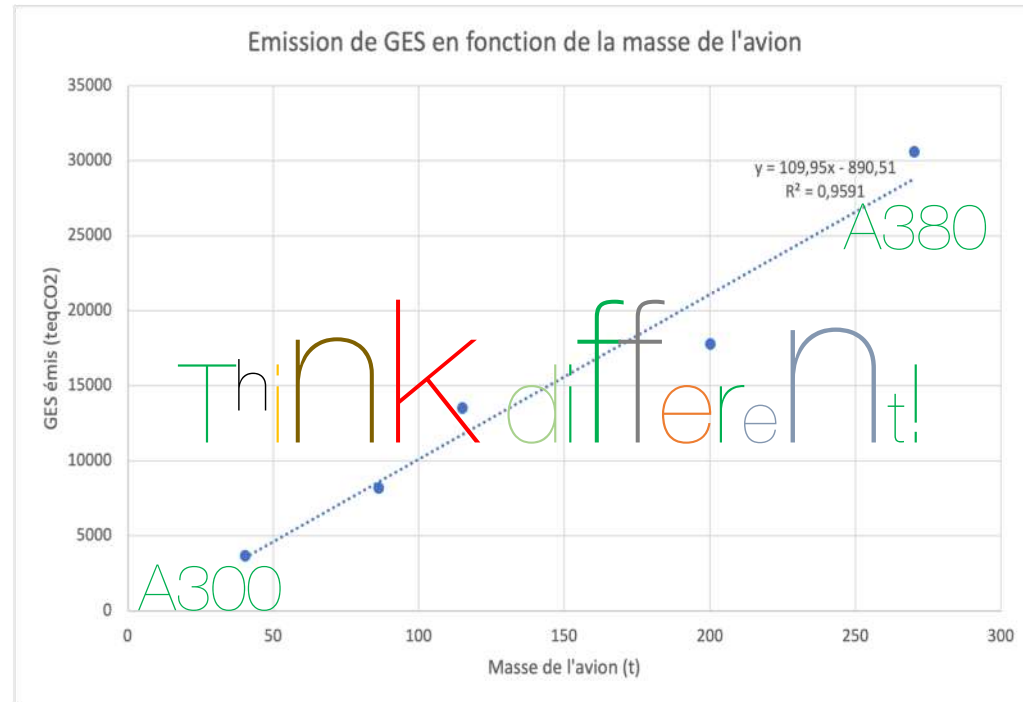


Energy requirement



Rank1 on actual aircraft

At the first order
 $\min \{\text{mass}\}$ is
proportional to
 $\min \{\text{CO}_2\}$



Stiffer, Lighter, Greener =

**add TOPOLOGY OPTIMIZATION + ARCHITECTED MATERIALS +
DIGITAL FABRICATION + ECODESIGN in the MDO of flexible wing**



**Thanks to all my Students
and Colleagues**