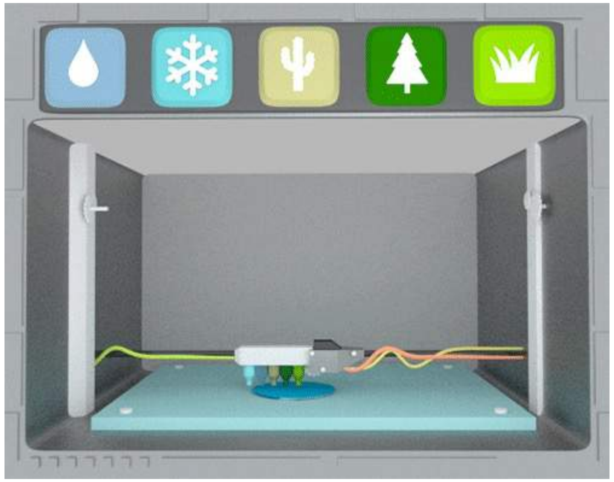


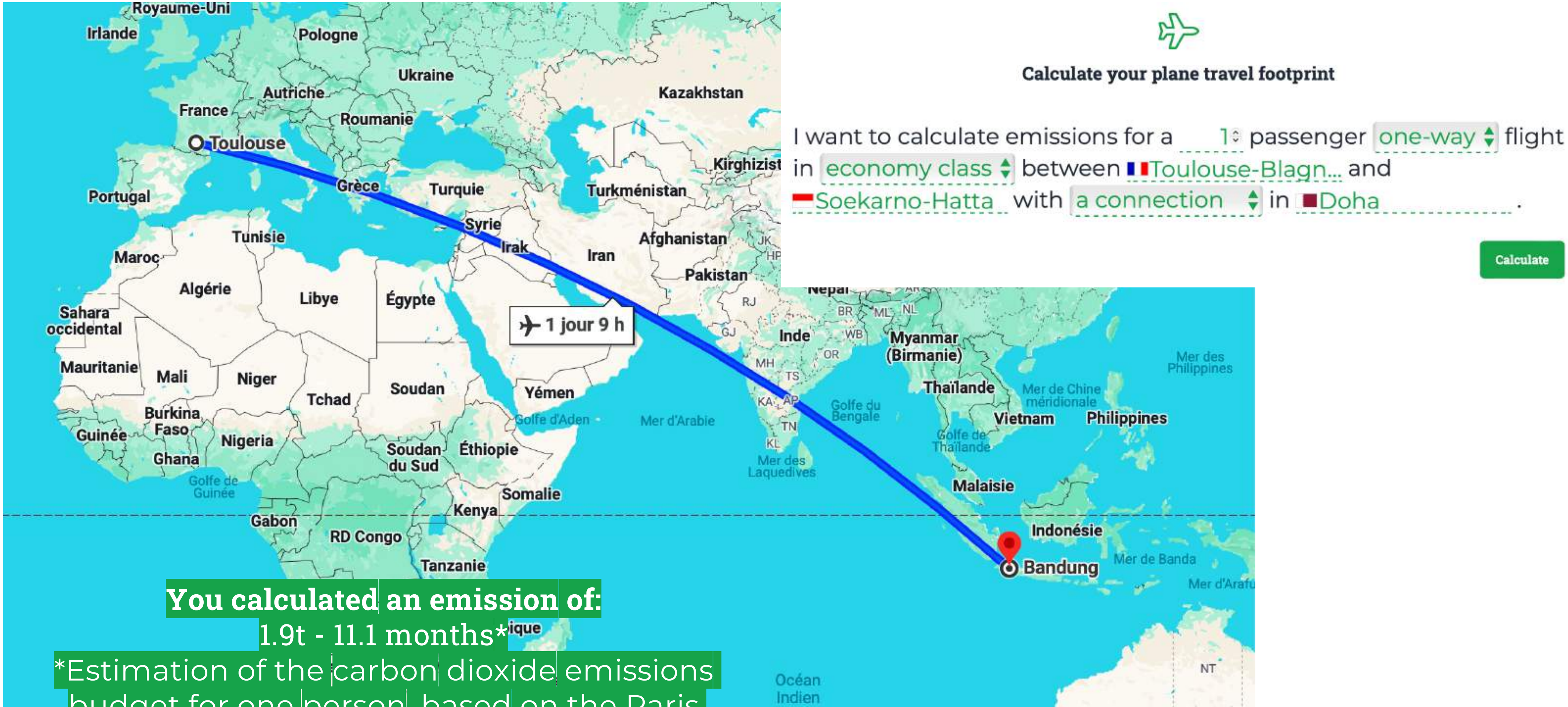
Source: 3D Printing World Environment Day GIF By General Electric

Latest advancements in engineering optimization technology

and its applications in supporting eco-friendly initiatives.

Prof. Joseph Morlier

ITB Seminar



You calculated an emission of:

1.9t - 11.1 months*

*Estimation of the carbon dioxide emissions budget for one person, based on the Paris Agreement objective of maintaining global temperature warming "well below" 2°C.

https://curb6.com/calculators/plane

SUPAERO’s Key Figures at a Glance

268
PhD students

40%
Foreign Students

140
Professors & Researchers

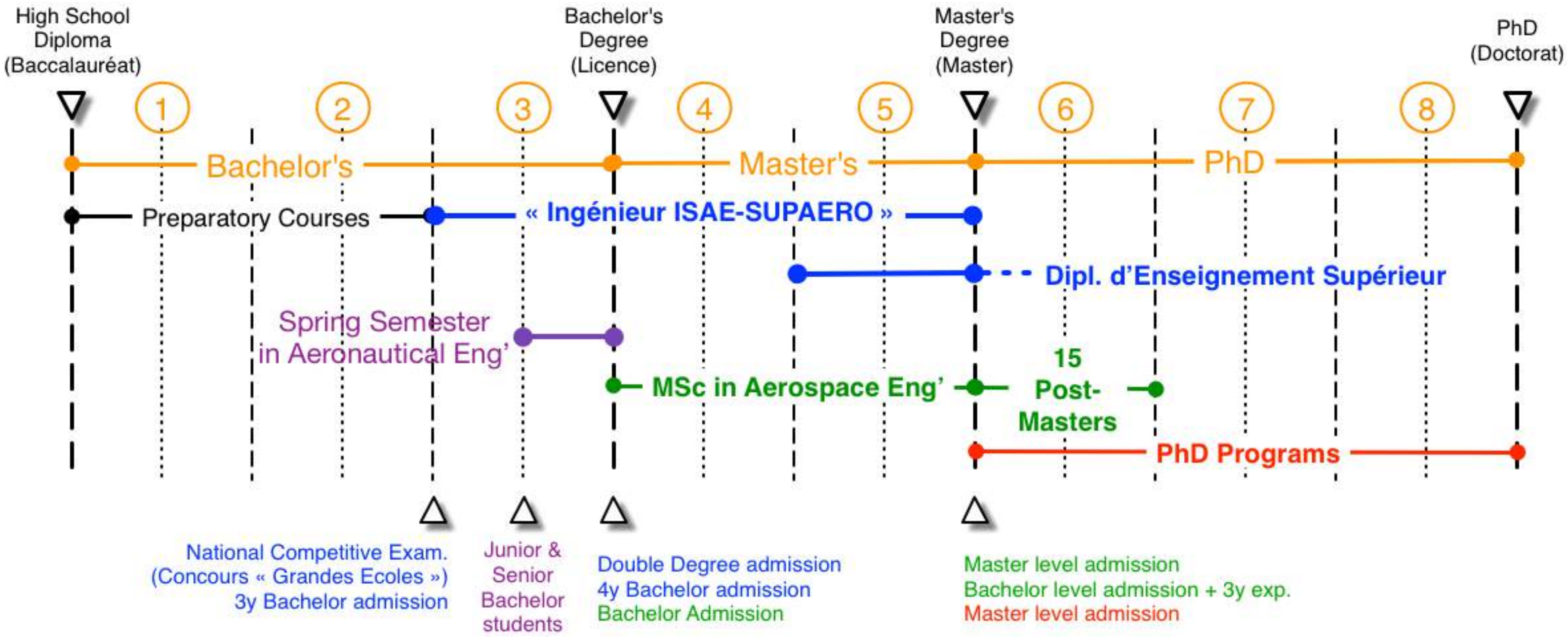
65 M€
Budget

25000
Alumnis

1 900
Students

> 100
Academic Agreements

SUPAERO’s program



Inside the Aerospace city !

Spring Semester in Aeronautical Engineering

Since 1909, some Pioneer Engineers

A few of our Alumni

Sky is Not the Limit

SSAE
SPRIN
AERO
ENGIN

Toulous
January
to May
Undergr
Application de

A worldwide reference in Aerosp
http://www.isae-supaero.fr

2022 ESA selection

Sophie Adenot, France
SUPAERO 2004

2022 ESA astronaut reserve selection

Anthea Comellini, Italy
SUPAERO 17 PhD 2021

Arnaud Prost, France
SUPAERO 2017

1992 ESA selection

Jean-François Clervoy, France
675 hours in space
SUPAERO 1983

2009 ESA selection

Thomas Pesquet, France
SUPAERO 2001

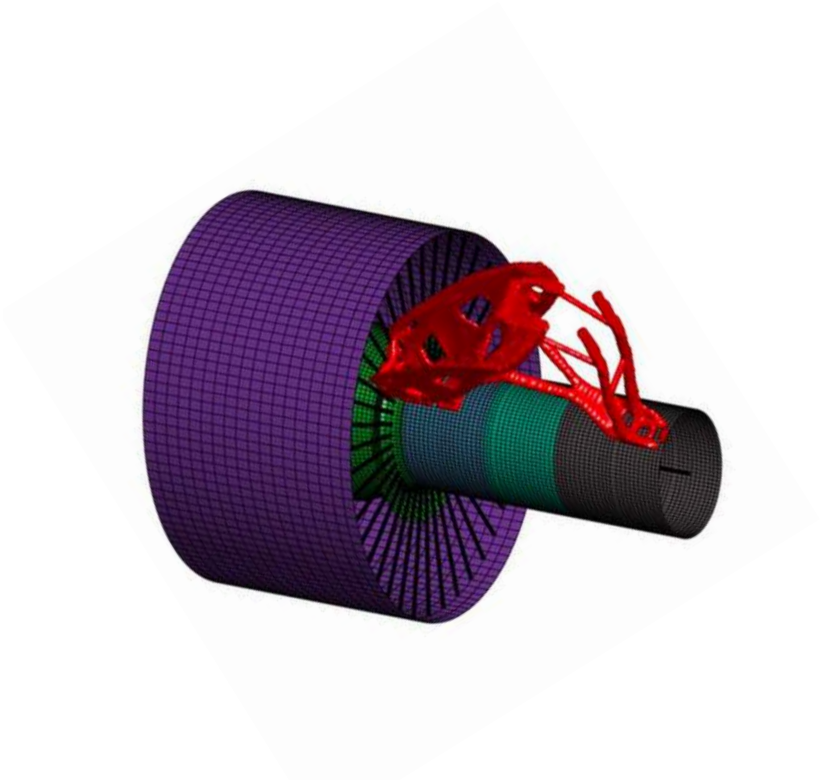
Samantha Cristoforetti, Italy
Erasmus SUPAERO 2007

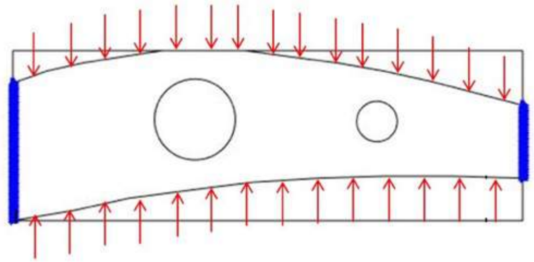
Luca Parmitano, Italy
PMP in experimental flight test engineering
SUPAERO 2009

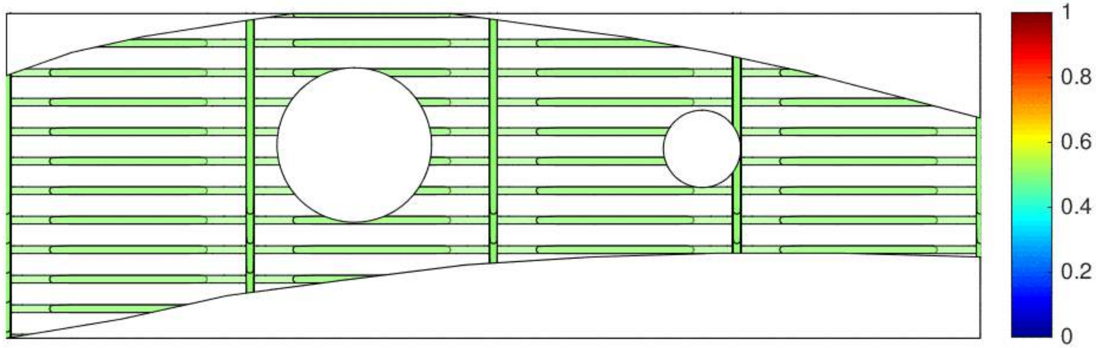
8

About Me?

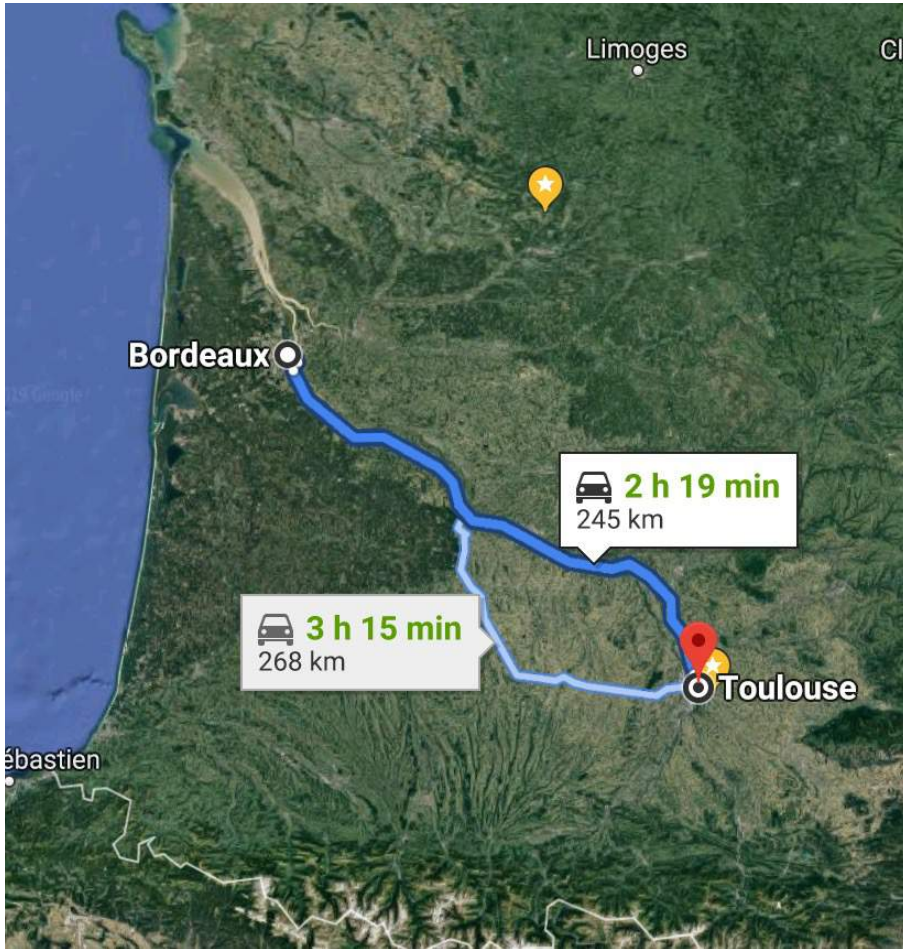
- Prof in Structural and Multidisciplinary Optimization







PhD in Bordeaux then… Toulouse



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:

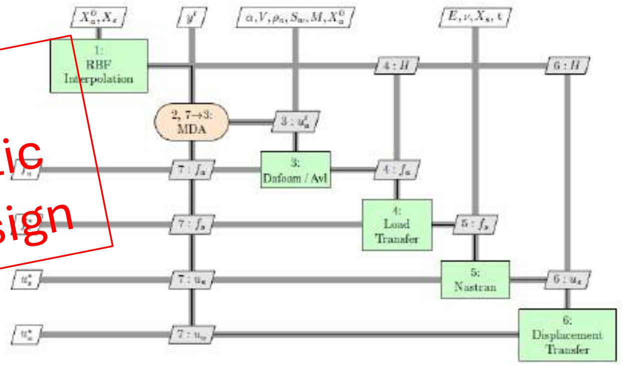
- In University of Michigan @MDOlab (summer 2017)
- in TU Delft/polytechnique Montréal/MDOlab (Summer 2022) with **ANR Grant 2021** (French Science Foundation)

About Me?

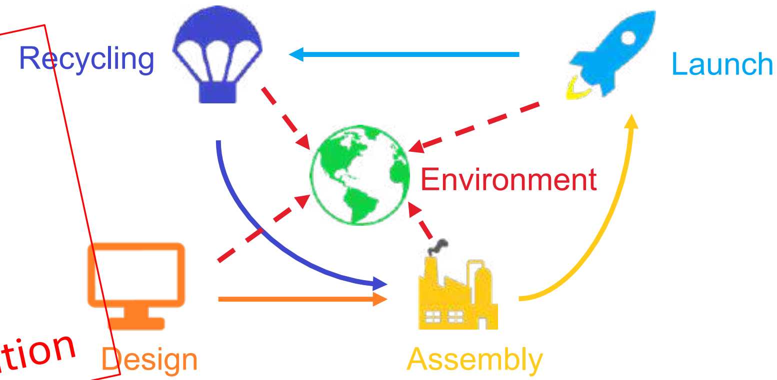
https://ica.cnrs.fr/en/author/jmorlier/

- 6 PhDs, 3 MsCs

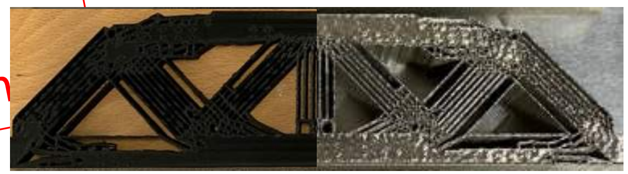
MDO for Aeroelastic Wing design



MDO for Aerospace systems Including LCA := EcoOptimization

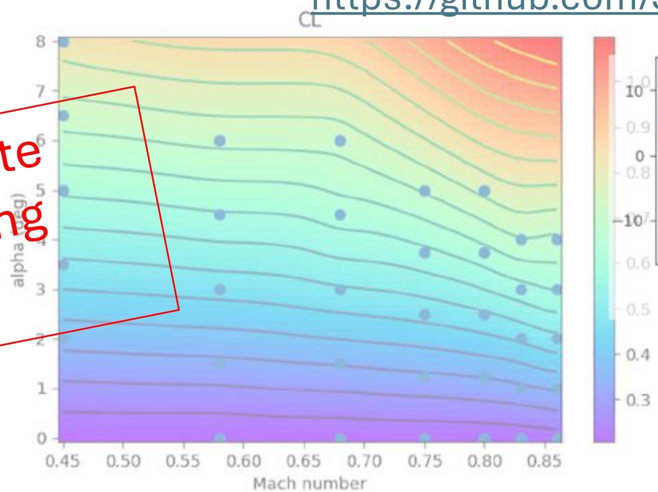


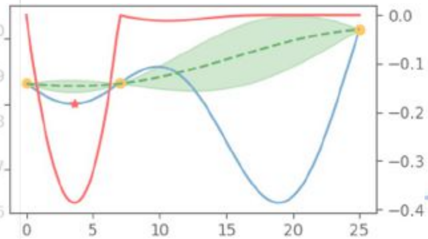
Digital fabrication



https://github.com/SMTorg/SMT

Surrogate modeling AI4E





AIRBUS

ONERA THE FRENCH AEROSPACE LAB

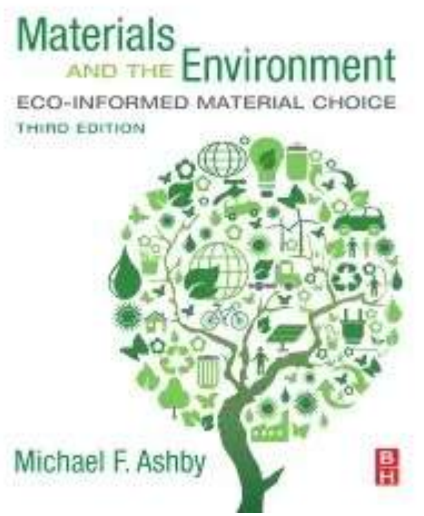
RMIT UNIVERSITY

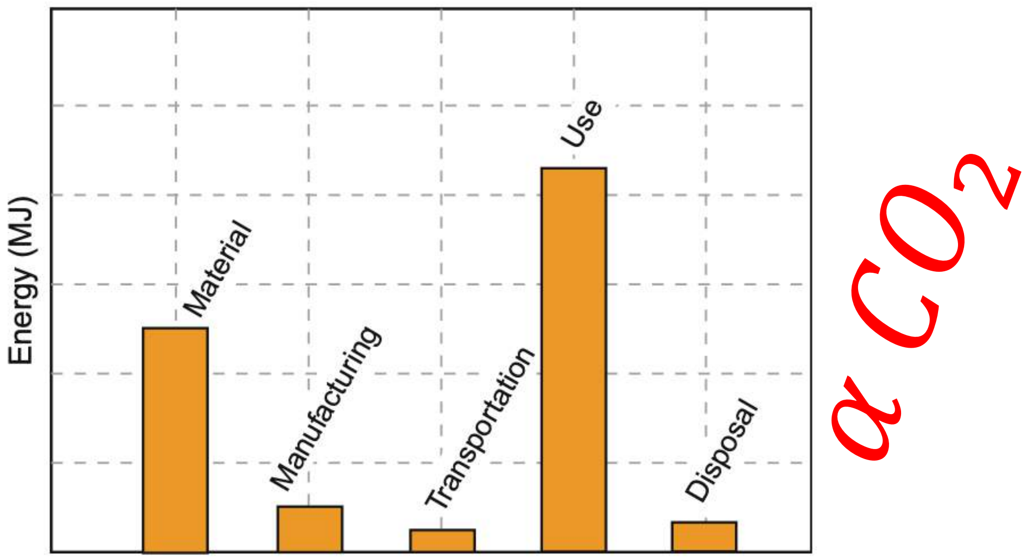
POLYTECHNIQUE MONTRÉAL UNIVERSITÉ D'INGÉNIERIE

TU Delft

UNIVERSITY OF MICHIGAN

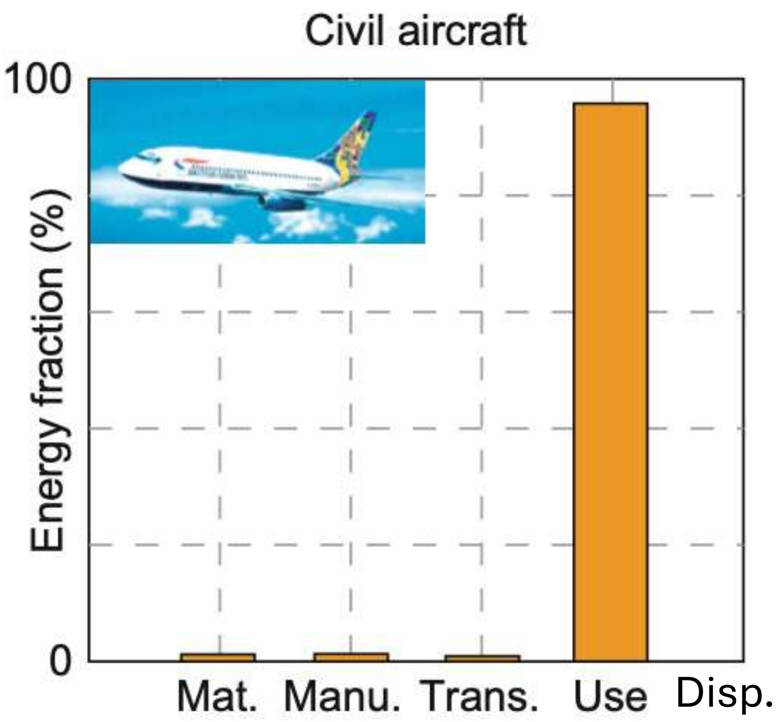
Footprint





Breakdown of energy into that associated with each life phase

Green aviation



Embodied energy

$$E_e = \frac{\sum \text{Estimated energy required for primary production}}{\text{Mass of primary material production}}$$

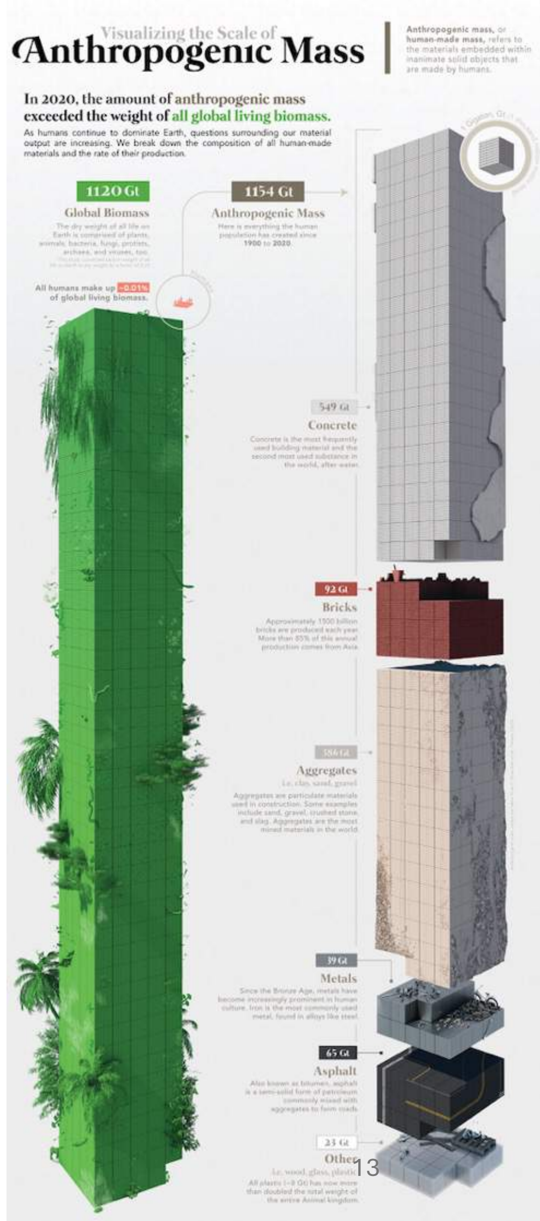
CO2 emission

$$E_c = \frac{\sum \text{Mass of CO2 arising from production}}{\text{Mass of material produced}}$$

An important fact

Massive Demand in Energy and Materials

Over the past century Anthropogenic mass has increased rapidly, doubling approximately every 20 years. The collective mass of these materials has gone from 3% of the world's biomass in 1900 to being on par with it today

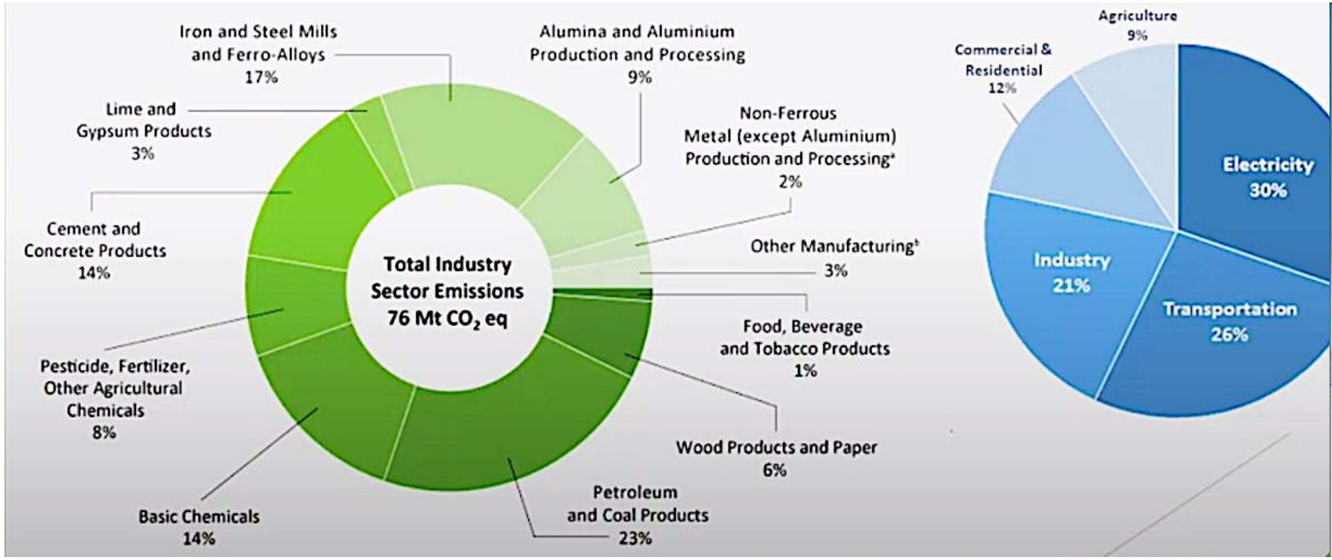


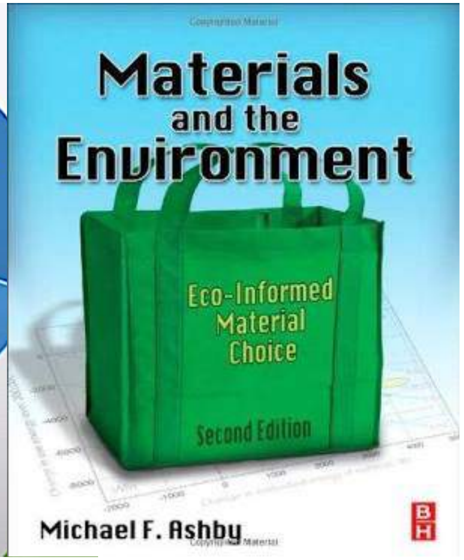
Materials and Energy ressources are linked and limited…

#Structural materials used in a massive way → huge environmental impact

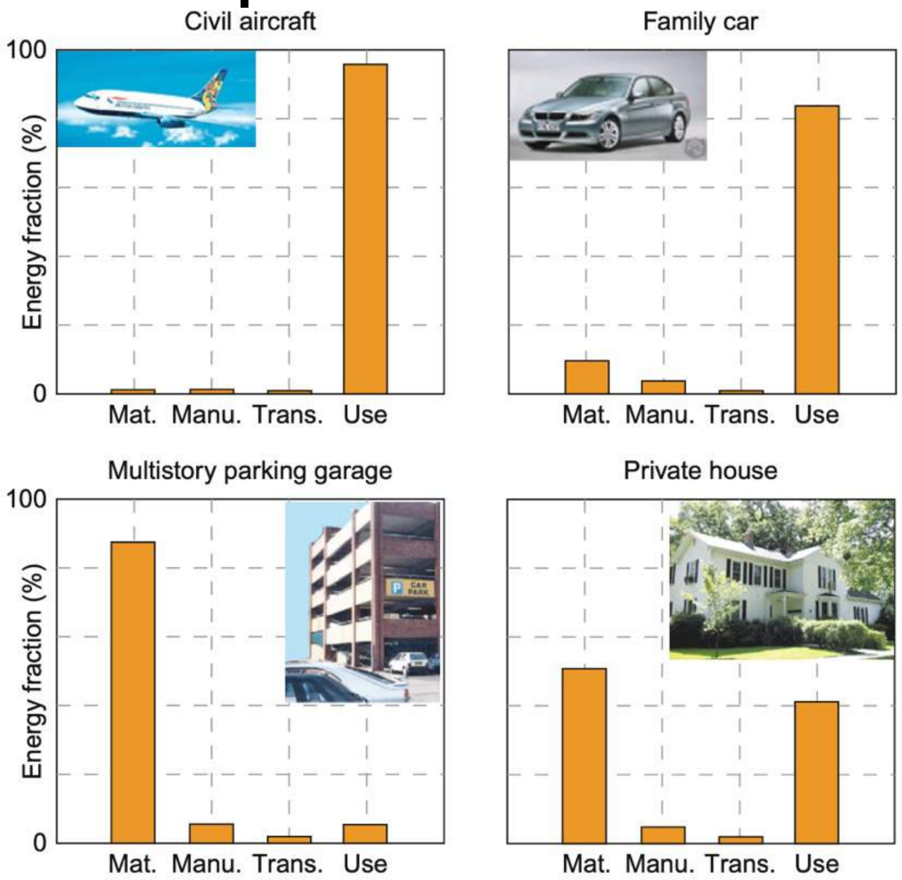
#The essential technologies for the transition, in particular green energy, will translate into considerable demand for metals that have become strategic.

#In anticipation of 2050, the total tonnage of concrete, steel, aluminum etc… necessary for the development of these energies will be 2 to 8 times the world production of 2010. !!!

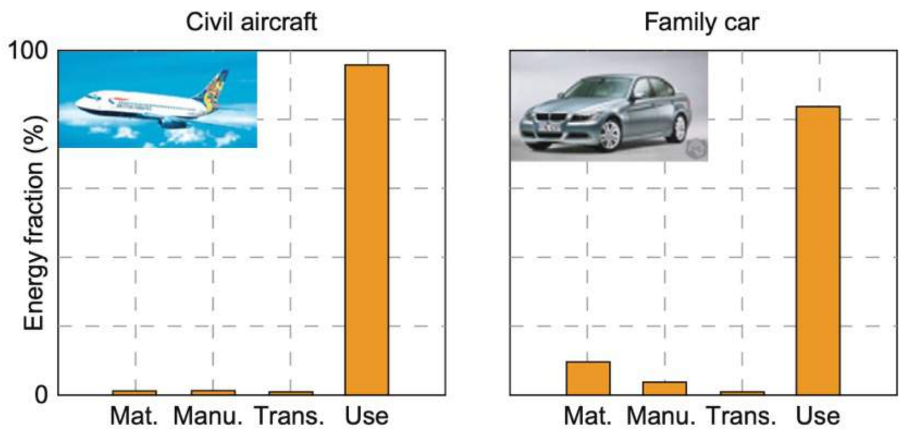


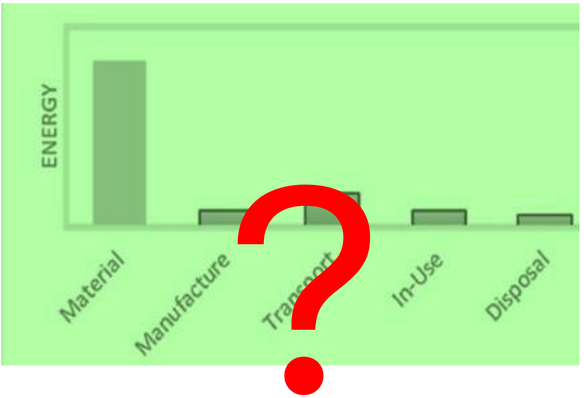


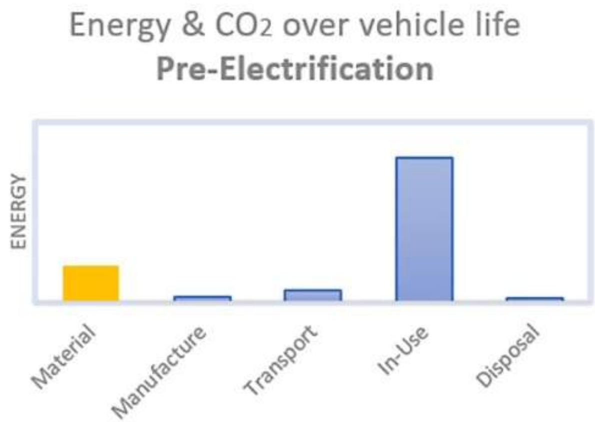
Different products ... different impacts

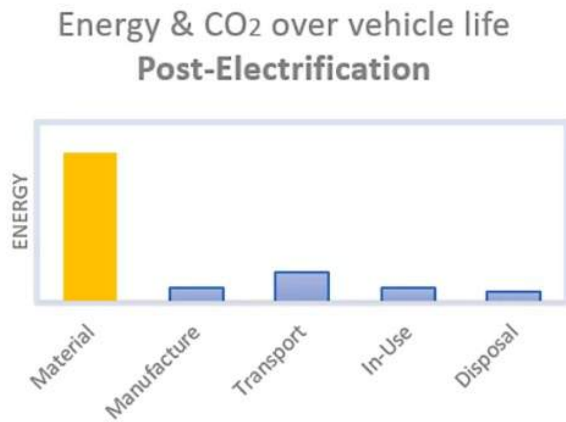


Electrification example (from automotive)





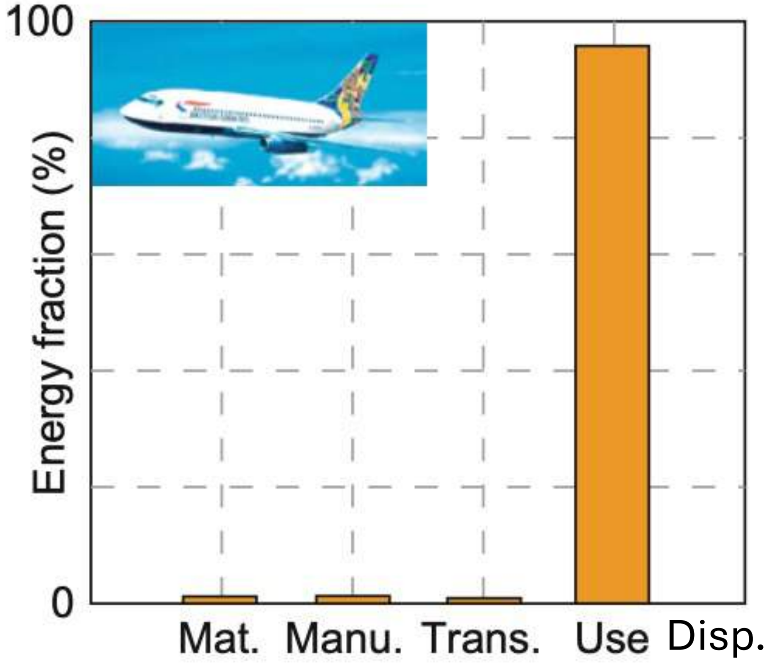




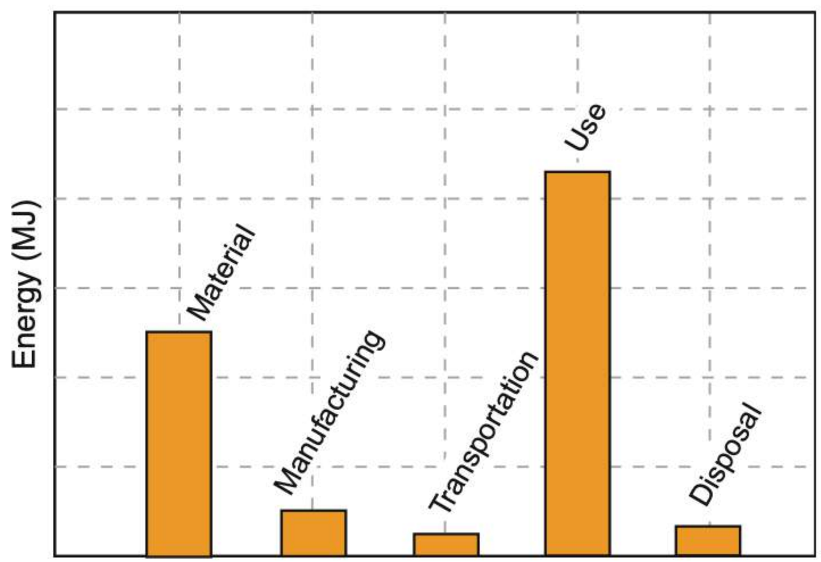
Energy ∝ CO_2 footprint

Fuel burn
+ non CO_2
such as contrails

Civil aircraft



Future Sustainable Air vehicule



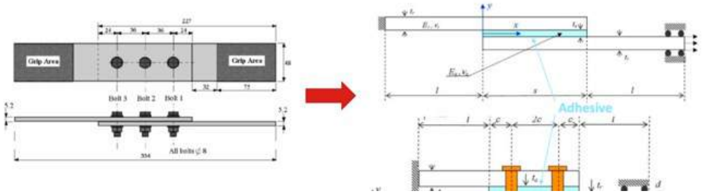
Breakdown of energy into that associated with each life phase

Hydrogène, SAF, Electric/Hybrid Propulsion…

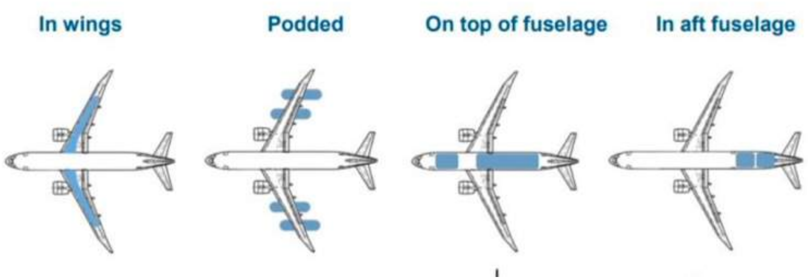
Structures/materials

Advanced assembling

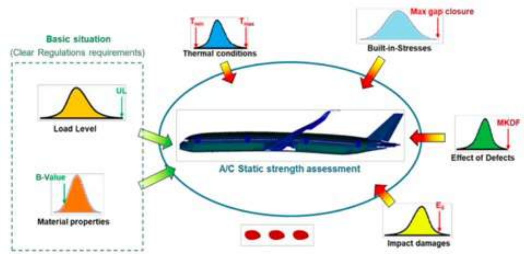
- Replacing rivets/bolts with bonding in aeronautical assemblies



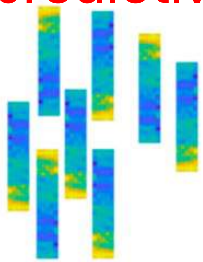
Advanced Structures for H2 tank



Worst case design

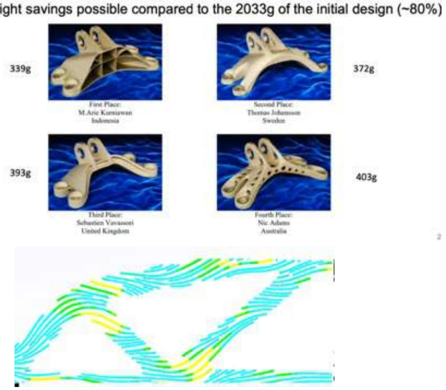


AI predictive maintenance



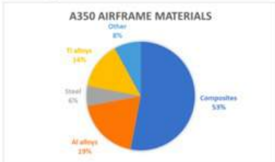
ALM and topogy optimization

- Massive weight savings possible compared to the 2033g of the initial design (~80%)



Advanced materials/processes

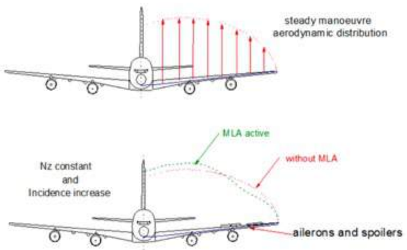
- Composites

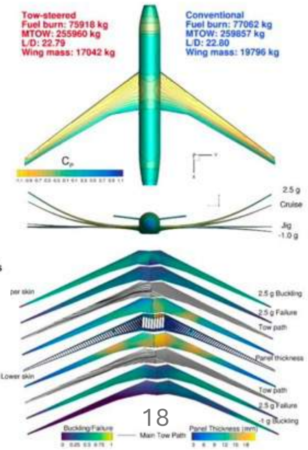


- Composite materials + advanced airframe design and optimization ➔ ~13t (~12%) airframe weight savings ➔ ~20t (~8%) MEW weight savings ➔ 6% fuel savings

FSI/Load Alleviation / HARW

Reference fuel burn: 87558kg





Environmental impact of the aerospace manufacturing sector

HTTPS://TINYURL.COM/CO2AEROSPACE

https://microlearning.groupe-isae.fr/nugget/environmental-impact-of-the-aerospace-manufacturing-sector/view/4530ea46-9f08-4230-8f5f-fd1570ccc69f#nugget_top

Quiz

- Guess Who's Who? CFRP vs Aluminium

Eco properties: material				
Global production, main component	2.8×10^4			metric ton/yr
Embodied energy, primary production	450	–	500	MJ/kg
CO_2 footprint, primary production	33	–	36	kg/kg
Water usage	360	–	1,367	L/kg
Eco properties: processing				
Simple composite molding energy	9	–	12.9	MJ/kg
Simple composite molding CO_2	0.77	–	0.89	kg/kg
Advanced composite molding energy	21	–	23	MJ/kg
Advanced composite molding CO_2	1.7	–	1.8	kg/kg
End of life				
Recycle fraction in current supply	0	–		%
Heat of combustion	31	–	33	MJ/kg
Combustion CO_2	3.1	–	3.3	kg/kg

Eco properties: material	
Global production, main component	37×10^6 metric ton/yr
Reserves	2.0×10^9 metric ton
Embodied energy, primary production	200–220 MJ/kg
CO_2 footprint, primary production	11–13 kg/kg
Water usage	495–1490 l/kg
Eco-indicator	710 millipoints/kg
Eco properties: processing	
Casting energy	11–12.2 MJ/kg
Casting CO_2 footprint	0.82–0.91 kg/kg
Deformation processing energy	3.3–6.8 MJ/kg
Deformation processing CO_2 footprint	0.19–0.23 kg/kg
End of life	
Embodied energy, recycling	22–39 MJ/kg
CO_2 footprint, recycling	1.9–2.3 kg/kg
Recycle fraction in current supply	41–45%

source: materials and the environnement , Prof Ashby

Au programme

Sustainable aviation methods and tools

An overview perspective

Prof. Joseph Morlier

(AUN) – ITB Summer Camp 2024 1

Next Tuesday

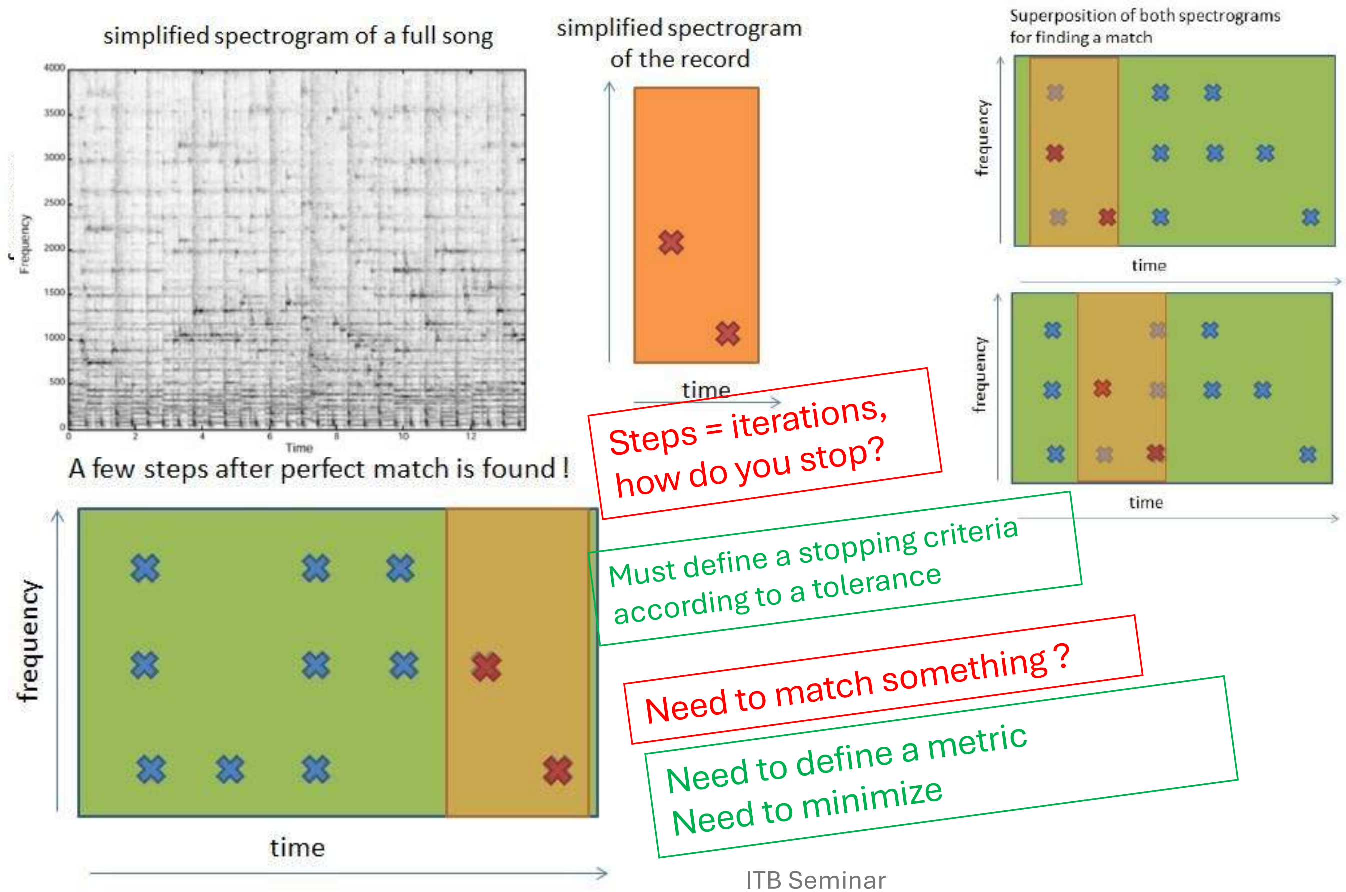
1. Engineering optimization
2. Eco friendly structures
3. Design acceleration through SMT

Au programme

1. **Engineering optimization**
2. Eco friendly structures
3. Design acceleration through SMT

Optimization is everywhere

http://coding-geek.com/how-shazam-works/



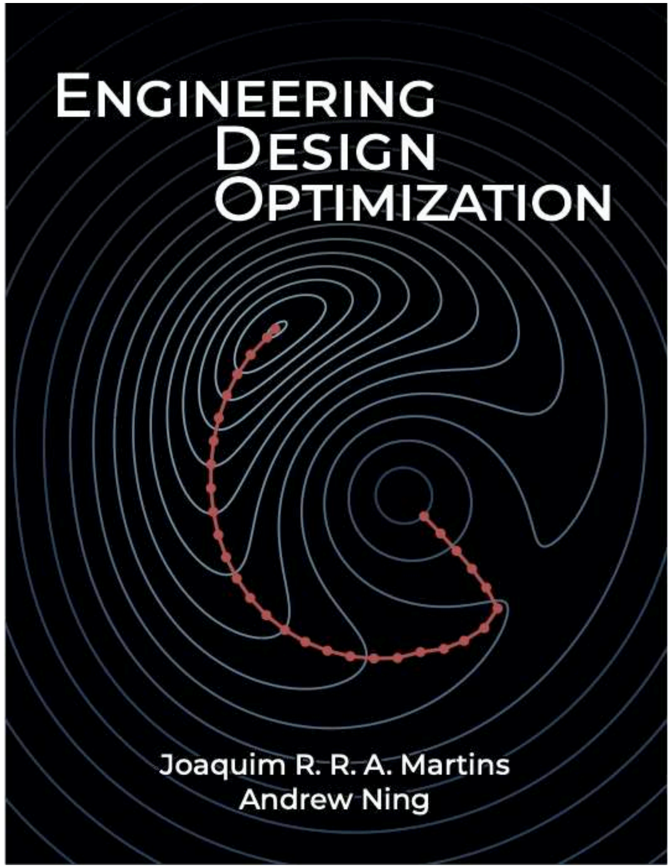
Steps = iterations,
how do you stop?

Must define a stopping criteria
according to a tolerance

Need to match something ?

Need to define a metric
Need to minimize

Good Starting Point (x0)



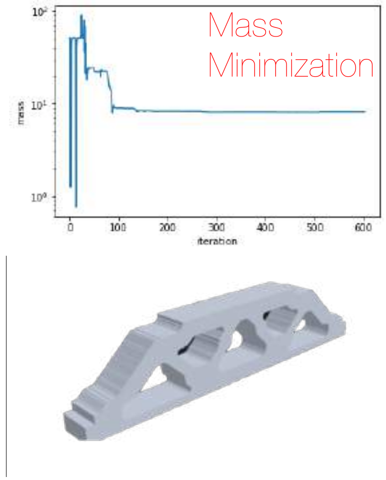
Aircraft Design

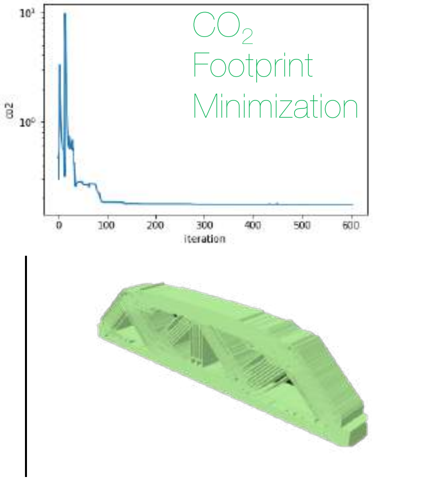
Fluid x control x physics x applied maths x structures &materials

Strong coupling Between Disciplines

	Avionics group 1	Electrical group 2	Escape system 3	Armament 4	Landing gear 5	Hydraulies group 6	Flight control system 7	Environment and control system 8	Power plant group 9	Fatigue group 10	Aero elastic group 11	Stress group 12	Materials group 13	Fly wheel 14	Empennage group 15	Rear fuselage 16	Fuselage group 17
Avionics group 1	●	●	●	●	●	●	●	●	●						●	●	●
Electrical group 2	●	●	●	●	●	●	●	●	●					●	●	●	●
Escape system 3	●	●	●	●													●
Armament 4	●	●		●						●	●	●	●		●		●
Landing gear 5	●	●			●	●				●	●	●			●		●
Hydraulies group 6						●			●							●	●
Flight control system 7	●	●					●			●	●	●	●	●	●	●	●
Environment and control 8								●		●	●	●					●
Power plant group 9	●	●				●			●	●	●	●				●	
Fatigue group 10			●	●	●	●	●	●	●	●	●	●		●	●	●	●
Aero elastic group 11			●	●	●	●	●	●	●	●	●	●		●	●	●	●
Stress group 12		●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
Materials gruop 13										●	●	●	●	●	●	●	●
Empennage group 14	●	●					●			●	●	●	●	●		●	
Wing group 15		●		●	●				●	●	●	●	●		●	●	
Rear fuselage 16	●	●				●	●		●	●	●	●	●	●	●	●	●
Fuselage group 17	●	●	●		●	●	●	●		●	●	●	●	●	●	●	●

Topology x Material x Process

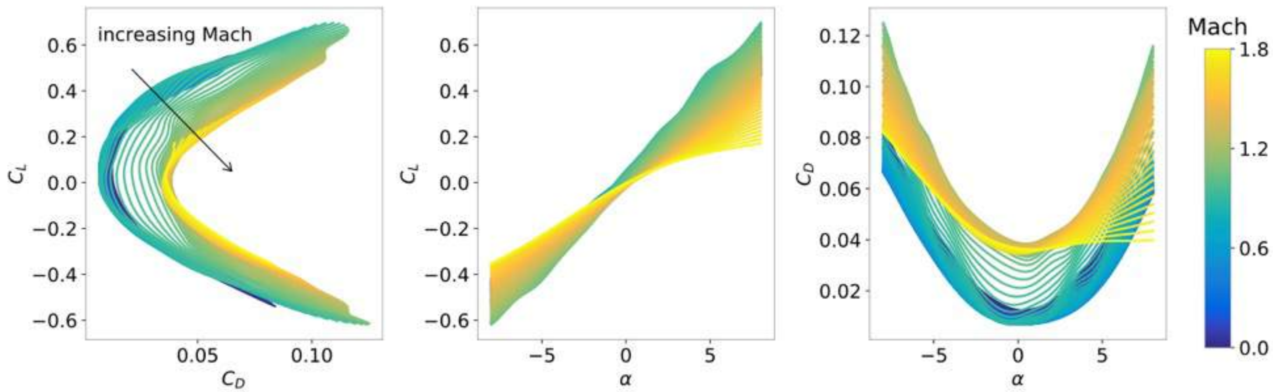


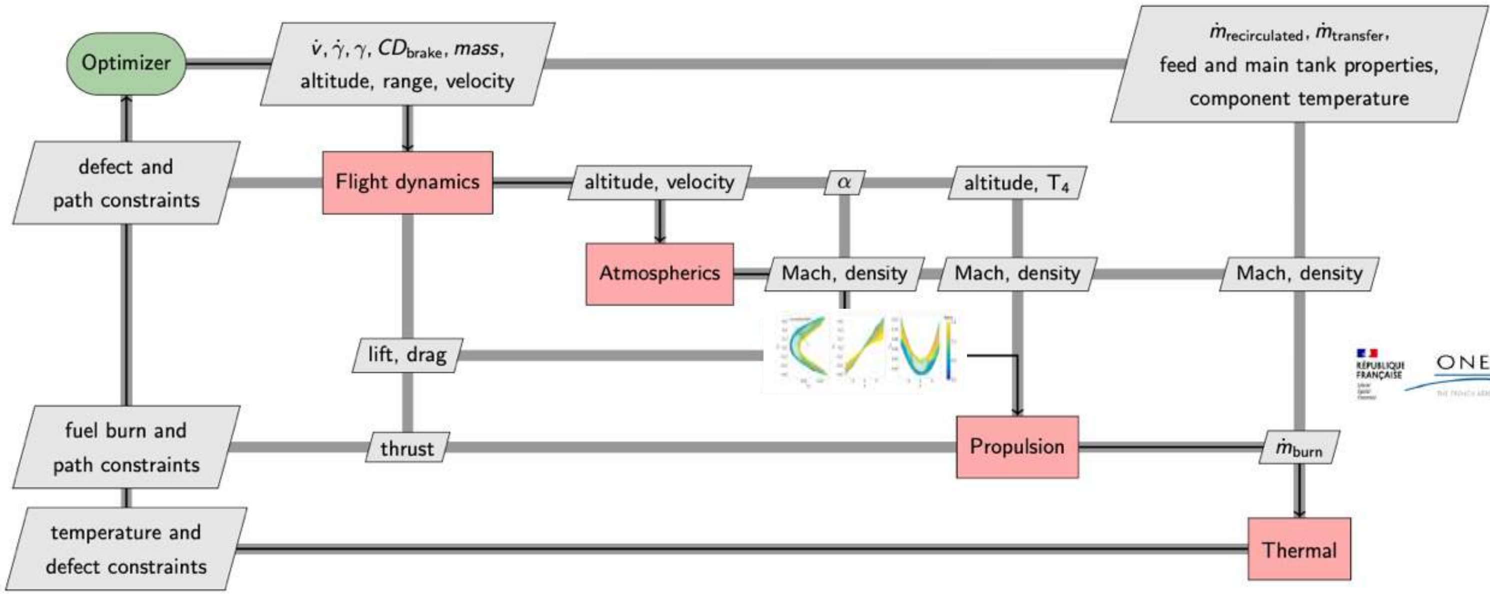


$$\text{Range} = V t_f = V \times \underbrace{\left(\frac{L}{D}\right)}_{\text{aircraft designer}} \times \underbrace{I_{sp}}_{\text{propulsion system designer}} \times \underbrace{\ln\left(\frac{W_i}{W_f}\right)}_{\text{structural designer}}.$$

Breguet was a French aircraft designer

MDO in a Nutshell





https://github.com/SMTorg/SMT

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.

4 disciplines

- Low cost satellite
- HALE: No propulsion

→Only CO2 footprint **PP**

(no Fuel Burn)

www.nature.com/scientificreports

scientific reports

Check for updates

OPEN

CO_2 footprint minimization of solar-powered HALE using MDO and eco-material selection

Edouard Duriez[1,3], Víctor Manuel Guadaño Martín[2,3] & Joseph Morlier[1,3]

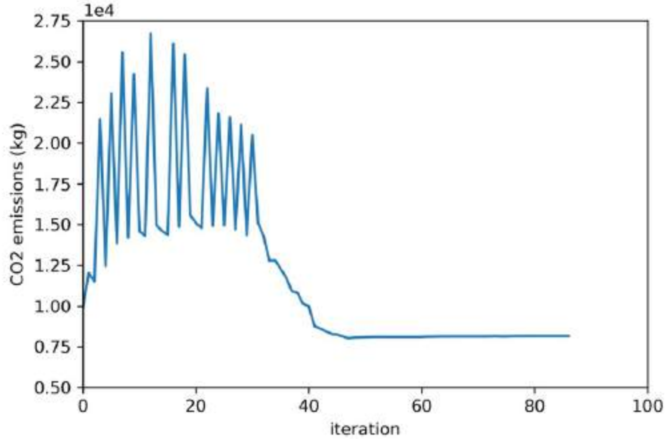
$$\text{Embodied carbon (kgCO}_2\text{e)} = \sum_{\text{Sum for all materials}} \left(\boxed{\text{Quantity (kg)}} \times \boxed{\text{Carbon factor (kgCO}_2\text{e/kg)}} \right)$$

Discipline	Method	Implementation	References
Aerodynamics	VLM	OAS	28
Structure	Wingbox beams	OAS	17
Energy	Simple in-house method	Section "OpenAeroStruct to Eco-HALE"	Data from[14]
Environmental	Proportional to mass	Section "MDO framework summary"	Data from[29,30]

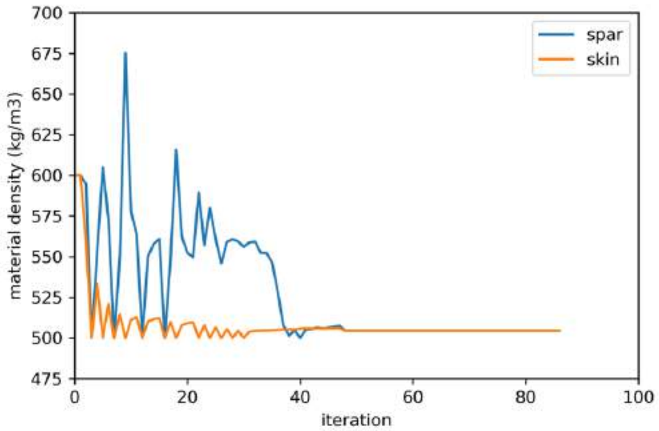
CO2 footprint minimization

X* is a UHAR Wing ;)

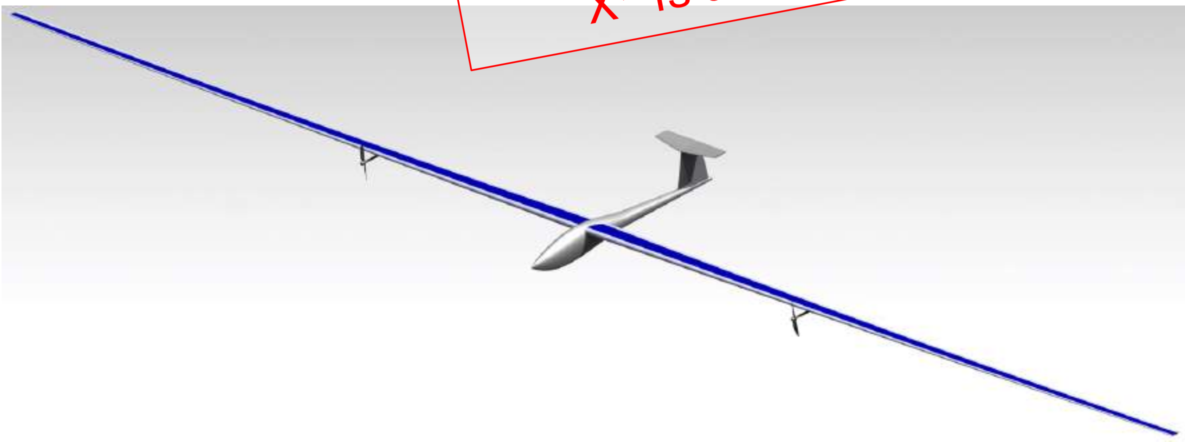
(a) Objective function: total CO2 emitted:



(b) Material density for skins and spars:



Convergence graphs



CAD model of the optimal HALE obtained

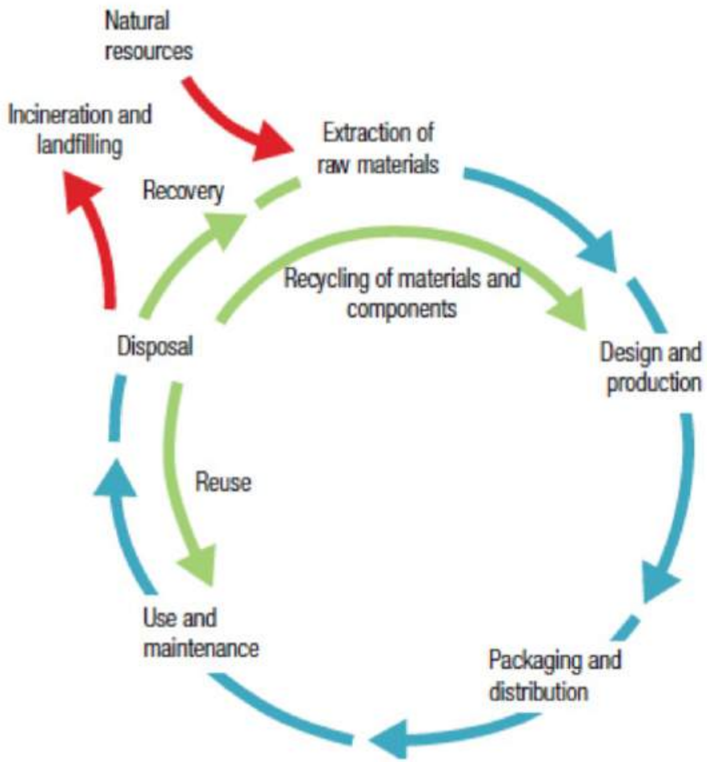
A slight increase in the total weight of the drone leads to an increase in the weight of the battery and the solar panel in order to propel a heavier drone,

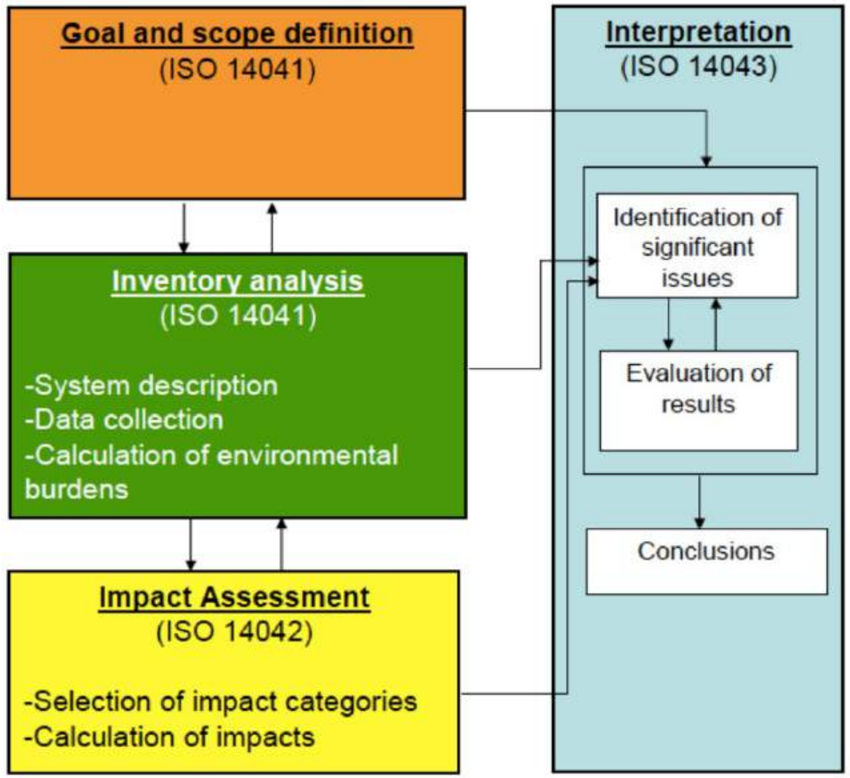
But also to: an increase in the weight of the wing structure that induces a more important lift to compensate → increase in the overall weight of the drone.

→ "snowball" effect.

Life Cycle Assessment

ISO norm:
- Proper goal and scope definition, including functional unit
- Inventory analysis and the database problem
- Selection of impacts, and difference between raw flux, midpoint, and endpoint impacts





A small LCA

A small LCA

Minus (-) need

Plus (+) produce

P2

Production of electricity:

– expressed in flow diagram terms:

2 liters of fuel →

→ 10 kWh of electricity

→ 1 kg of CO_2

→ 0.1 kg of SO_2

– expressed in mathematical terms:

$$\begin{pmatrix} -2 \\ 10 \\ 1 \\ 0.1 \\ 0 \end{pmatrix}$$

Need ***X2*** liters of fuel to produce ***Y2*** kWh of electricity and ***Z21*** kg of CO2 and ***Z22*** kg of SO_2

P1

Production of fuel:

– expressed in flow diagram terms:

50 liters of crude oil →

→ 100 liters of fuel

→ 10 kg of CO_2

→ 2 kg of SO_2

– expressed in mathematical terms:

$$\begin{pmatrix} 100 \\ 0 \\ 10 \\ 2 \\ -50 \end{pmatrix}$$

But to produce ***Y1*** liters of fuel,
You need ***X1*** liters of crude oil
and you produce ***Z11*** kg of CO2
and ***Z12*** kg of SO_2

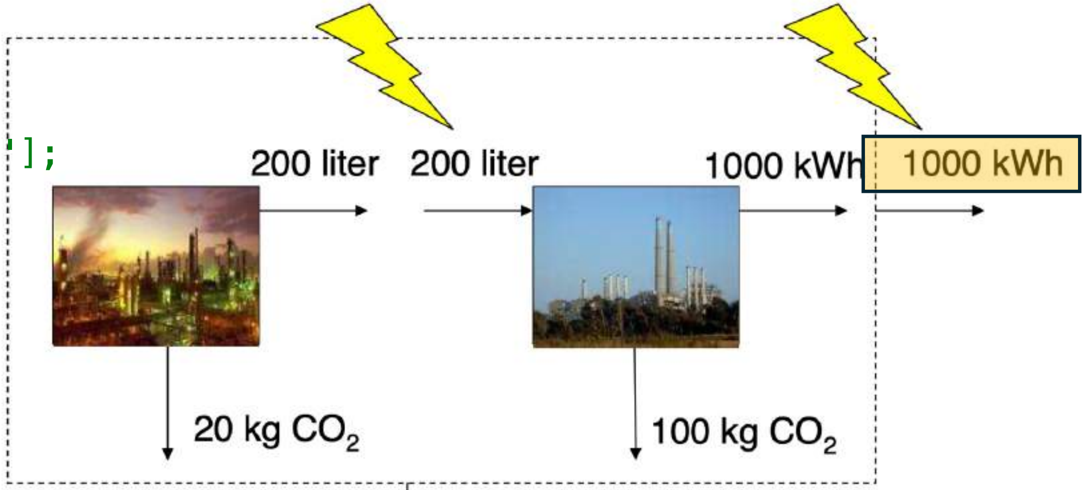
Solve a Linear system

We need to match supply and demand.

```
%process=['fuel production'; 'electricity production'];
%econflow=['litre of fuel'; 'kWh of electricity'];
%envflow=['kg of carbon dioxide'; 'kg of sulphur
dioxide'; 'litre of crude oil'];


%definition of the system:
%the technology matrix
A=[-2 100;10 0];
%the intervention matrix
B=[1 10;0.1 2;0 -50];
%the final demand vector
f=[0; 1000];


LCAcalc
```



Need 2*50=100L Crude oil

Produce 2*2+100*0.1=14Kg SO_2

Produce 120kg CO_2

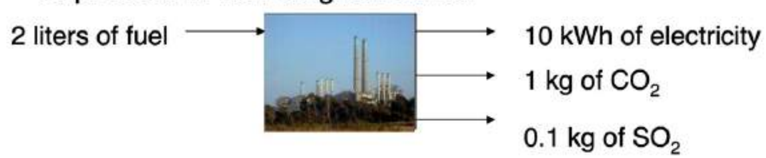
120 kg CO_2

P1 **Production of fuel**:

– expressed in flow diagram terms:

P2 **Production of electricity**:

– expressed in flow diagram terms:



Phases of an LCA

- Goal and scope definition
- Inventory
- **Impact assessment**
- Interpretation

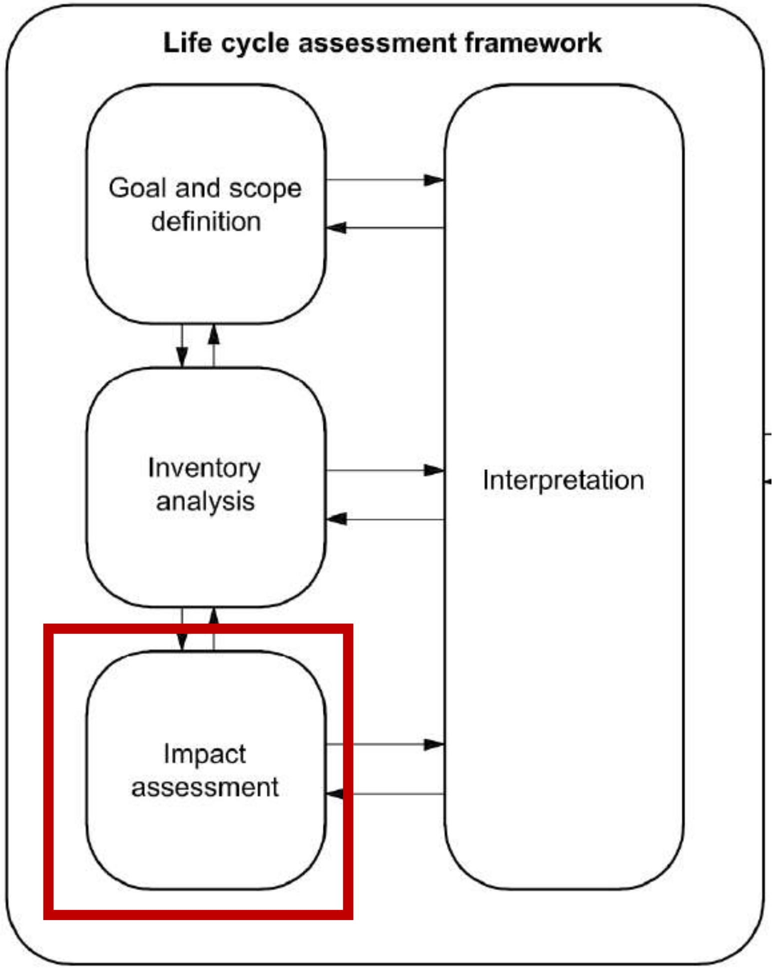


Figure: ISO 14040

Eco-design and MDAO

MDAO

- Custom code or software
- Many simulations on low amounts of variables
- Engineering teams

Life Cycle Assessment (LCA)

- Independent software (OpenLCA, Simapro, etc...)
- Single calls on large external databases (Ecoinvent, ILCD, etc...)
- Dedicated teams or consultancies

Our python tool

<u>Proposed solution: LCA4MDAO tool</u>

- *OpenMDAO* and *Brightway2*: all in Python
- Direct linkage between *OpenMDAO* variables and *Brightway2* database entries
- LCA computation is tuned so that we avoid repetitive (and useless) tasks

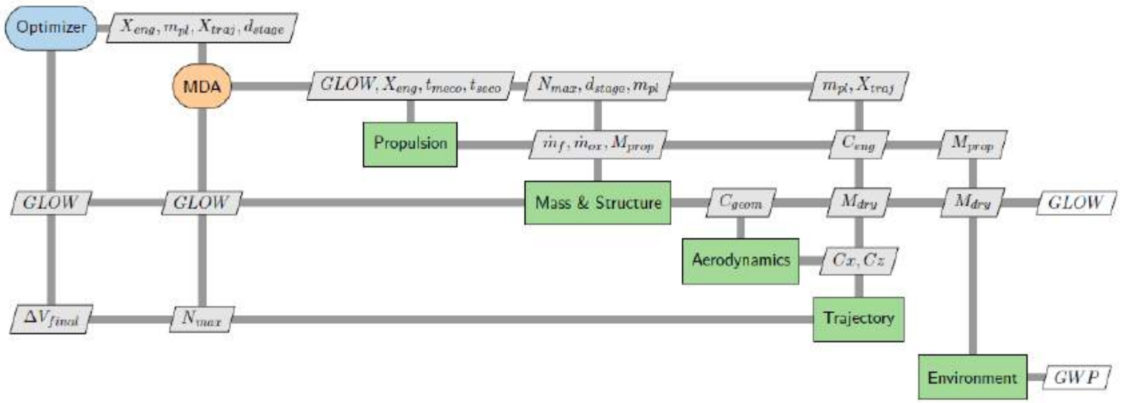
Mutel, C. (2017). Brightway: an open source framework for life cycle assessment. Journal of Open Source Software, 2(12), 236.

Gray, J. S., Hwang, J. T., Martins, J. R., Moore, K. T., & Naylor, B. A. (2019). OpenMDAO: An open-source framework for multidisciplinary design, analysis, and optimization. Structural and Multidisciplinary Optimization, 59, 1075-1104.

First try ;)

https://hal.science/hal-03888108/

Objective function : GLOW
Design variables : $X_{eng}, m_{pl}, X_{traj}, d_{stage}$
Constraints : $\Delta V_{final} \geq 0$



73rd International Astronautical Congress (IAC) 2022 – Paris, France

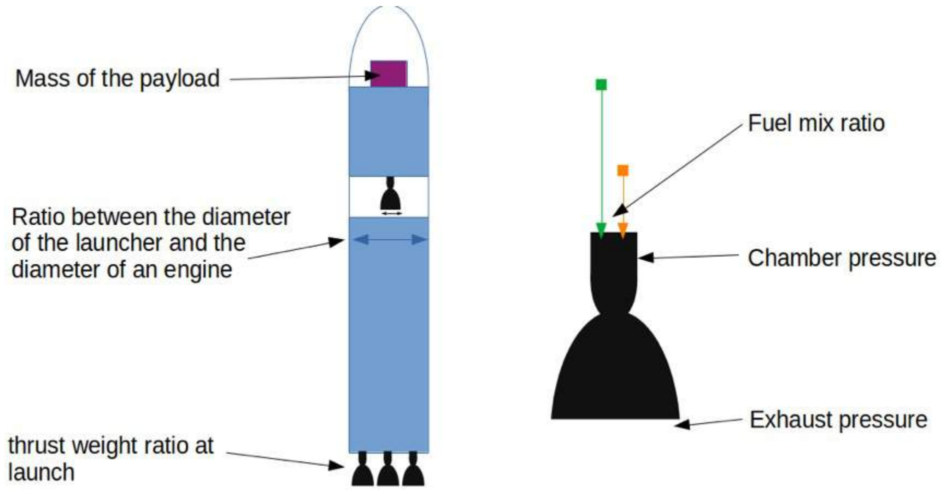
IAC-22,D2,IPB,26,x71719

Impact of Life Cycle Assessment Considerations on Launch Vehicle Design

Thomas Bellier[1, 2, *], Annafederica Urbano[1], Joseph Morlier[1], Cees Bil[2], and Adrian Pudsey[2]

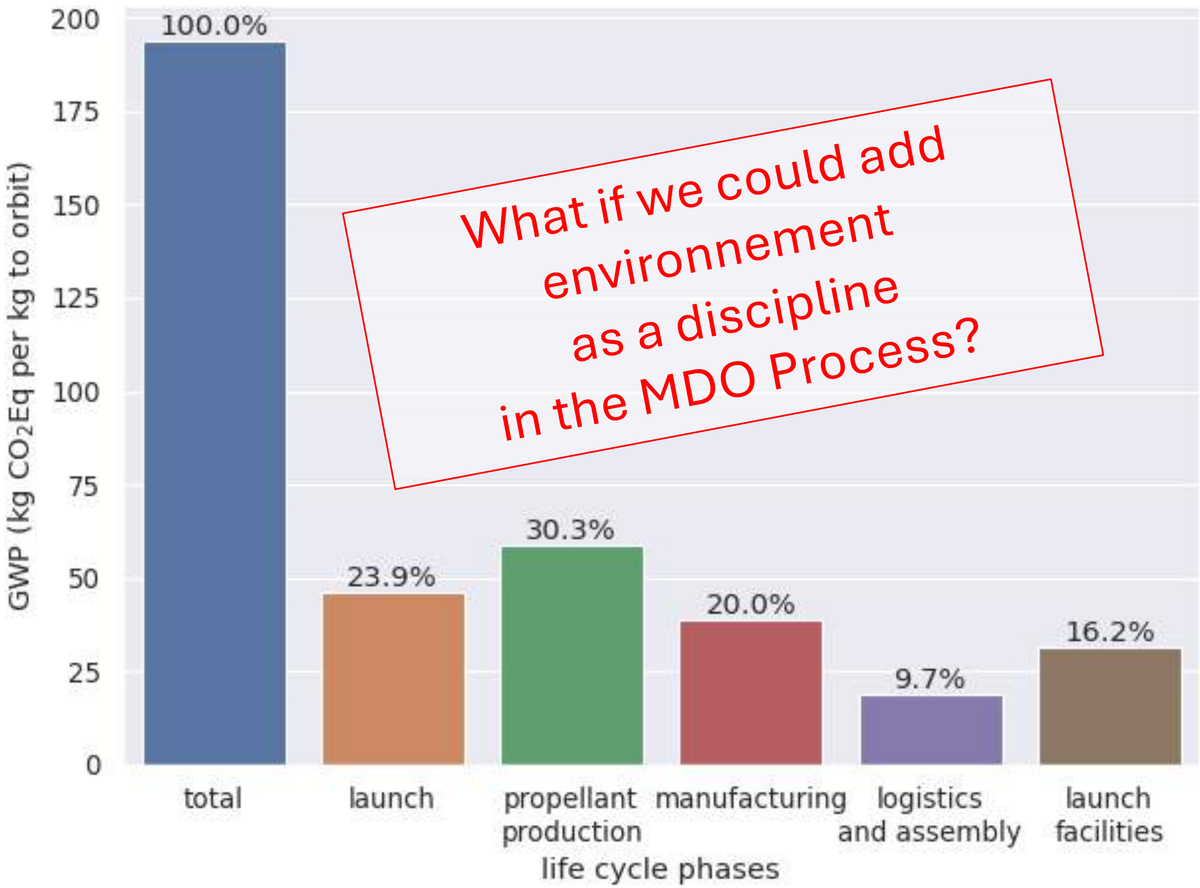
[1] *Institut Supérieur de l'Aéronautique et de l'Espace SUPAERO, Université de Toulouse, Toulouse, France*
[2] *Royal Melbourne Institute of Technology (RMIT), Melbourne, Australia*

[*]Corresponding author
Email: thomas.bellier@isae-supaero.fr



X* and LCA (X*)

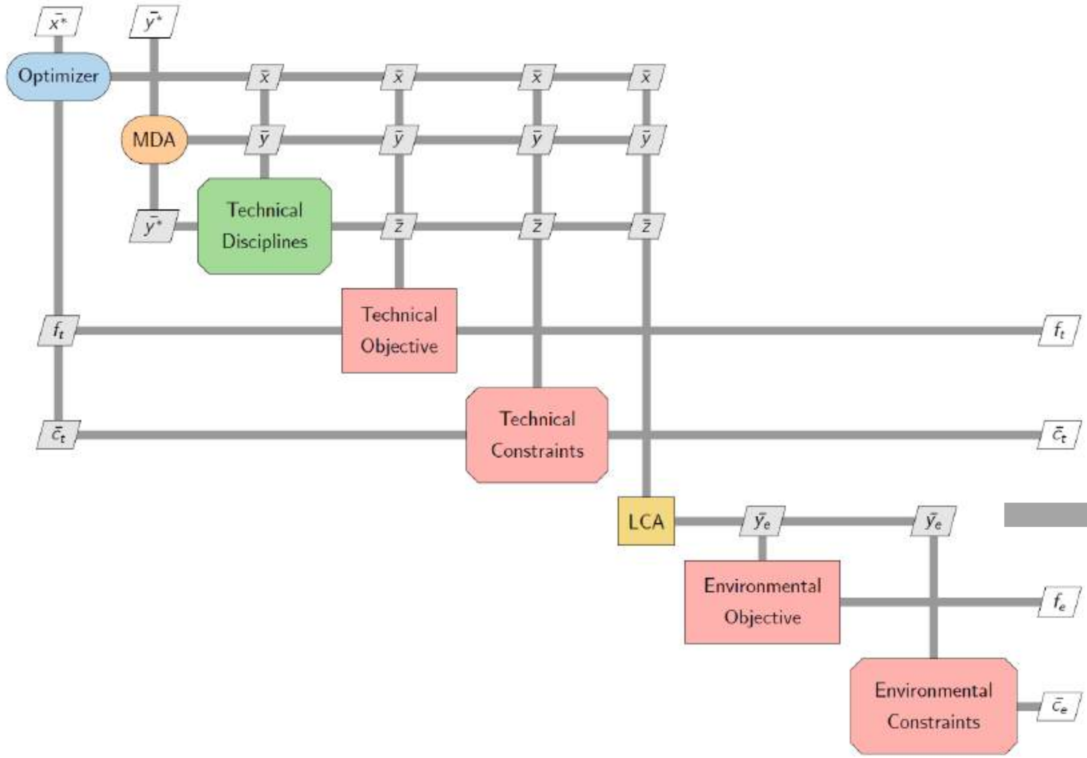
And avoid Greenwashing !!!

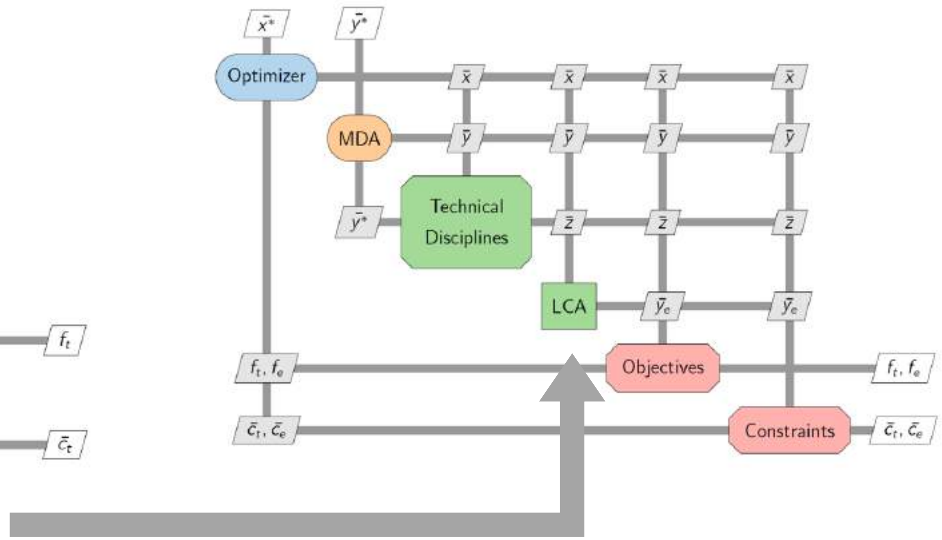


What if we could add environnement as a discipline in the MDO Process?

Early LCA results demonstrate that manufacturing take into account 20% of Global Warming Potential (wrt 1% in Aircraft)

With XDSM





LCA integrated: environmental outputs available in all modules

MOO

%f1=Minimize (f_sellar) and f2=minimise (GWP)

f1=Minimize (-range) and f2=minimise (GWP) % second problem

$$f = \alpha * f1 + (1 - \alpha) * f2$$

https://pymoo.org

Hybrid Aircraft Problem (MDOlab)

- Hybridised King Air C90GT from OpenConcept, built in *OpenMDAO* format
- Four disciplines:
  - Aero (wing geometry)
  - Propulsion (with hybrid system)
  - Structure
  - Trajectory simulation
- 6 variables converted into LCA database entries

Model parameter	Ecoinvent entry
Battery weight	battery cell production, Li-ion
Motor weight	electric motor production, vehicle
Engine weight	internal combustion engine production, passenger car
Empty weight	aluminium production, primary, ingot
Fuel used	market for kerosene
Electricity used	market group for electricity, low voltage

Benjamin J. Brelje and Joaquim R. R. A. Martins, "Development of a Conceptual Design Model for Aircraft Electric Propulsion with Efficient Gradients", 2018 AIAA/IEEE Electric Aircraft Technologies Symposium, AIAA Propulsion and Energy Forum, (AIAA 2018-4979) DOI: 10.2514/6.2018-4979

Eytan J. Adler and Joaquim R. R. A. Martins, "Efficient Aerostructural Wing Optimization Considering Mission Analysis", Journal of Aircraft, 2022. DOI: 10.2514/1.c037096

Design Variables

Trajectory optimization overconstrained i.e.; standard mission

Table 3 presents the design variables values and results after optimisation for this problem, with the range fixed at 400NM and using the GWP as the sole objective, using COBYLA [41]. Figure 6 presents the resulting trajectory and energy consumption for this 400 nautical miles range solution.

Table 3: Example of hybrid aircraft optimisation for a range of 400*NM*

variable	min	init	max	value	units
MTOW	4000	5000	5700	5700	*kg*
wing surface	15	25	40	34	m^2
engine power	0	1000	3000	298	*kW*
motor power	450	1000	3000	652	*kW*
battery weight	20	1000	3000	1607	*kg*
fuel capacity	500	1000	3000	500	*kg*
cruise hybridisation	0	0.5	1	0.71	
climb hybridisation	0	1	1	0.785	
descent hybridisation	0	0.5	1	0.337	
GWP				0.712	$kgCO_2eq/km$

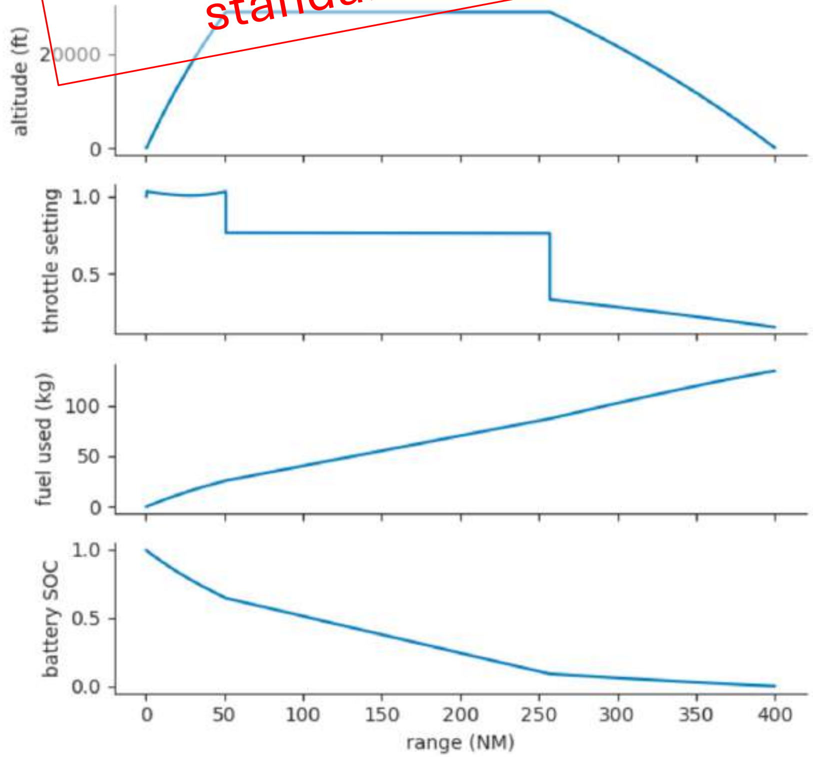
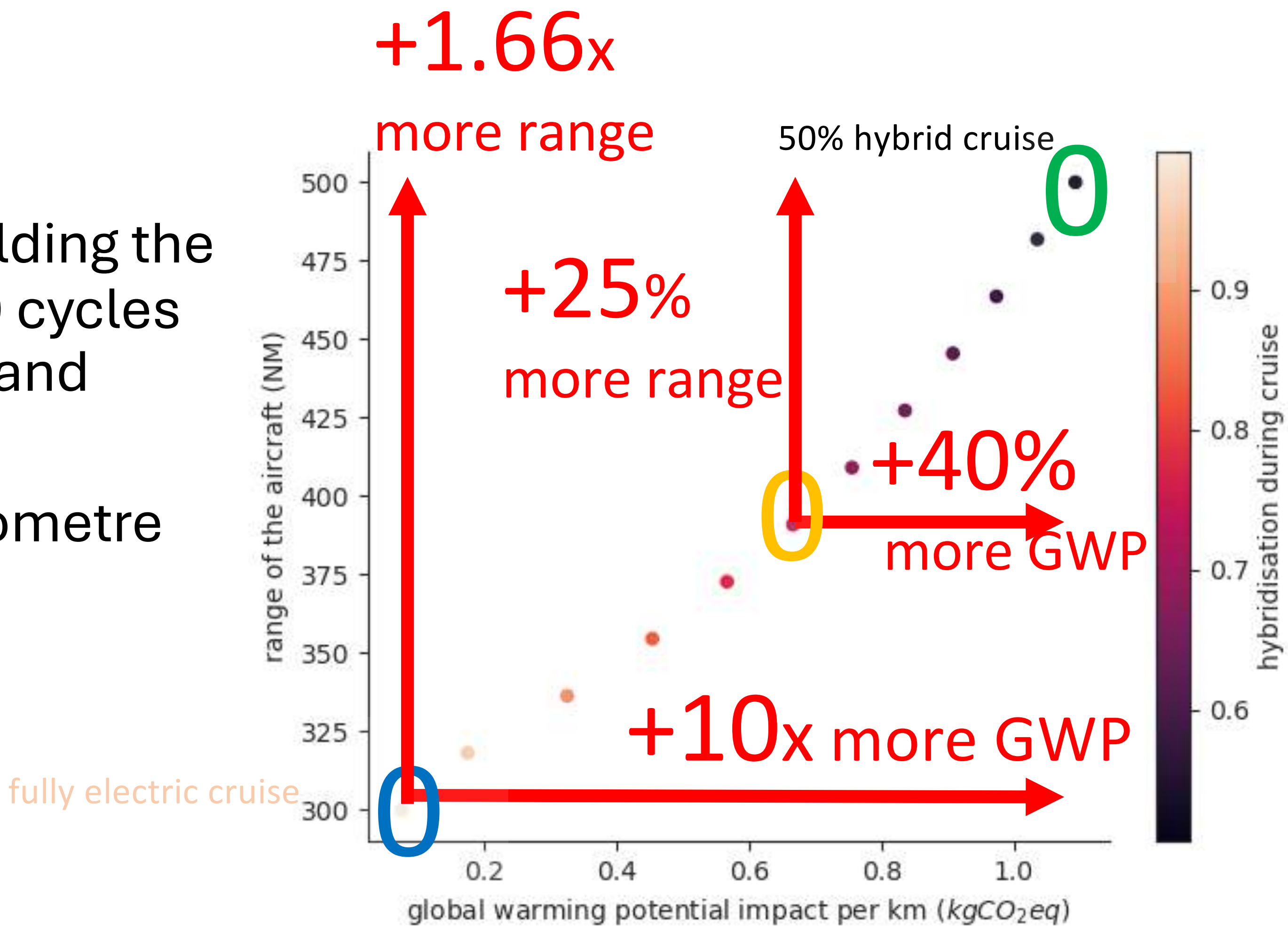


Figure 6: Optimal trajectory and energy utilisation for a hybrid aircraft with 400 nautical miles range

minimise (GWP)
wrt range=400NM

Results MOO

- LCA scope include building the aircraft and flying 1000 cycles at max range with fuel and electricity
- Functional unit is a kilometre flown

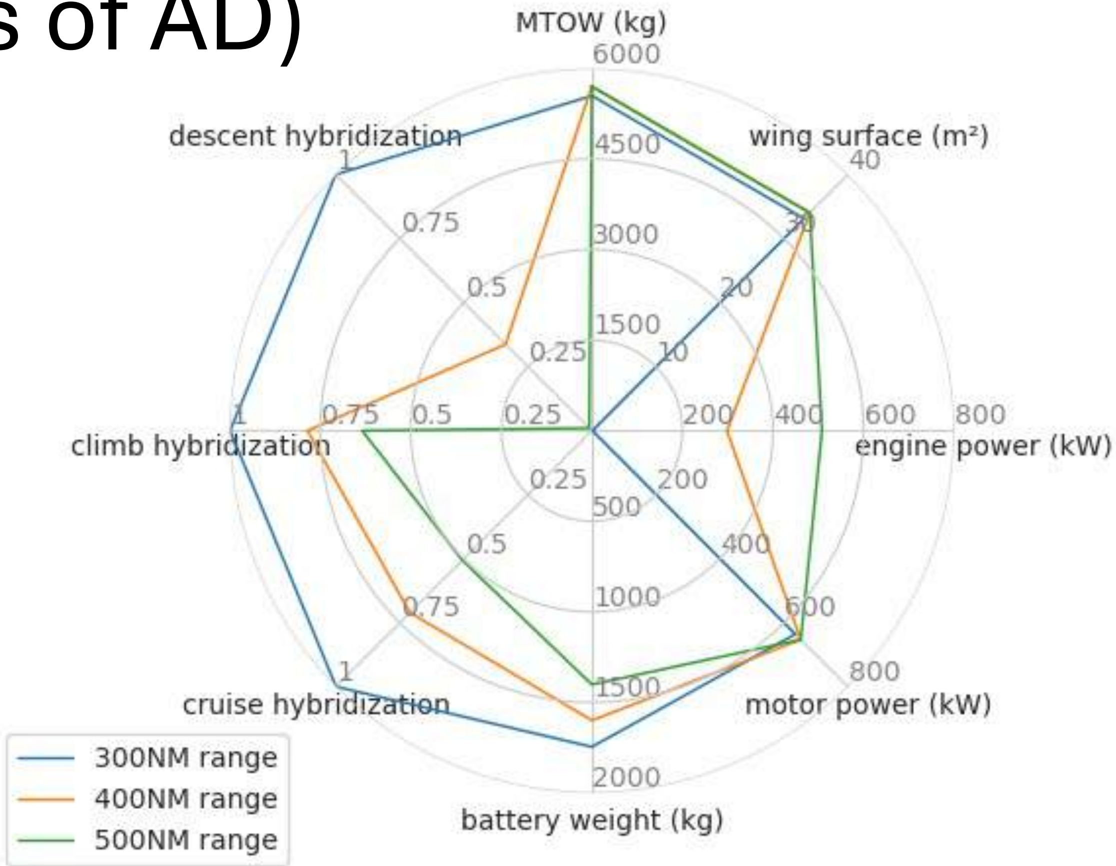


Results (link to physics of AD)

For the design variables, reducing the range:

- increases the hybridization
- reduces the engine size
- increases the battery weight

variable	value	units
MTOW	5700	kg
wing surface	34	m^2
engine power	298	kW
motor power	652	kW
battery weight	1607	kg
fuel capacity	500	kg
cruise hybridisation	0.71	
climb hybridisation	0.785	
descent hybridisation	0.337	
GWP	0.712	$kgCO_2eq/km$



LCA4MDAO

- LCA4MDAO
https://github.com/mid2SUPAERO/LCA4MDAO

- **LCA database ecoinvent**
https://ecoinvent.org/database

- Brightway2
https://github.com/brightway-lca

- OpenMDAO
https://github.com/OpenMDAO

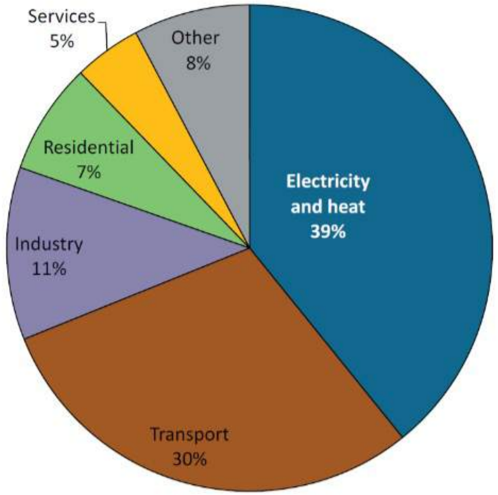
Au programme

1. Engineering optimization

2. Eco friendly structures

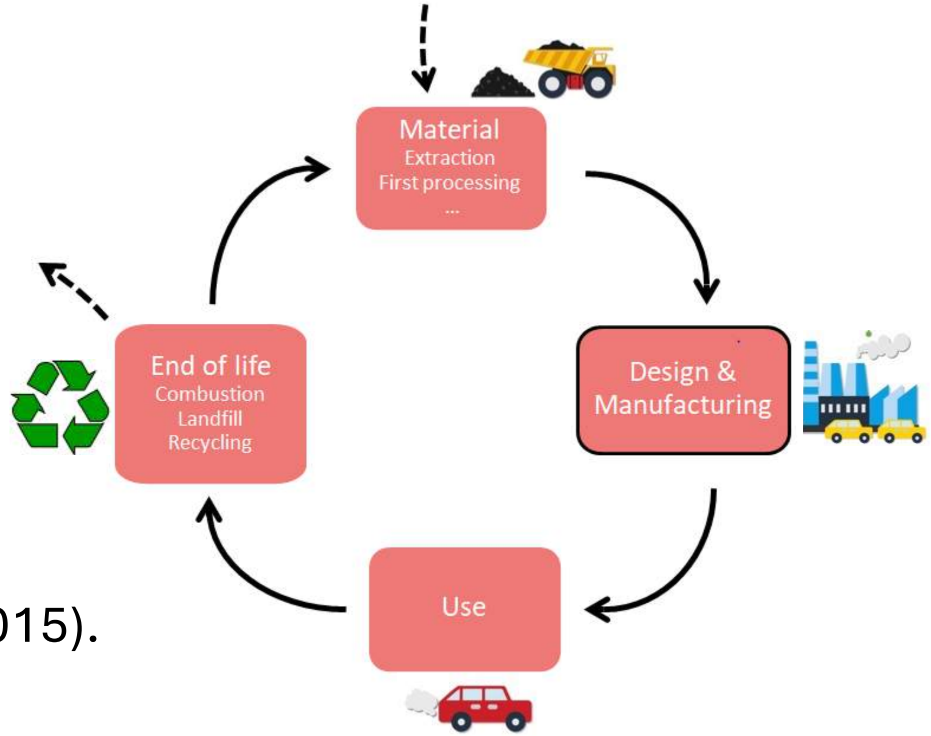
3. Design acceleration through SMT

Overview



CO_2 emissions of the OECD (2015).

International Energy Agency IEA. Energy and CO2 emissions in the OECD. 2017

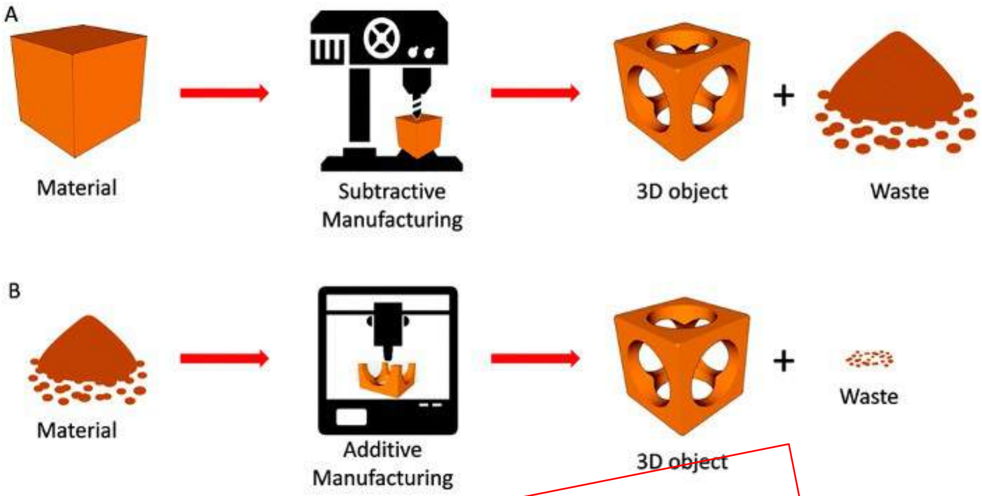


Vehicle life cycle

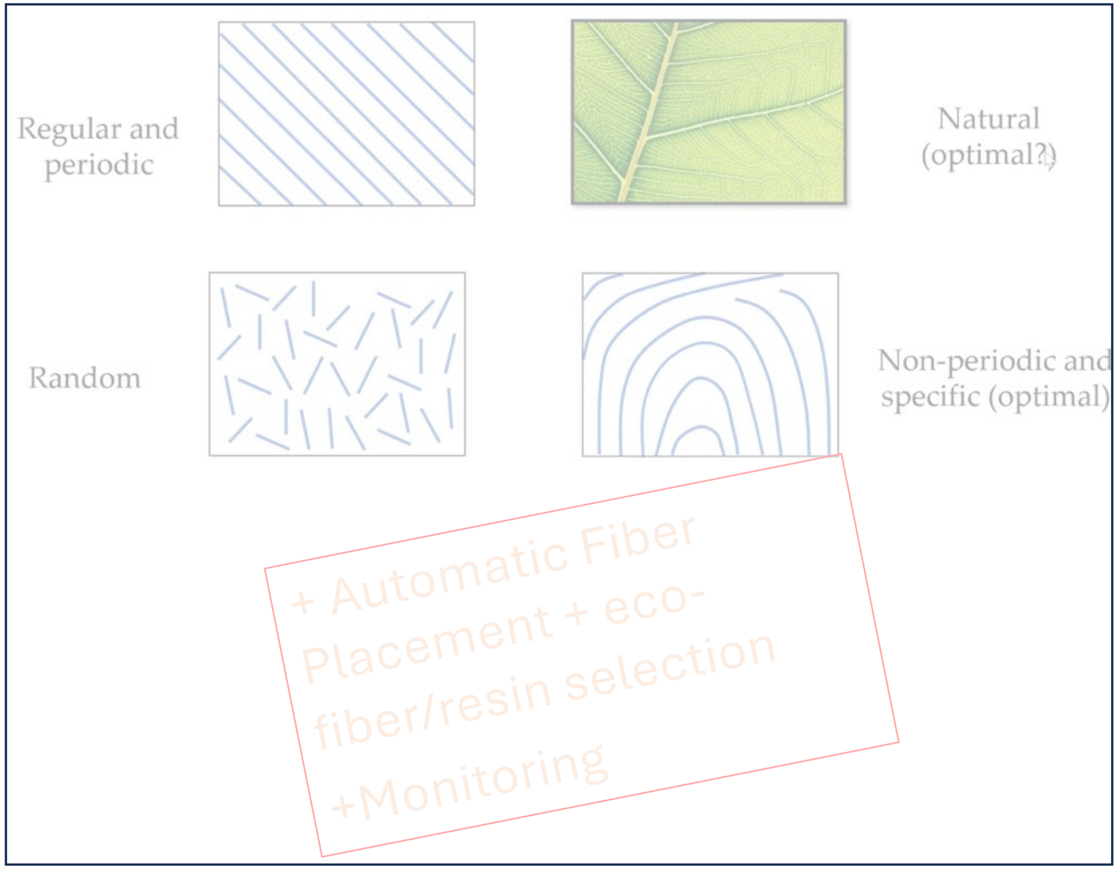
Q : How to find structural designs, materials and additive manufacturing processes with the lowest life-cycle CO_2 footprint**?**

Process is AM, but WHY?

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



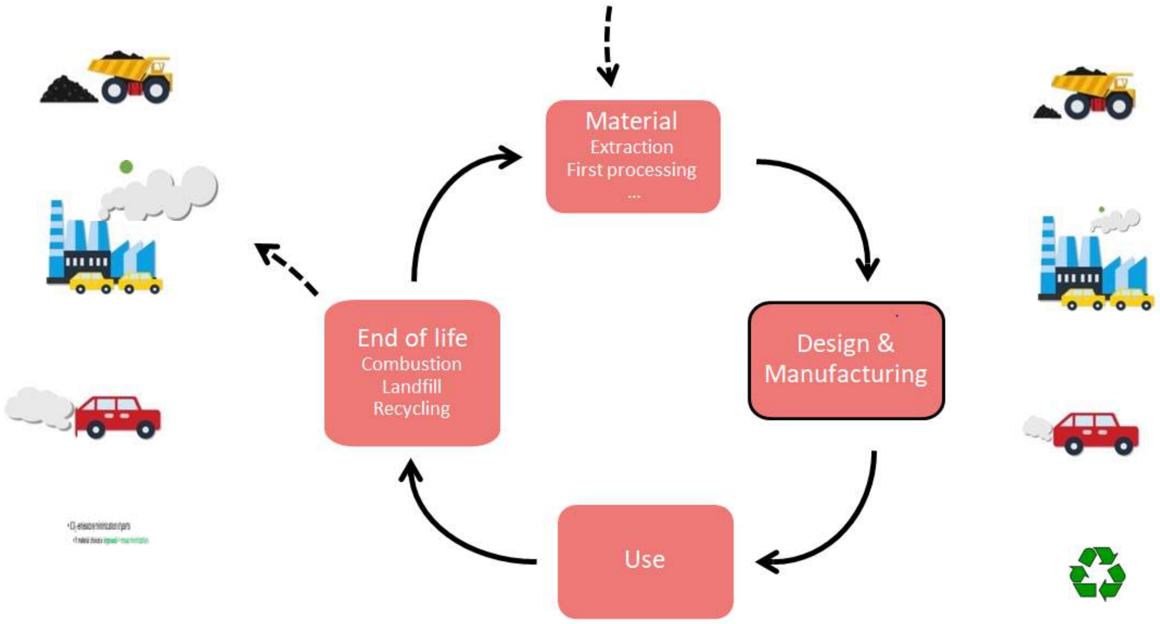
+Near 100% material utilization +Recyclability, Buy to fly ratio
+LCA of 3D printing machine
+Monitoring



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

Hypothesis 1

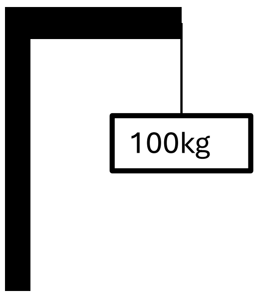
- CO_2 emissions minimization of parts
  - If material choice is **imposed** => mass minimization

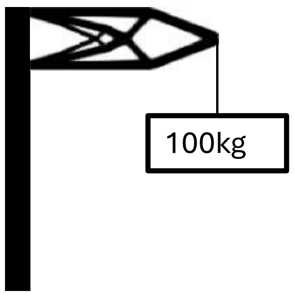


Vehicle life cycle

Mass minimization of parts

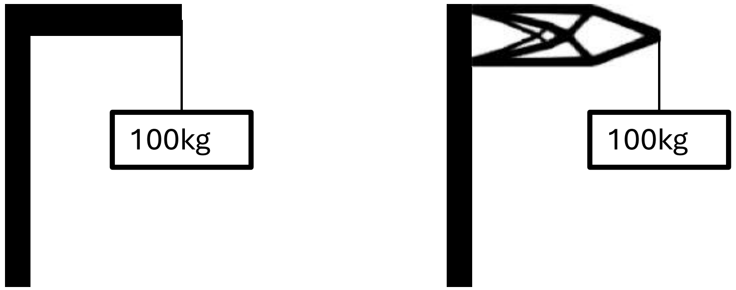
- Redesign through topology optimization
  => same performance





Mass minimization of parts

- Redesign through topology optimization
  => same performance but lower mass



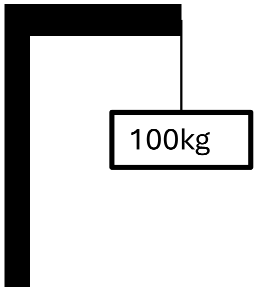
Ecodesign/Manufacturing

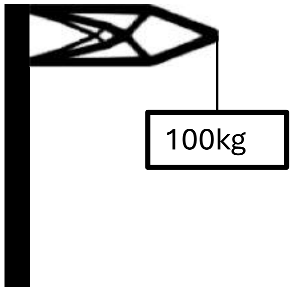
- Mass minimization of parts
  - And some additional constraints

(see Enrico's PhD)

- Reparability
- Fail-safe design
- Reusability and robot for assembly (see NASA MADCAT)

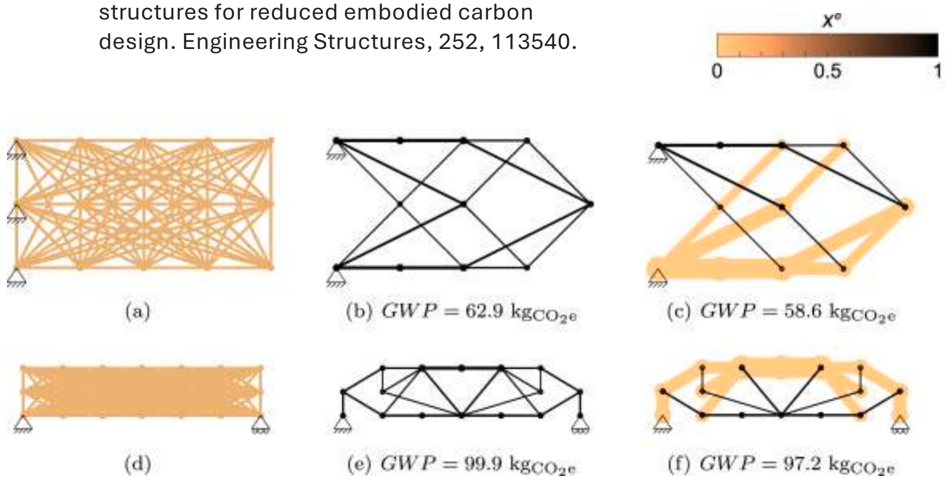
Liu, Y., Wang, Z., Lu, H., Ye, J., Zhao, Y., & Xie, Y. M. (2023, September). Layout optimization of truss structures with modular constraints. In Structures (Vol. 55, pp. 1460-1469). Elsevier.

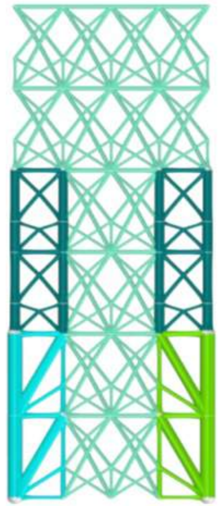




- Multimaterial
- GWP under stress

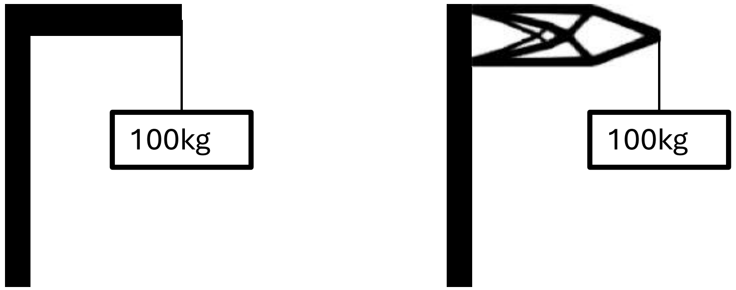
Ching, E., & Carstensen, J. V. (2022). Truss topology optimization of timber–steel structures for reduced embodied carbon design. Engineering Structures, 252, 113540.



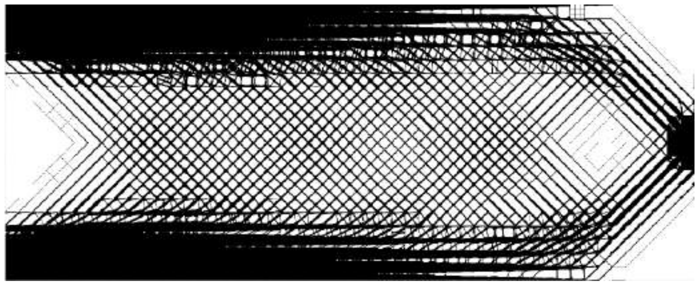


Mass minimization of parts

- Redesign through topology optimization
  => same performance but lower mass

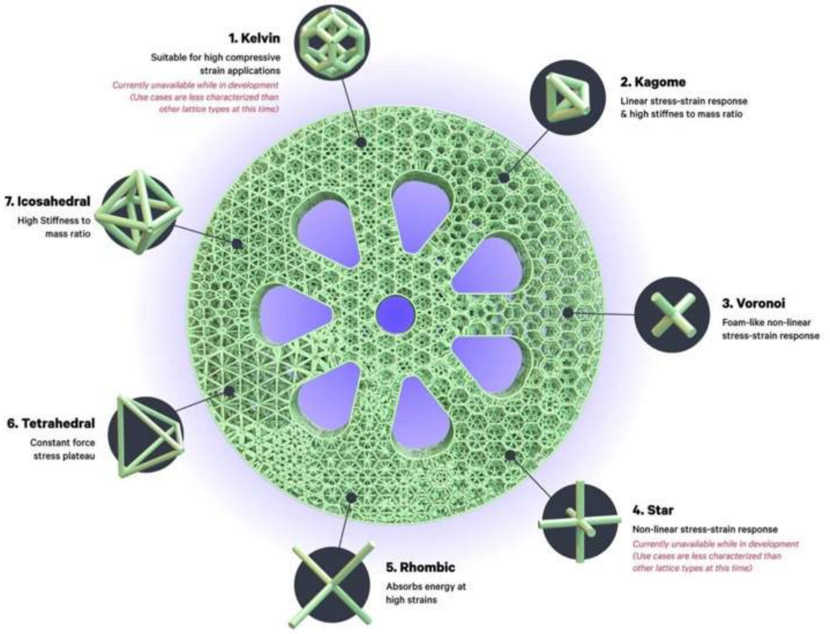


– One step further : multiscale topology optimization



Unit cell/material/process

Eco Material selection
Eco Process selection

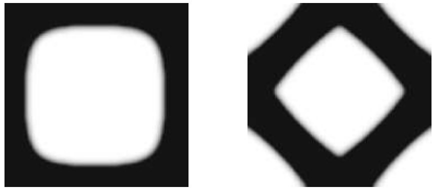


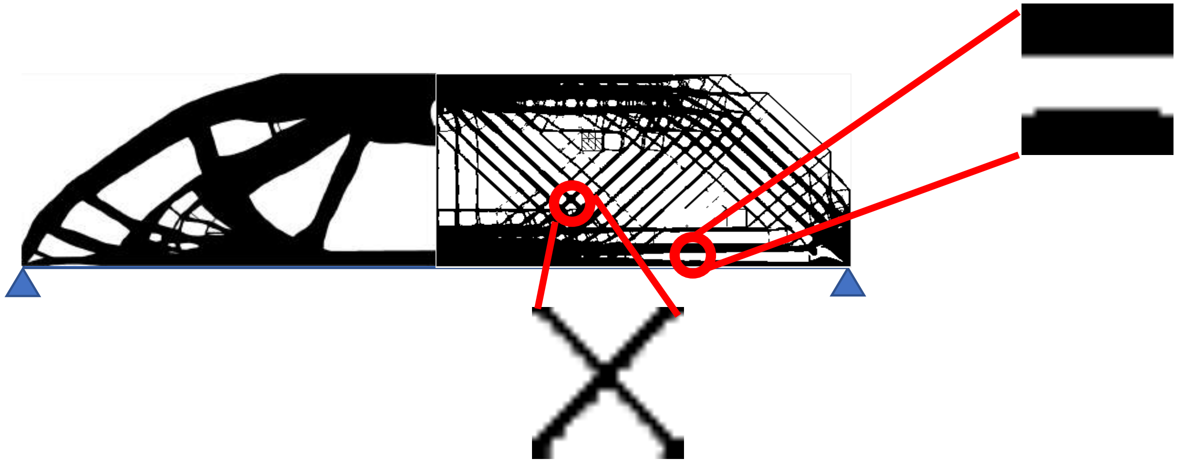
Unit cell design (anisotropy)

Digital materials as **new design variables** in Multidisciplinary Optimization

Multi-scale TO (well connected + locally-oriented)

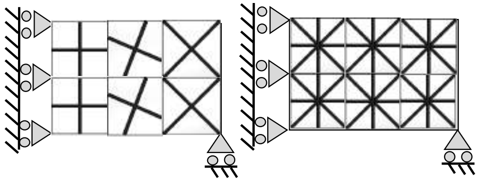
A two level optimization that combines Unit cell design & Topology Optimization



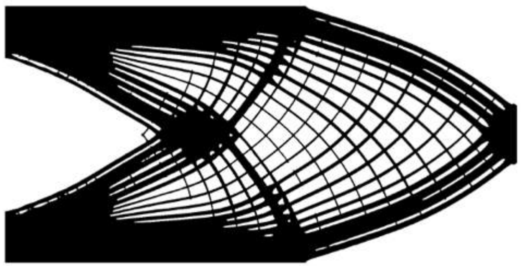


Xia L, Breitkopf P (2015) Design of materials using topology optimization and energy-based homogenization approach in Matlab. Struct Multidisc Optim 52(6):1229–1241.
Wu, Jun, Ole Sigmund, and Jeroen P. Groen. "Topology optimization of multi-scale structures: a review." Structural and Multidisciplinary Optimization 63.3 (2021): 1455-1480.

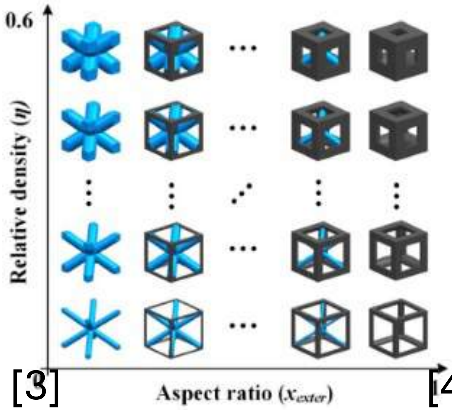
Main MTO methods



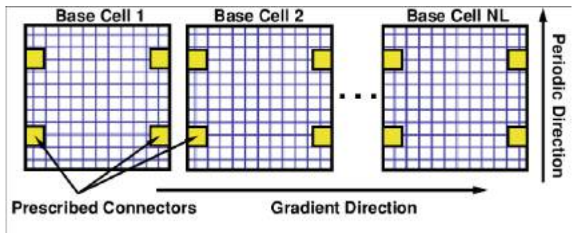
Approach	Examples	Connectivity	Locally adapted	Speed	Manufacturability
De-homogenization	[1],[2]				
Parametrized lattice	[3]				
Connectors	[4]				



[2]



[3]



[4]

[1] Grégoire Allaire, Perle Geoffroy-Donders et Olivier Pantz. « Topology optimization of modulated and oriented periodic microstructures by the homogenization method ». en. In : *Computers & Mathematics with Applications*.
[2] Groen, Jeroen P., and Ole Sigmund. "Homogenization-Based Topology Optimization for High-Resolution Manufacturable Microstructures." *International Journal for Numerical Methods in Engineering*
[3] Wang, Chuang, et al. "Concurrent Design of Hierarchical Structures with Three-Dimensional Parameterized Lattice Microstructures for Additive Manufacturing." *Structural and Multidisciplinary Optimization*
[4] Zhou S, Li Q (2008) Design of graded two-phase microstructures for tailored elasticity gradients. Journal of Materials Science
[5] Wu, Jun, et al. "Topology Optimization of Multi-Scale Structures: A Review." *Structural and Multidisciplinary Optimization*

Multiscale Topology Optimization

Macroscale Problem

need to solve

$$\underset{x^i_{\text{dens}}, x^i_a, x^i_b, \ldots}{\text{minimize}} \quad c = u^T K u$$

$$\text{subject } to \quad Ku = f$$

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

$$\epsilon < \rho_{i,j} < 1$$

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

best unit cell per quad

Microscale Problem Unit cell with 3 properties

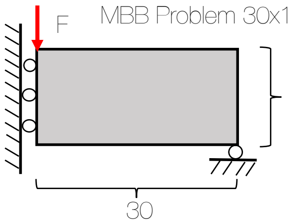
macro-density, angle, cubicity

$$\underset{\rho_{i,j}}{\text{minimize}} \quad c_i = E^{i\alpha}_{1111} \times \left(1 - \frac{x^i_{\text{cub}}}{2}\right) + E^{i\alpha}_{2222} \times \frac{x^i_{\text{cub}}}{2}$$

$$\text{subject to} \quad K_i u_i^{A(pq)} = f_i^{(pq)}$$

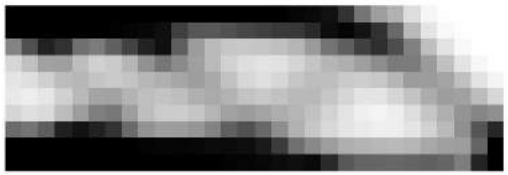
$$\sum_{j=1}^{m} \rho_{i,j} \leq m \times x^i_{\text{dens}}$$

MBB Problem 30x10 macro elements

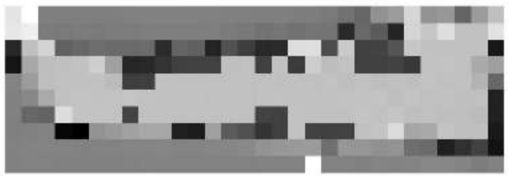


Theoretical compliance 192.7

Density of the cells

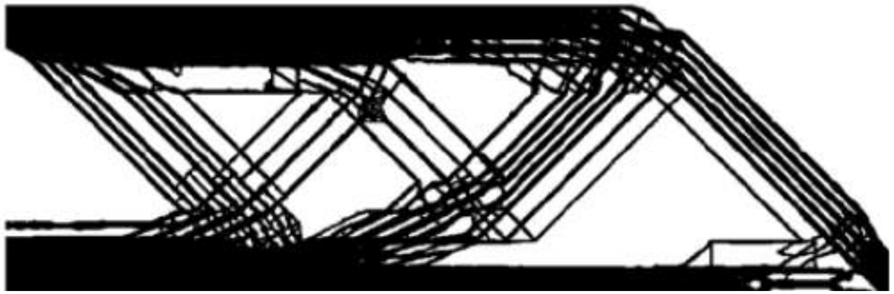


Orientation of the cells



Cubicity of the cells

Since the objective is to create micro-structure with optimal properties towards specific directions, the objective function is a weighted function of the two components $E\alpha$ 1111 and $E\alpha$ 2222

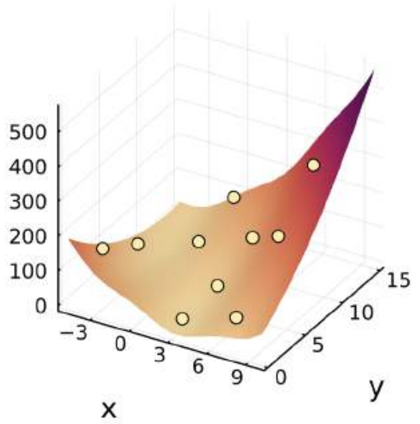


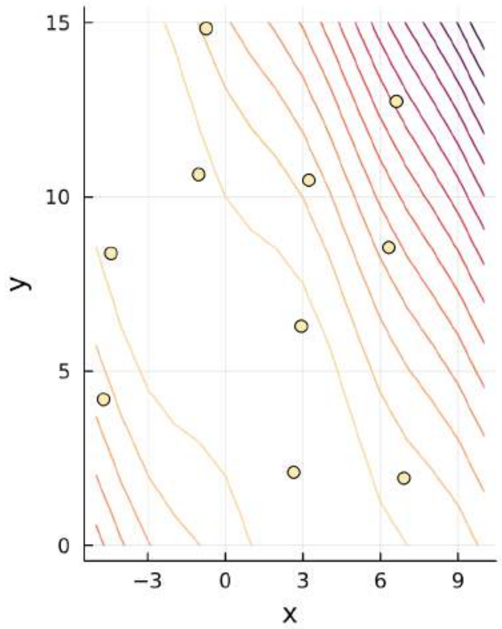
Comparison

- Top88 versus EMTO

How to speed up?

- To address speed issue ($t_{tot} = t_{cell} * n_{cell} * n_{it}$; $t_{cell} = 10'$)





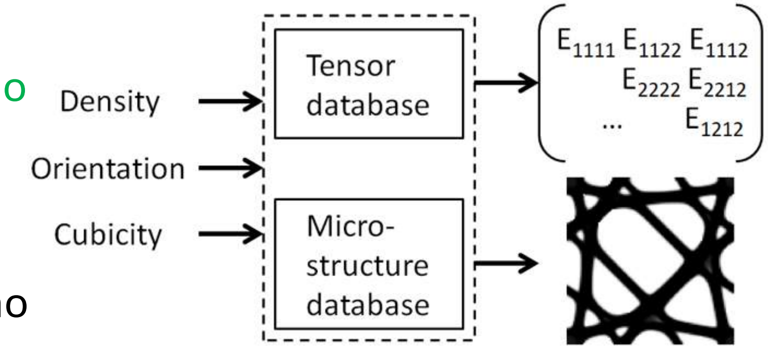
https://github.com/SMTorg/SMT

database:
https://data.mendeley.com/datasets/b5hyzxg7fv/1
DOI: 10.17632/b5hyzxg7fv.1

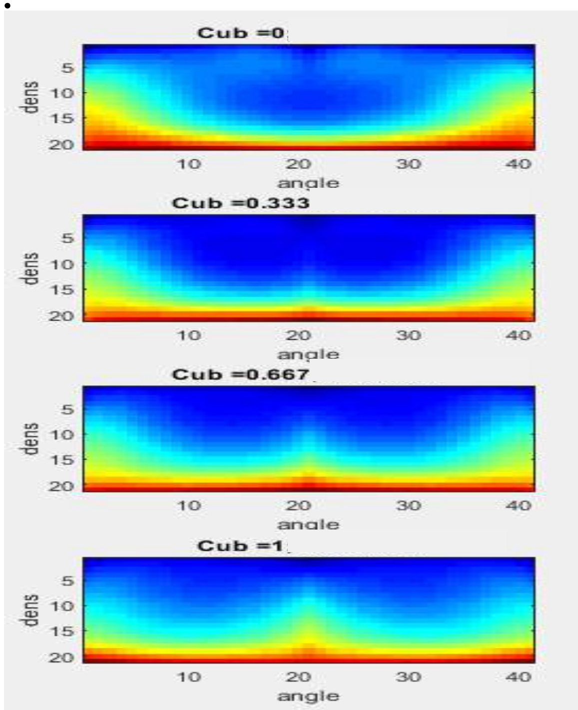
- t_{tot} =10'' on 200-300 macro-element design

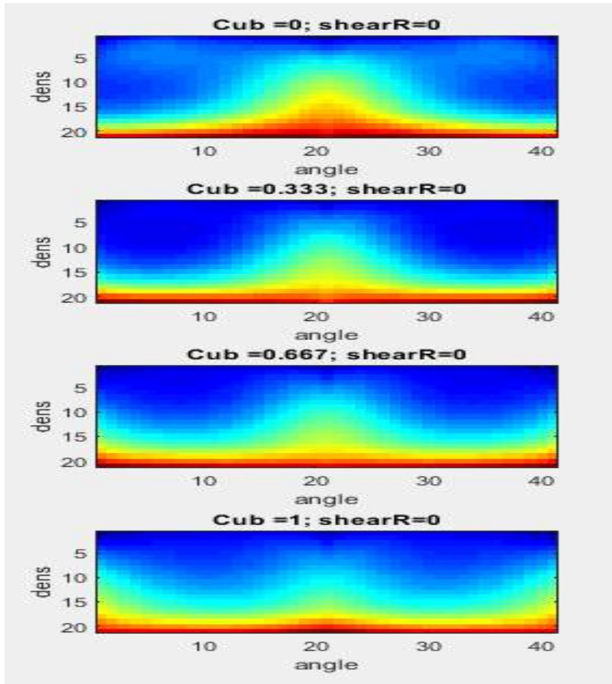
Elastic tensor's surrogate

to Avoid Nelement*cellOptimization at each macroOptimizatio



- 3 inputs : macro-density, angle, cubicity
- 6 outputs : elastic tensor values
- Gaussian interpolation : capture local effects but mitigate no
- E1111: E2222:





Efficient Multiscale Topology Optimization

Macroscale Problem

$$\underset{x^i_{dens}, x^i_a, x^i_b, \dots}{\text{minimize}} \quad c = u^T K u$$

$$\text{subject } to \quad Ku = f$$

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

$$\epsilon < \rho_{i,j} < 1$$

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

Nearest Optimal

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

Gaussian Process Regression

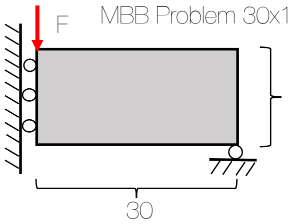
$$\mathbf{E}_{\text{pred}}(x^i) = \frac{\sum_{l=1}^{k} G(x^i, x_l)\mathbf{E}_{\text{db}}(x_l)}{\sum_{l=1}^{k} G(x^i, x_l)}$$

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

$$x^{i\prime} = [x^i_{\text{dens}} + \Delta, x^i_{\text{or}}, x^i_{\text{cub}}] \qquad \Delta = 0.01$$

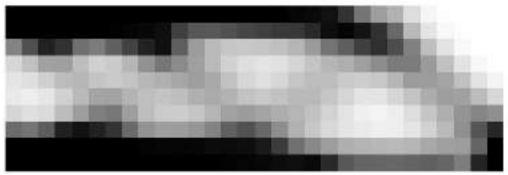
$$\frac{\partial \mathbf{E}_{\text{pred}}}{\partial x_{\text{dens}}}(x^i) \approx \frac{\mathbf{E}_{\text{pred}}(x^{i\prime}) - \mathbf{E}_{\text{pred}}(x^i)}{\Delta}$$

MBB Problem 30x10 macro elements



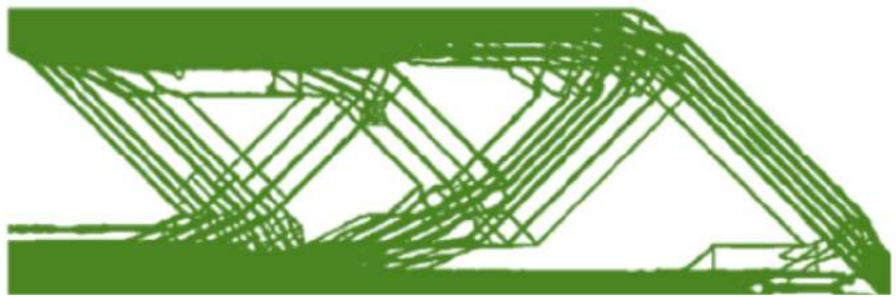
Theoretical compliance 192.7

Density of the cells



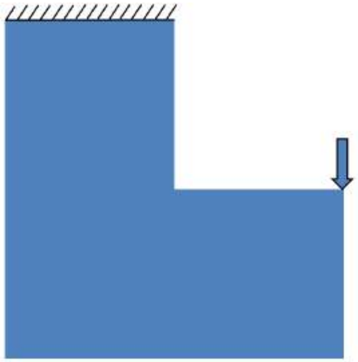
Orientation of the cells

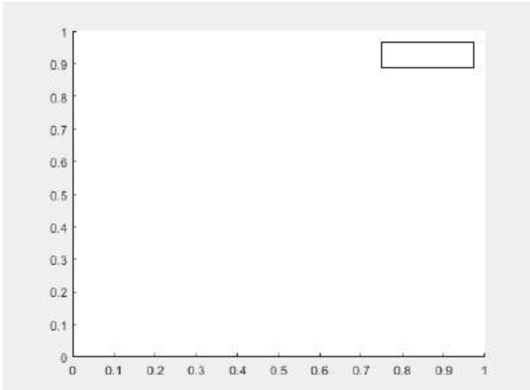
Cubicity of the cells

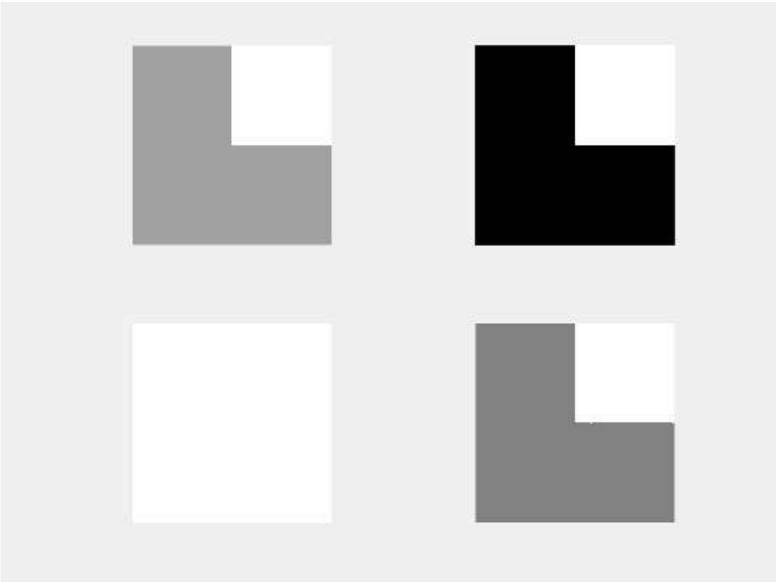


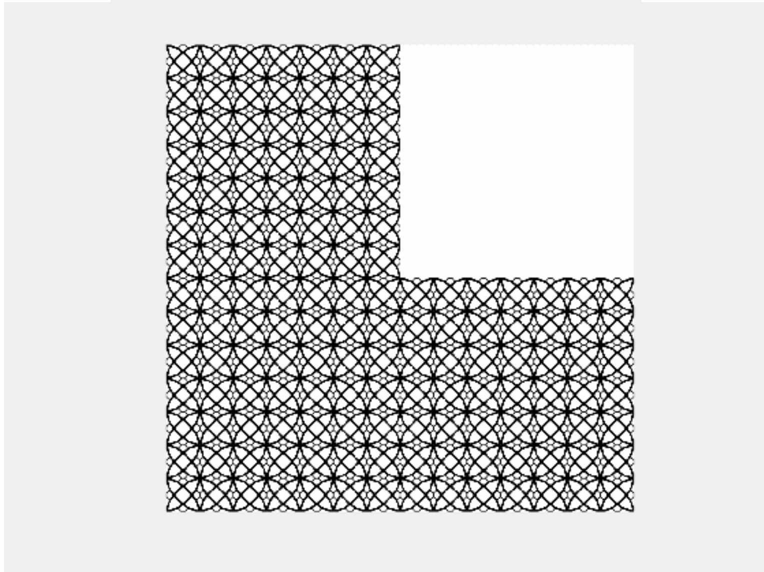
Result on classical test cases

- Validation on
 small grid
$\Rightarrow$ Evaluate
full-scale design



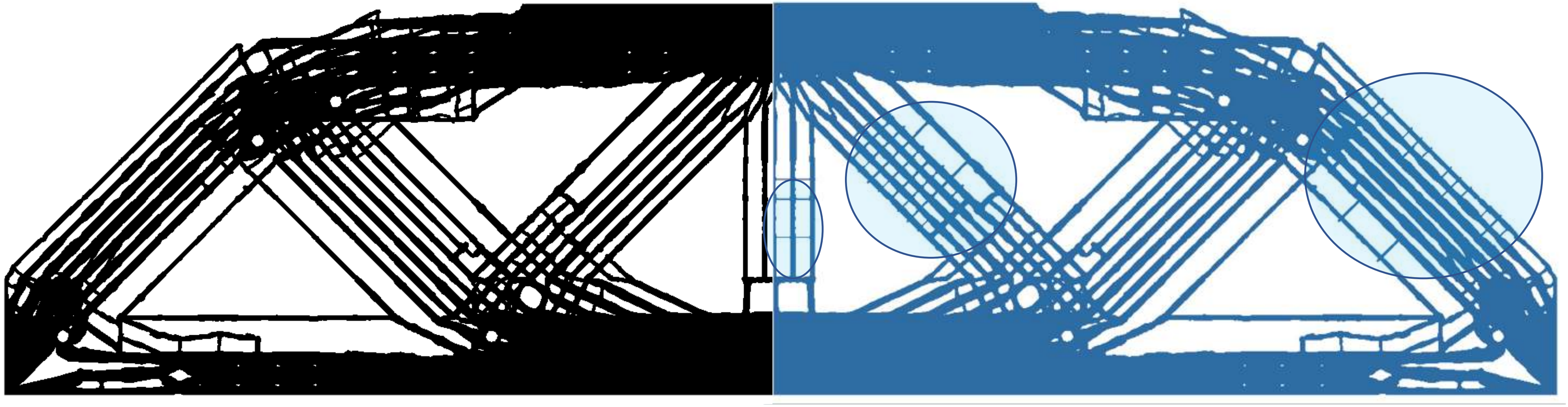




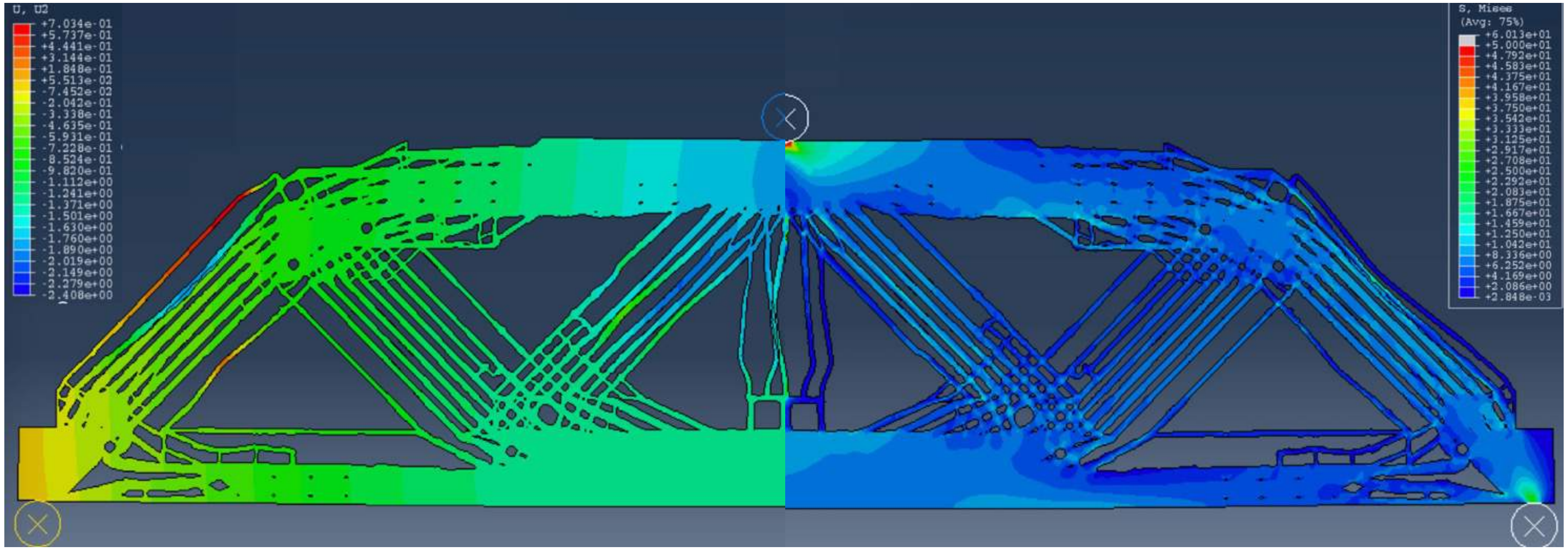


- 4x14*14 design variables;   stopping criteria : tolfun< 10^{-3}

Do you see a difference (Left2Right)?



EMTO 3pts bending (disp vs stress)

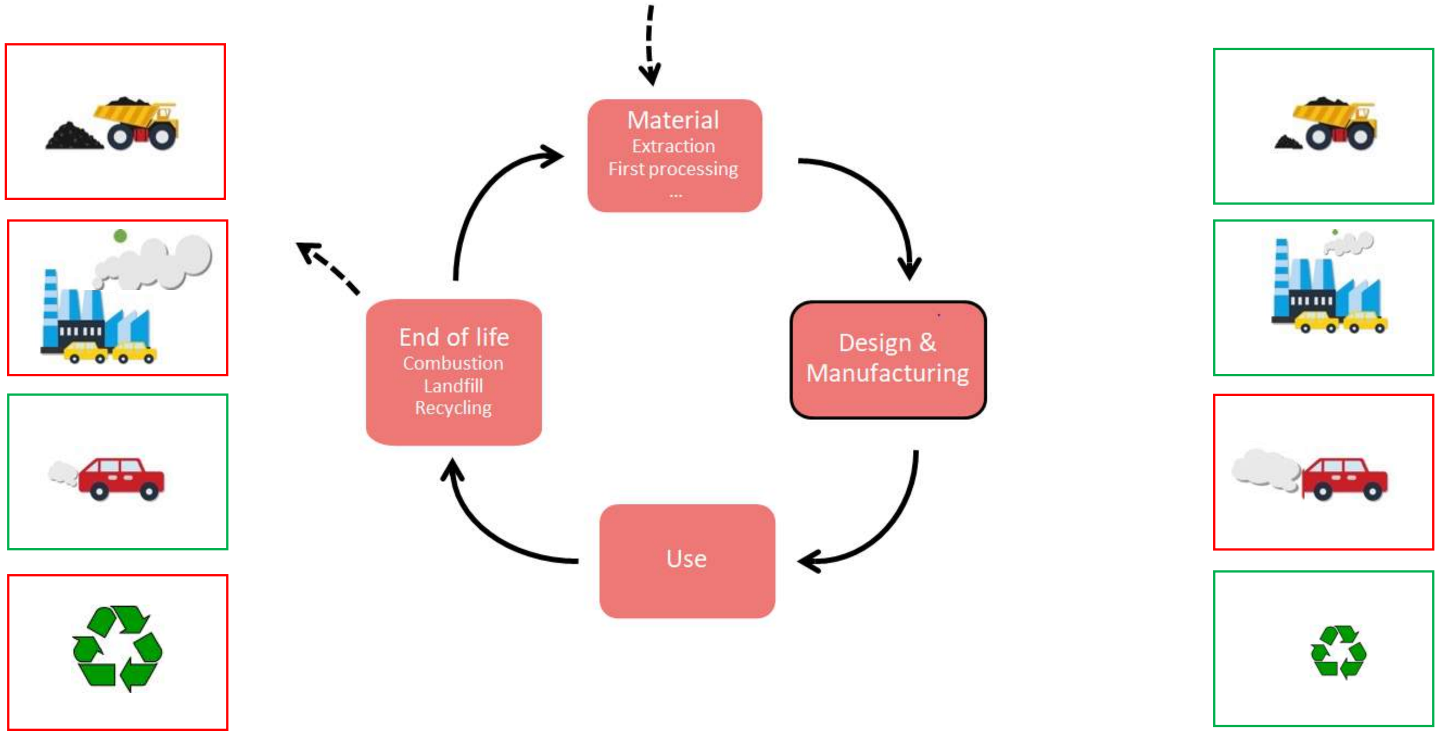


Selective Laser Melting (SLM)

ABAQUS REANALYSE

Hypothesis 2

- CO_2 emissions minimization of parts
  - If material choice is **free** => more complicated



First zoom

Procedia CIRP
Volume 109, 2022, Pages 454-459

Ecodesign with topology optimization

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

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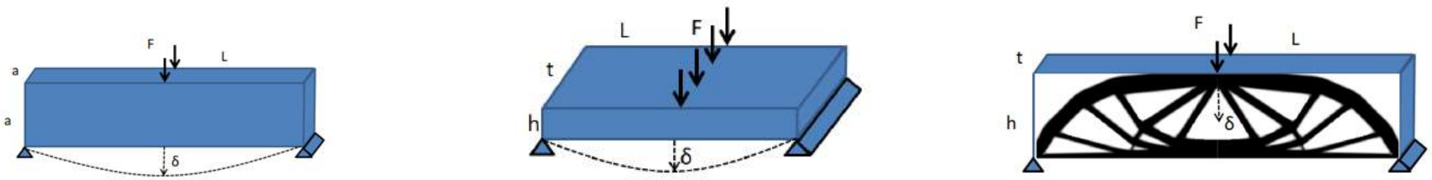
https://doi.org/10.1016/j.procir.2022.05.278 Get rights and content

Missing point from Ashby's theory: The absence of a simple analytical relation between compliance and volume fraction.

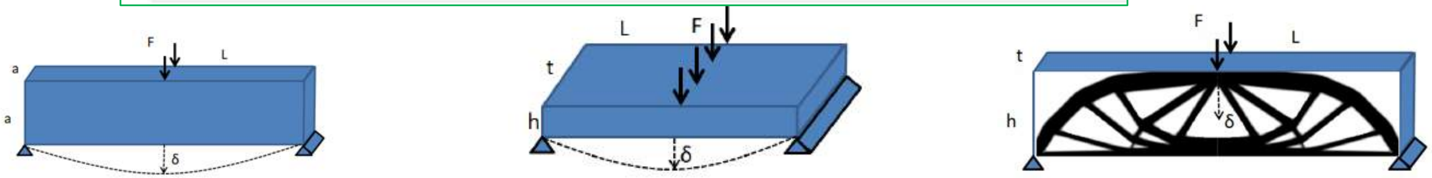


Material index

- If fixed material and process, CO_2 minimization = mass minimization
- Material choice through indices introduced by Ashby

  => uncouple material choice and part sizing
- Include the geometrical design (Ɗ) in the variables :

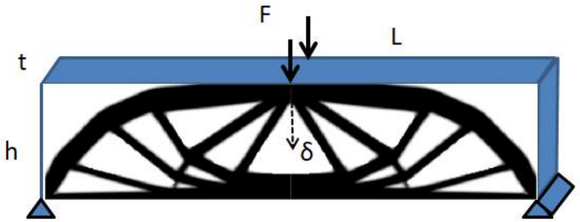
Properties	Bending beam (Ashby)	Bending plate (Ashby)	Duriez et al. (2022b)
Free variables	a, m	h, m	t, $\mathscr{D}$, m
Fixed	L, $\mathscr{D}$	L, t, $\mathscr{D}$	L_{max}, h_{max}
Constraint	δ_{max}	δ_{max}	δ_{max}



Ashby, M.F., 2004. Materials selection in mechanical design. 2. ed., reprinted ed., Elsevier Butterworth-Heinemann, Amsterdam.

Deriving the material index

- Problem considered:



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

- Objective function:

$$CO_2{}^{tot} = CO_2{}^{mat} \times M + CO_2{}^{veh} \times LD \times M$$

How many miles does an airplane like a 777 fly over the course of its lifetime?

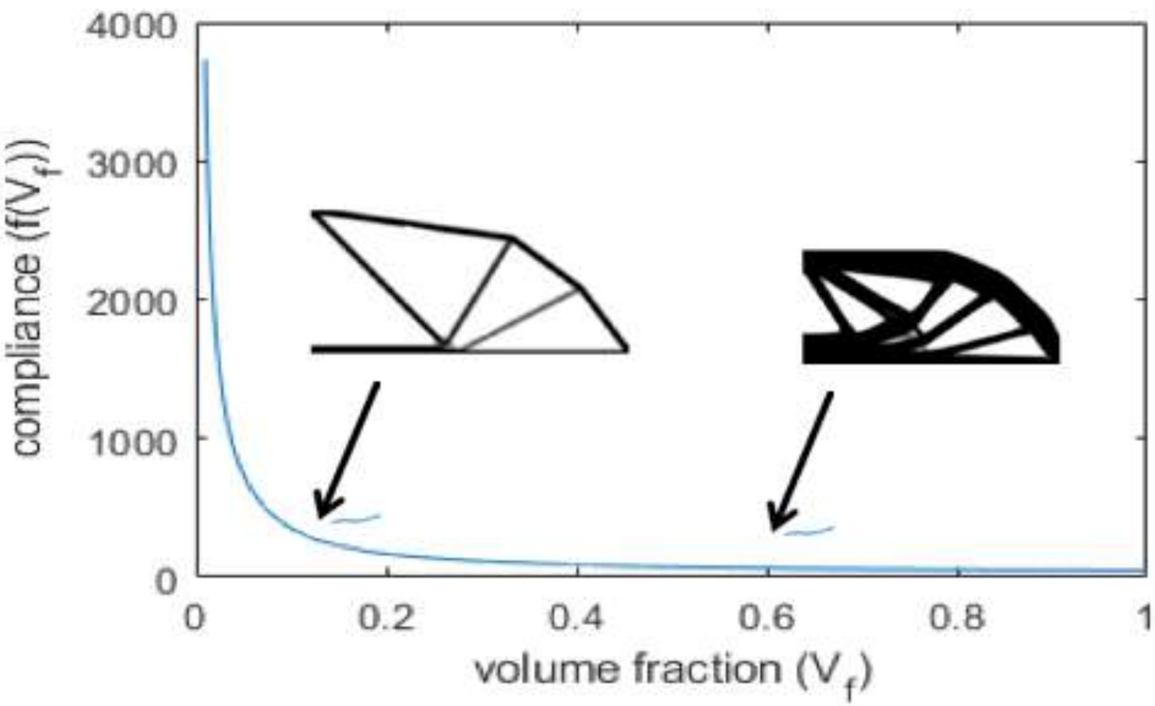
777: A 30-year lifetime. 3,500 hours a year as an average. An average speed of 500 miles per hour. 30 x 3500 x 500 = 52,500,000 miles i.e. LD.

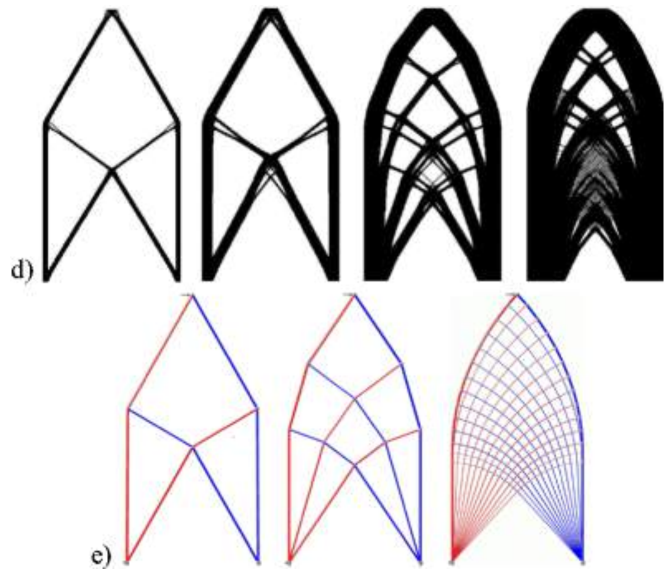
Topology optimization pareto front

V_f : volume fraction (ratio of space containing material)

f(V_f) : compliance – volume fraction pareto front

Edouard Duriez, Miguel Charlotte, Catherine Azzaro-Pantel et al. On some properties of the compliance-volume fraction Pareto front in topology optimization useful for material selection., 27 December 2022, PREPRINT (Version 1) available at Research Square [https://doi.org/10.21203/rs.3.rs-2390440/v1]

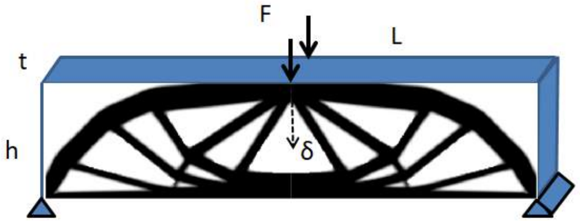




Sigmund, O., Aage, N., & Andreassen, E. (2016). On the (non-) optimality of Michell structures. Structural and Multidisciplinary Optimization, 54, 361-373.

Deriving the material index

- Problem considered:



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

- Objective function:

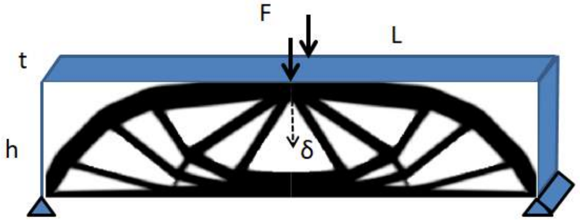
$$CO_2{}^{tot} = CO_2{}^{mat} \times M + CO_2{}^{veh} \times LD \times M$$

Deriving the material inde›

starting from $C = U^T K U = U^T F = U(i_F)F(i_F) = FU(i_F)$

$$M = \rho t L h V_f$$

- Problem considered:



compliance

$$C \leq F\delta_{max}$$

$$\frac{f(V_f)F}{tE} = \delta_{max}$$

If t is a free variable, it can be chosen as in compliance to achieve the minimum mass.

$$t = \frac{f(V_f)F}{\delta_{max}E} \quad \text{thus} \quad M = \frac{LhF}{\delta_{max}}\frac{\rho}{E}f(V_f)V_f$$

$$CO_2^{\,tot} = \underbrace{\left(CO_2^{\,mat} + LD\ CO_2^{\,veh}\right)\times\frac{\rho}{E}}_{\text{Material } f_3(M)}\ \underbrace{\frac{LhF}{\delta_{max}}}_{\text{functional } f_1(F)}\ \underbrace{f(V_f)V_f}_{\text{topology index } f_2(G)}$$

REMINDER !!

- Many materials
- Competing properties

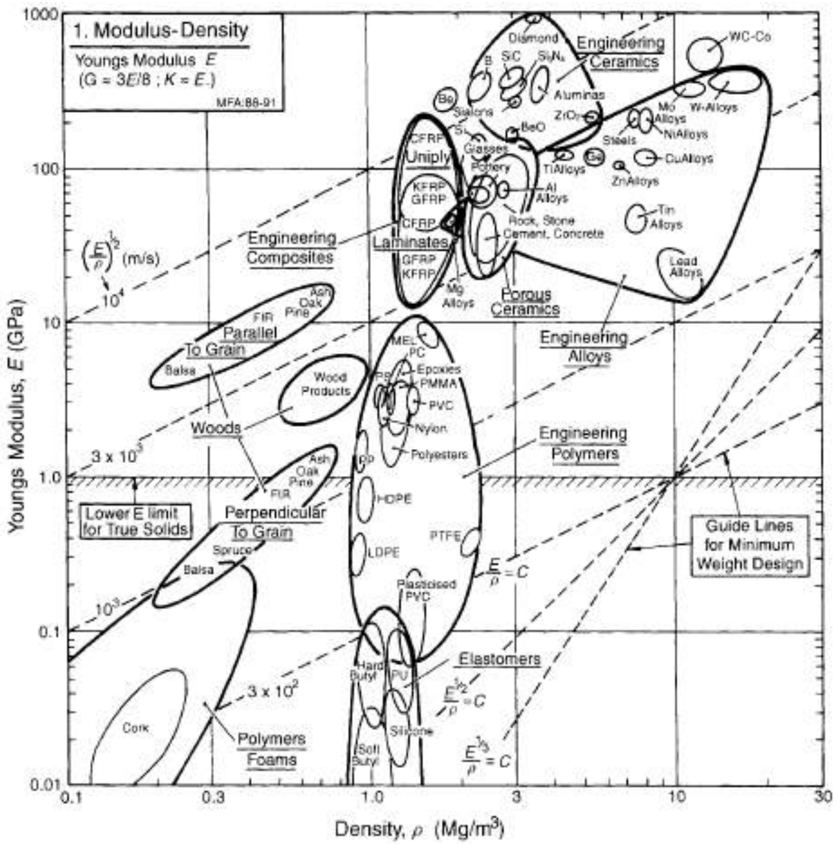
- => Ashby indexes: $f_3(M)$

P=$f_1(F)$ x $f_2(G)$x $f_3(M)$

F: Functional constraints

G: Geometrical constraints

M: Material properties

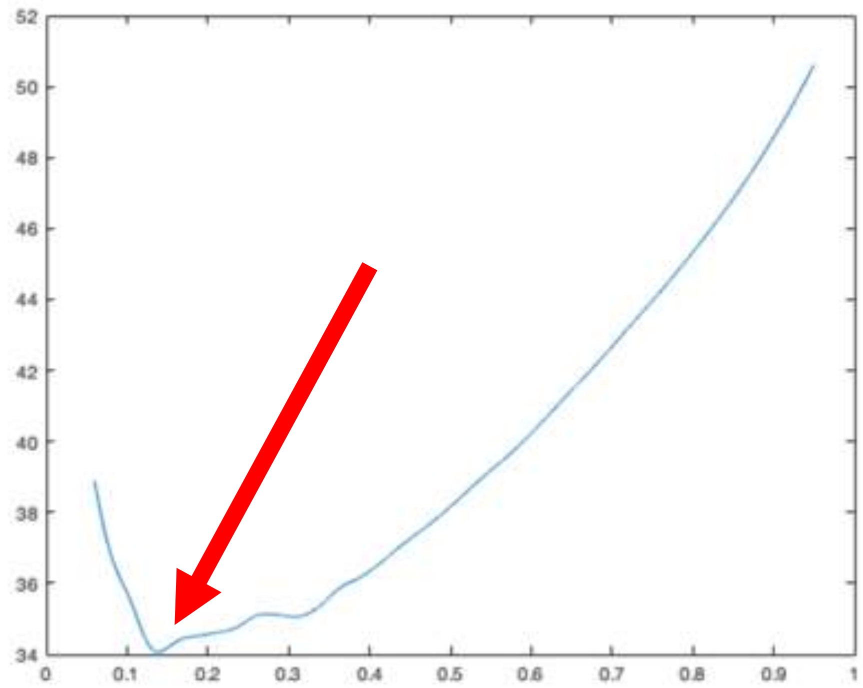


M. F. Ashby et Kara Johnson. « Materials and Design : The Art and Science of Material Selection in Product Design ». In : 2002.

Minimize topology index

topology index $f_2(G)$

- Topology index : $f(V_f)V_f$:
  Minimize this to minimize mass
- Thickness t is finally adjusted tc satisfy constraint



Data for Material index

functional improvement can be found in lightweight components for transport systems

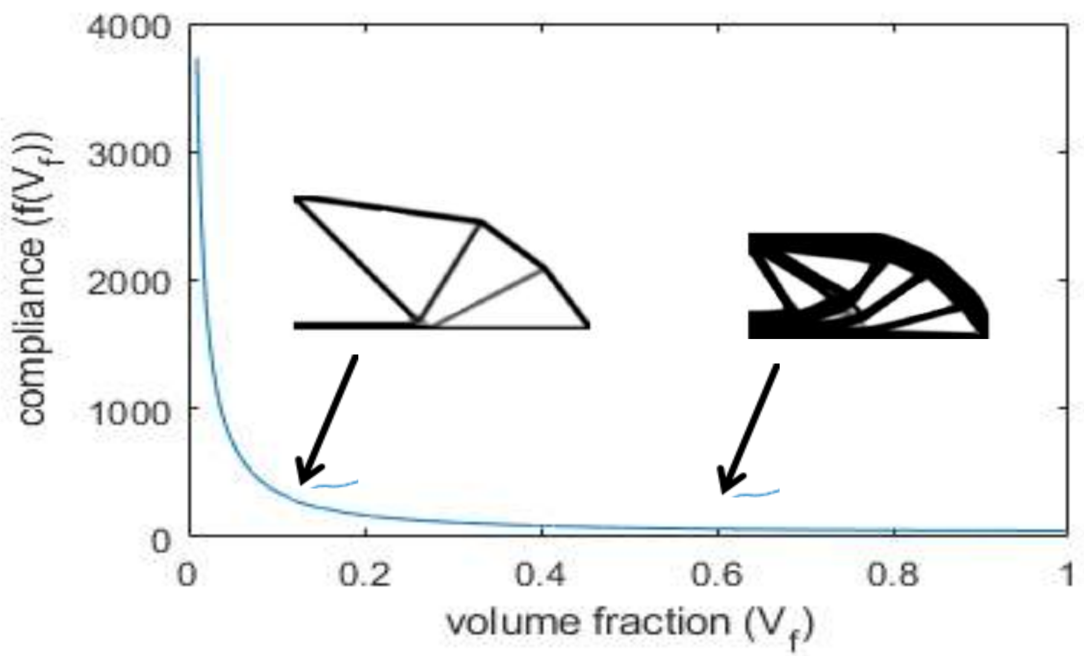
Table 8. Fuel consumption reduction coefficients for different vehicle types and related life time impact savings per kg of weight reduction.

Transport system	Energy source	FRC [26]	Service life	Eco-Impact (ReCiPe H/A)	Life time savings (ReCiPe H/A)	Equivalent electrical energy
Gasoline car	Gasoline	0.5 l / (100kg*100km)	200000km	0.121 Pts/l	1.21 Pts/kg	85 MJ
Diesel car	Diesel	0.24 l / (100kg*100km)	200000km	0.141 Pts/l	0.68 Pts/kg	48 MJ
Short distance train	Electricity	300 kJ / (1000kg*km)	$3.5*10^6$ km	0.051 Pts/kWh	14.88 Pts/kg	1050 MJ
Long distance train	Electricity	100 kJ / (1000kg*km)	$10*10^6$ km	0.051 Pts/kWh	14.17 Pts/kg	1000 MJ
Short distance aircraft	Kerosene	12.5 ton / (100kg*year)	25 year	0.134 Pts/l	335 Pts/kg	23647 MJ
Long distance aircraft	Kerosene	$\boxed{\text{103 ton / (100kg*year)}}$	25 year	0.134 Pts/l	2760 Pts/kg	194852 MJ

Kellens, Karel, et al. "Environmental impact of additive manufacturing processes: does AM contribute to a more sustainable way of part manufacturing?." Procedia Cirp 61 (2017): 582-587.

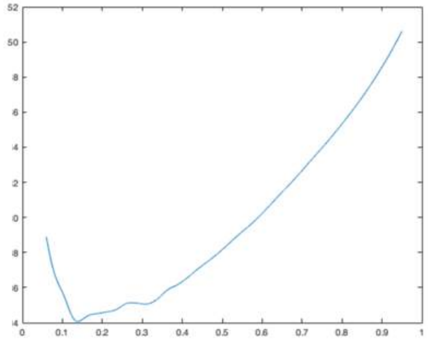
Code

```
%Al alloy Stainless Steel Ti alloy inconel
Emat=[70.8, 197, 115, 205].*10^9;
rhomat=[2795, 7915, 4425, 7900];
co2mat=[13, 6.15, 40.4, 15.5];
L=2; %m
h=0.5; %m
delta_max=0.005;
F=20000;

life=25;
FRC=103; %tonco2/100kg/year
lifekero=FRC*life*1000/100;  %kgco2/kg
%from ADEME : jet A in France or europe :  3.83kgeCO2/kg.
emitkero=3.83; %kgco2 / kg kerosen
lifeco2=lifekero*emitkero;
co2veh=lifeco2/lveh; %kgCO2/km

load('complHRr3.csv')
cP1=complHRr3(:,2);
%filtering
   win=1000;
   xgauss=0:1:win-1;
   sig=win/8;
   ygauss=1/(sig*sqrt(2*pi))*exp(-0.5*(xgauss-(win-1)/2).^2./sig^2);
   cFiltG=conv(cP1,ygauss);
   cFiltGT=cFiltG(win:end-win);
%
%cpareto=complHRr3(:,2); %raw pareto %Pando % multistart
cpareto=cFiltGT;
vpareto= 0.01:0.0001:1;
vpareto=vpareto(win/2:end-win/2-1);%
figure(1)
plot(vpareto, cpareto);
```



Code (bis)

```
figure(2)
plot(vpareto,vpareto'.*cpareto);

[optimalvfv,optimalvf]=min(vpareto'.*cpareto);
optVf=vpareto(optimalvf);

%Al alloy Stainless Steel Ti alloy inconel
for material=1:4 % 2 or 3 or 4

thick(material)=cpareto(optimalvf)*F/delta_max/Emat(material);
mass(material)=L*h*thick(material)*optVf*rhomat(material);
co2mat(material)
Idx_veh(material)=(Emat(material)/rhomat(material))*(co2mat(material)+lveh*co2veh)
Idx_bridge(material)=(Emat(material)/rhomat(material))*(co2mat(material))

Impact_CO2veh(material)=(co2mat(material)+lveh*co2veh)*mass(material);

Impact_CO2bridge(material)=(co2mat(material))*mass(material);
```



Al alloy Stainless Steel Ti alloy inconel

Material $f_3(M)$ IS

$$Idx = ({CO_2}^{mat} + LD\,{CO_2}^{veh}) \times \frac{\rho}{E}$$

Search for lower Idx
depending on the application

mass = 5.3807 5.4761 5.2445 5.2525

co2mat = 13.0000 6.1500 40.4000 15.5000

Impact_CO2veh = 1.0e+05 * 5.3073 5.4011 5.1744 5.1809

Impact_CO2bridge = 69.9492 33.6783 211.8788 81.4133

Idx_veh = 1.0e+12 * 2.4985 2.4548 2.5641 2.5596

Idx_bridge =1.0e+09 * 0.3293 0.1531 1.0499 0.4022

Results

- Results change depending on the application:

- Aircraft

Material	E (GPa)	ρ (kg/m^3)	CO^i_{2mat} $(kgCO_2/kg)$	Idx $(kgCO_2/N/m)$
Al alloy	70.8	2795	13.0	3.90×10^{-3}
Stainless steel	197	7915	6.15	3.97×10^{-3}
Ti alloy	115	4425	40.4	3.80×10^{-3}
Inconel 713	205	7900	15.5	3.81×10^{-3}

mass : 5,24kg 5.2445

CO_2 emissions:
517 tons 1.0e+05 * 5.1744

- Pedestrian bridge

Material	E (GPa)	ρ (kg/m^3)	CO^i_{2mat} $(kgCO_2/kg)$	Idx $(kgCO_2/N/m)$
Al alloy	70.8	2795	13.0	5.13×10^{-7}
Stainless steel	197	7915	6.15	2.47×10^{-7}
Ti alloy	115	4425	40.4	1.56×10^{-6}
Inconel 713	205	7900	15.5	5.97×10^{-7}

mass : 5,47kg 5.4761

CO_2 emissions:
33,67 kg
33.6783

To go deeper

Cleaner Environmental Systems
Volume 9, June 2023, 100114

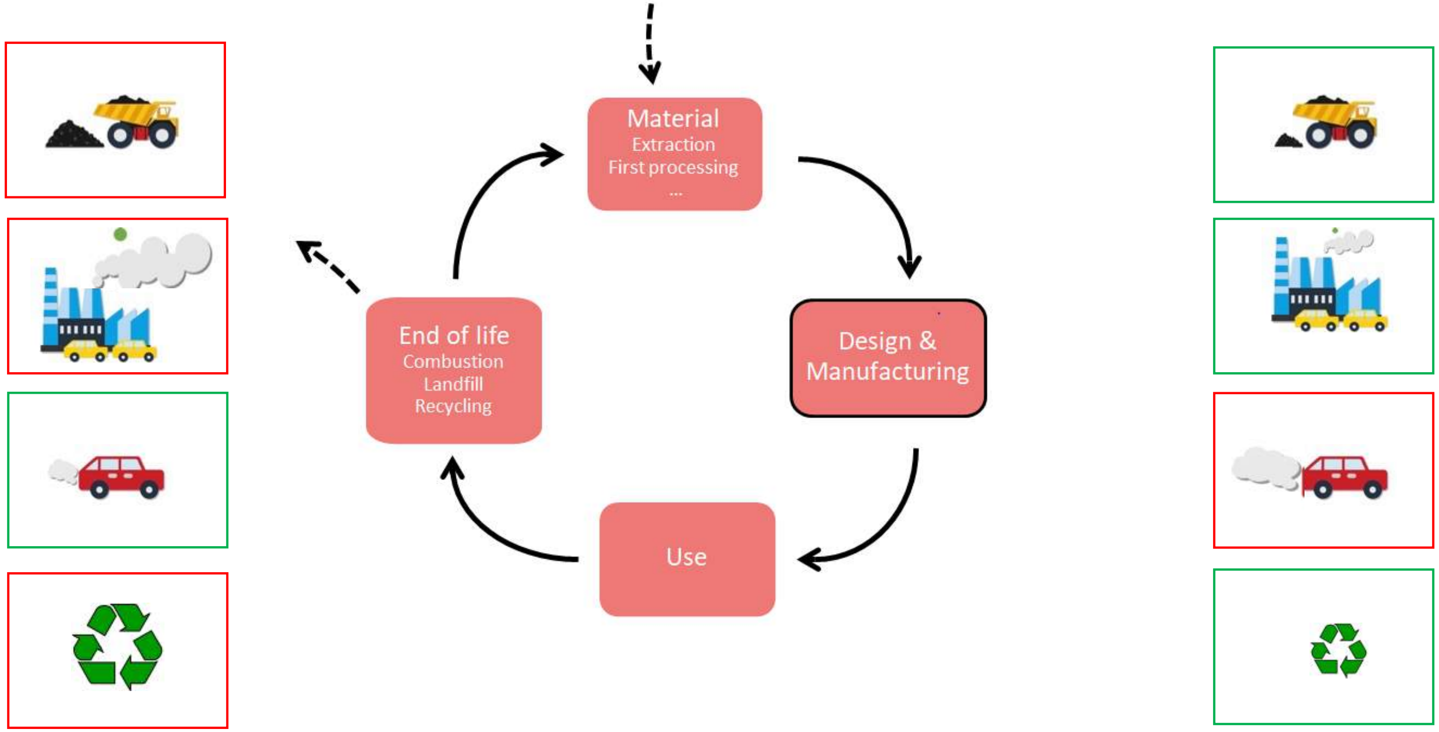
A fast method of material, design and process eco-selection via topology optimization, for additive manufactured structures

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

Properties	**Bending beam (Ashby)**	**Bending plate (Ashby)**	**Duriez et al. (2022b)**	**Our problem**
Free variables	a, m	h, m	t, $\mathscr{D}$, m	$\mathscr{D}, m, p$
Fixed	L, $\mathscr{D}$	L, t, $\mathscr{D}$	$L_{\max}$, $h_{\max}$	$L_{\max}$, $h_{\max}$, $t_{\max}$
Constraint	$\delta_{\max}$	$\delta_{\max}$	$\delta_{\max}$	$\delta_{\max}$

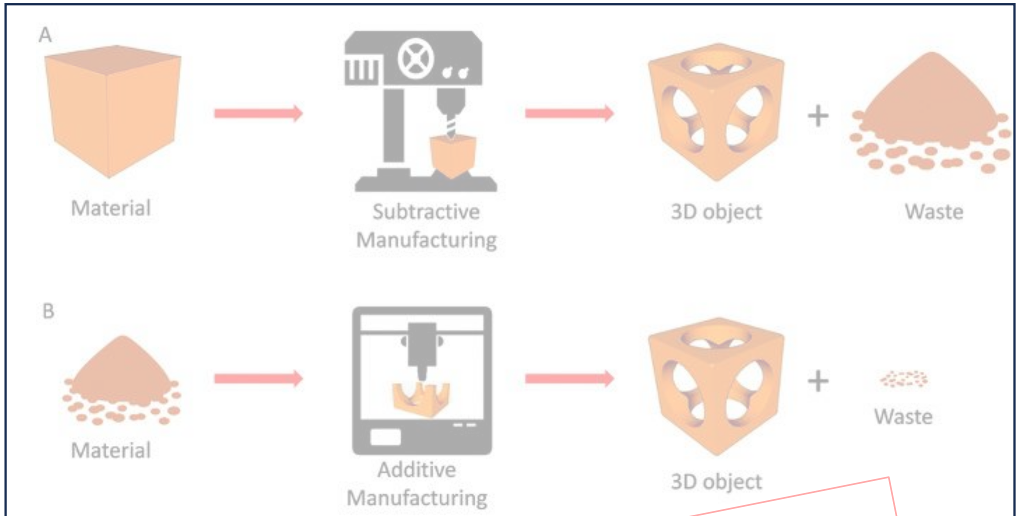
Hypothesis 2

- CO_2 emissions minimization of parts
  - If material choice is **free** => more complicated

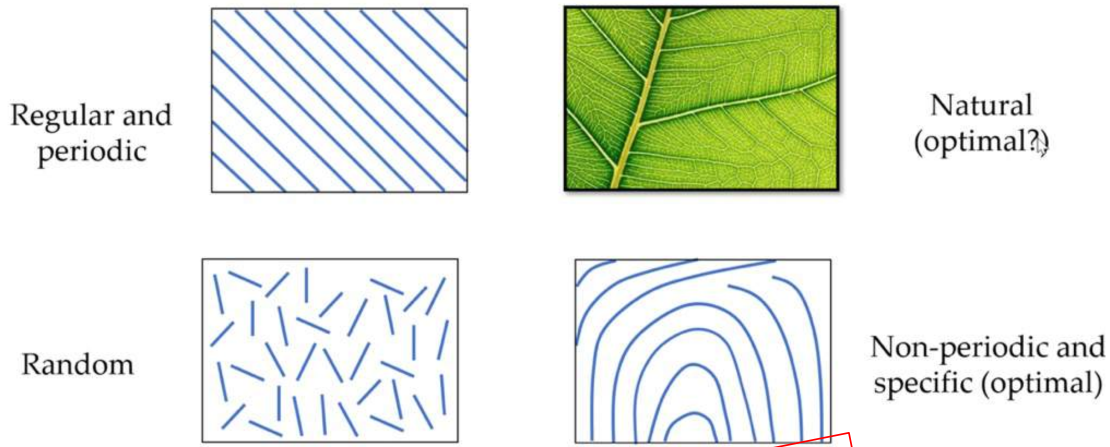


Process is AM, but WHY?

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



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

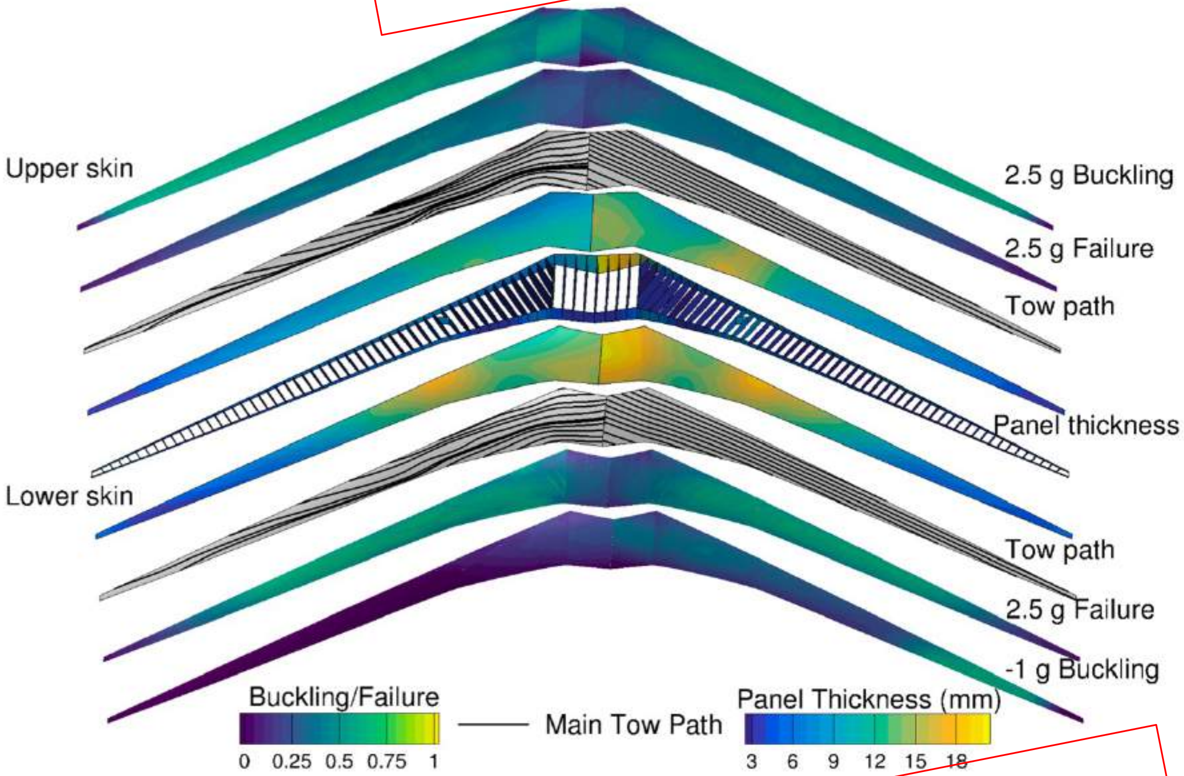


+ Automatic Fiber Placement + eco-fiber/resin selection
+Monitoring

Composites Fiber Placement as DVs

https://www.compositesworld.com/articles/tow-steering-part-2-the-next-generation

X* is a UHAR Wing ;)

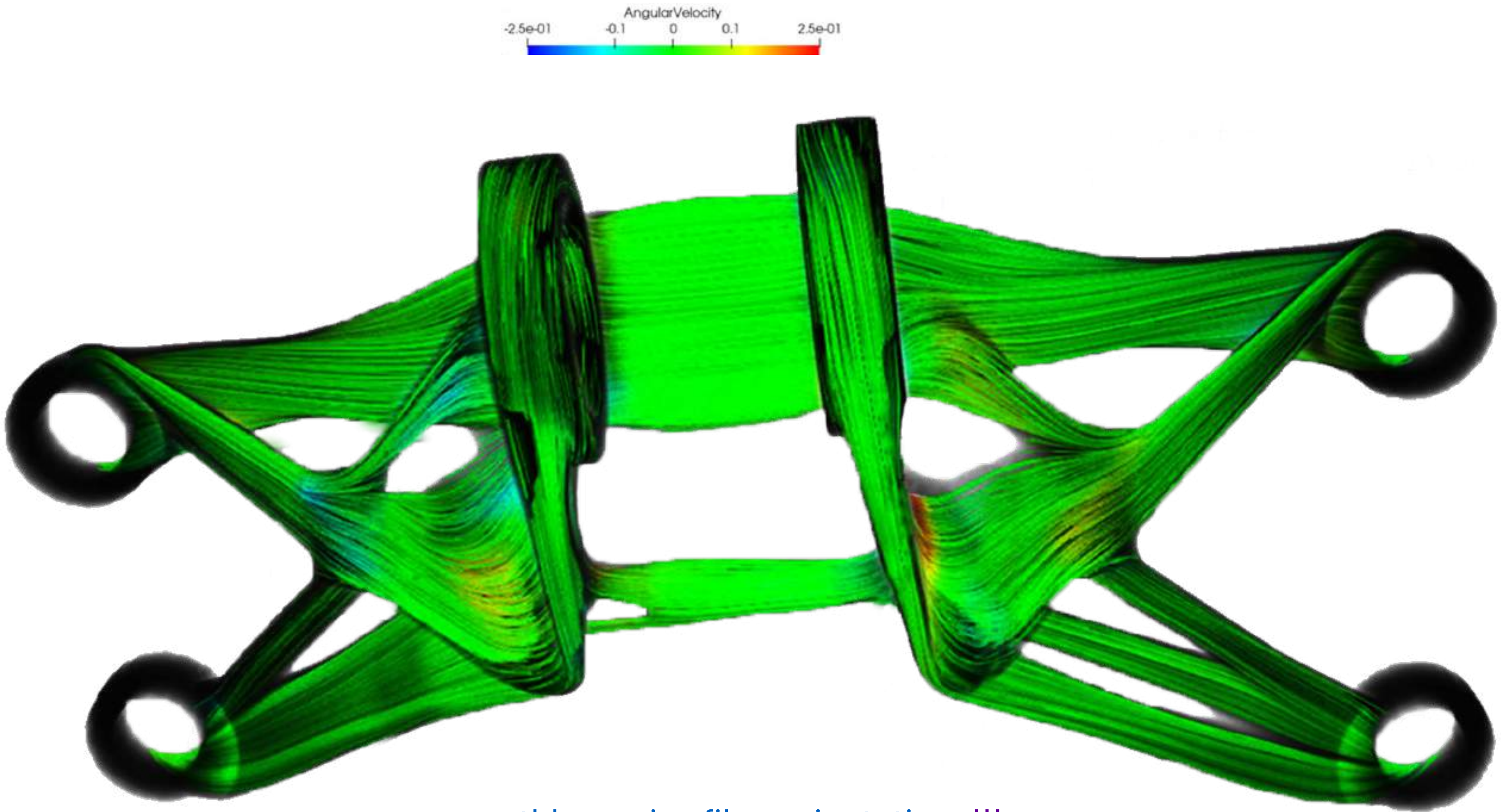


Brooks, T. R., Martins, J. R., & Kennedy, G. J. (2019). High-fidelity aerostructural optimization of tow-steered composite wings. Journal of Fluids and Structures, 88, 122-147.

Brooks, T. R., Martins, J. R., & Kennedy, G. J. (2020). Aerostructural tradeoffs for tow-steered composite wings. Journal of Aircraft, 57(5), 787-799.

Lower wing mass,
Less fuel burn

GE Bracket by Schmidt et al., Struct. Multidiscip. Optim. (2020)



smoothly varying fiber orientations!!!

Collaboration with TU Delft

In-plane fibre orientations

- Optimisation problem formulation

$$\min_{\boldsymbol{\rho},\boldsymbol{\theta}} c(\boldsymbol{\rho},\boldsymbol{\theta}) = \sum_e \rho_e^p \, \boldsymbol{u_e^T} \, \boldsymbol{k_0}(\theta_e) \, \boldsymbol{u_e^T}$$

$$\text{s.t.} \begin{cases} \frac{V(\boldsymbol{\rho})}{V_0} \leq f \\ \boldsymbol{KU} = \boldsymbol{F} \\ 0 < \rho_{min} \leq \boldsymbol{\rho} \leq 1 \\ -\pi \leq \boldsymbol{\theta} \leq \pi \end{cases}$$

solved with initial random point

The finite element analysis step calls the Ansys solver via the PyMAPDL interface

- Filters

$$\rho_e \widetilde{\frac{\partial c}{\partial \rho_e}} = \frac{1}{\sum_i H_{ei}^{\rho}} \sum_i H_{ei}^{\rho} \rho_i \frac{\partial c}{\partial \rho_i}$$

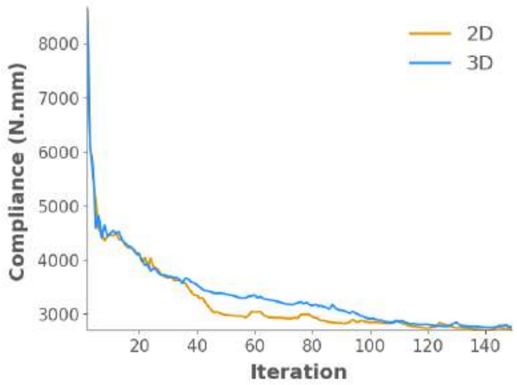
$$H_{ei}^{\rho} = \max(0, r_{\rho} - \Delta(e,i))$$

$$\tilde{\theta}_e = \frac{1}{\sum_i H_{ei}^{\theta} \rho_i} \sum_i H_{ei}^{\theta} \rho_i \theta_i$$

$$H_{ei}^{\theta} = \max(0, r_{\theta} - \Delta(e,i))$$

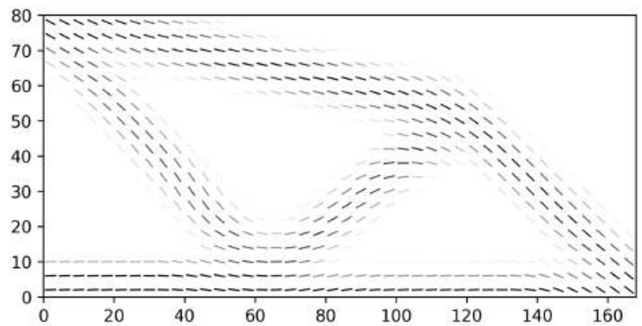
AFP

Problem 1 - MBB beam

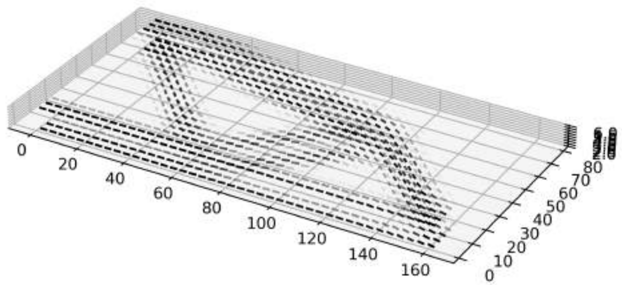


www.github.com/mid2SUPAERO/SOMP_Ansys/tree/csma

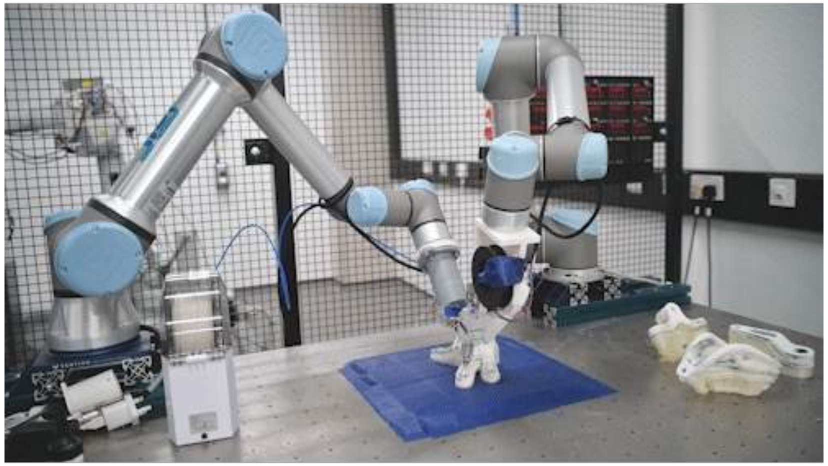
- 2D - Comp. = 2691 N.mm



- 3D - Comp. = 2733 N.mm

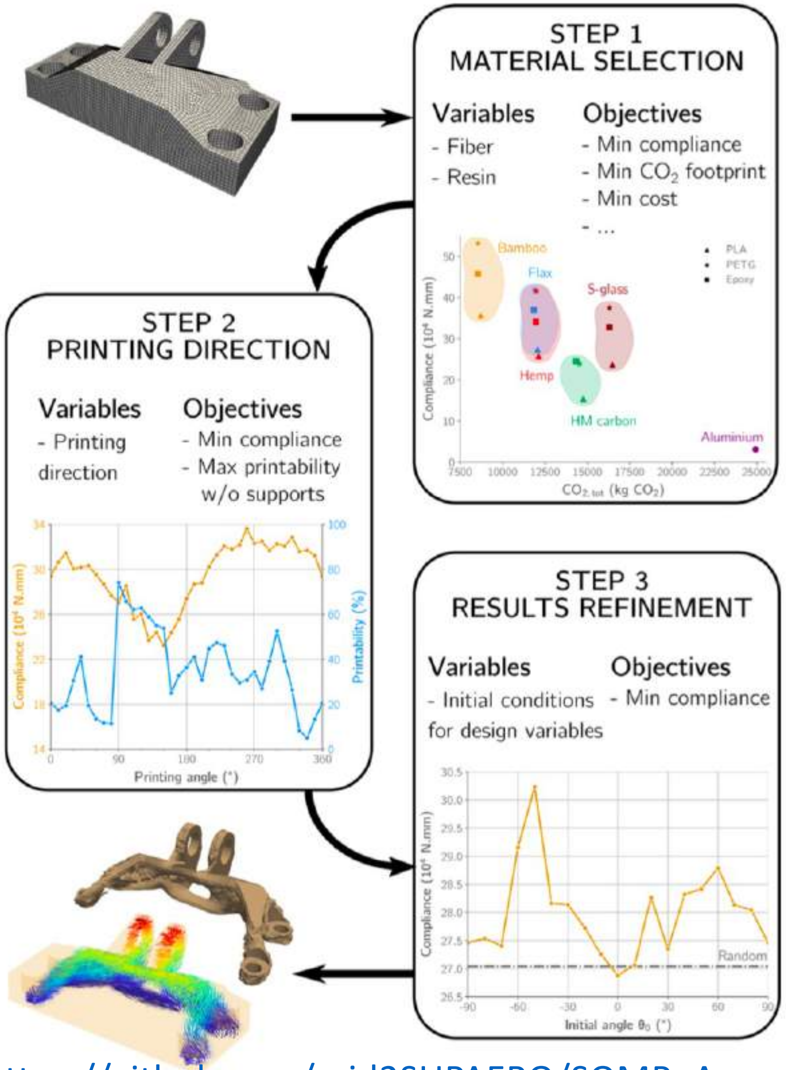


Inspired by spatial printing*



*Fang, G., Zhang, T., Huang, Y., Zhang, Z., Masania, K., & Wang, C. C. (2024). Exceptional mechanical performance by spatial printing with continuous fiber: Curved slicing, toolpath generation and physical verification. Additive Manufacturing, 104048.

https://www.youtube.com/watch?v=7Jxyu9uRMLo



https://github.com/mid2SUPAERO/SOMP_Ansys

Add Ecomaterial selection, printability

opensource 2D framework (but need an ANSYS LICENCE for 3D)

$$
\begin{aligned}
\min_{\boldsymbol{\rho},\boldsymbol{\theta},\boldsymbol{\alpha}} C(\boldsymbol{\rho},\boldsymbol{\theta},\boldsymbol{\alpha}) &= \left(\sum_{i\in LC} c_i(\boldsymbol{\rho},\boldsymbol{\theta},\boldsymbol{\alpha})^n\right)^{\frac{1}{n}} \\
&= \left(\sum_{i\in LC}\left(\sum_e \rho_e^p \boldsymbol{u}_{\boldsymbol{e},\boldsymbol{i}}^{\boldsymbol{T}} \boldsymbol{k}_0(\theta_e,\alpha_e)\boldsymbol{u}_{\boldsymbol{e},\boldsymbol{i}}\right)^n\right)^{\frac{1}{n}}
\end{aligned}
$$

$$
\text{s.t.}\ \begin{cases}
\frac{V(\boldsymbol{\rho})}{V_0} \leq f \\
\boldsymbol{KU} = \boldsymbol{F} \\
0 < \rho_{min} \leq \boldsymbol{\rho} \leq 1 \\
-\frac{\pi}{2} \leq \boldsymbol{\theta} \leq \frac{\pi}{2} \\
-\frac{\pi}{2} \leq \boldsymbol{\alpha} \leq \frac{\pi}{2}
\end{cases}
$$

$$
\frac{\partial C}{\partial \cdot} = \sum_{i\in LC} c_i^{n-1} C^{1-n} \frac{\partial c_i}{\partial \cdot}
$$

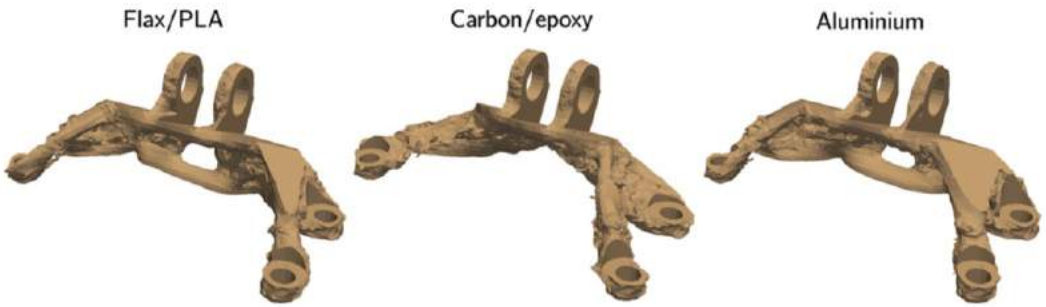


Figure 9: Isosurfaces of density 0.55 for different materials.

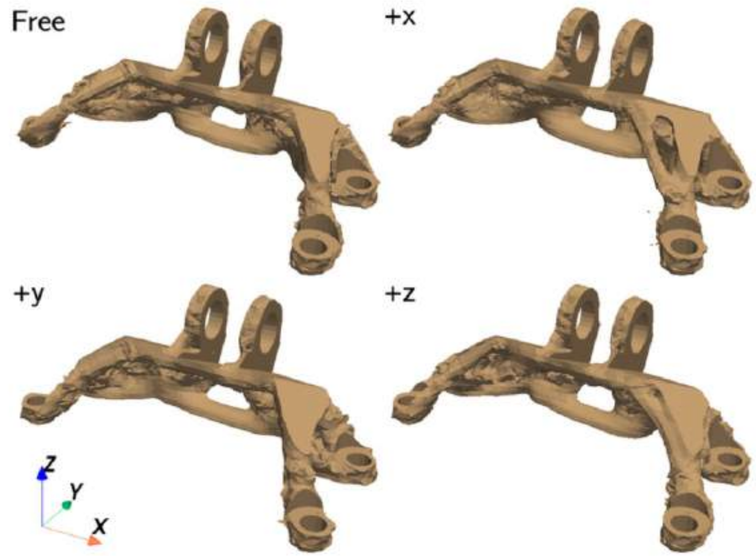
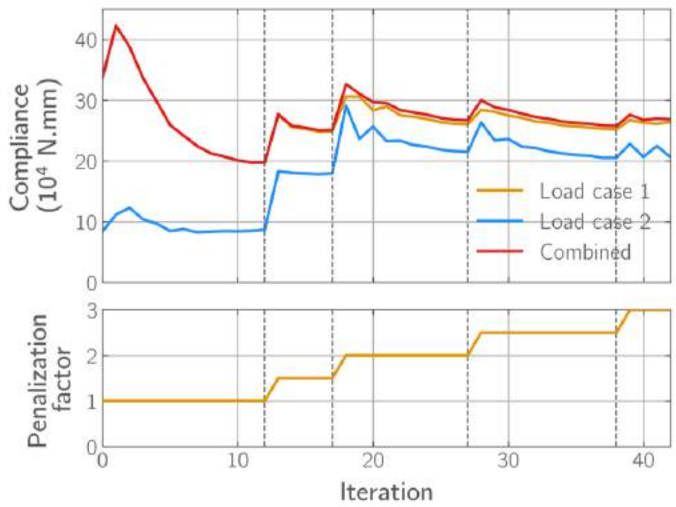
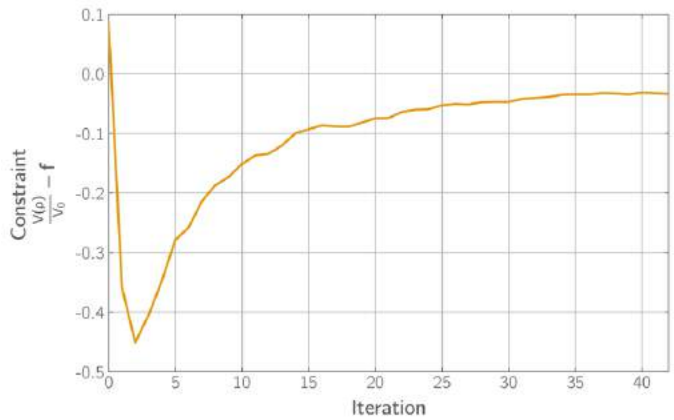


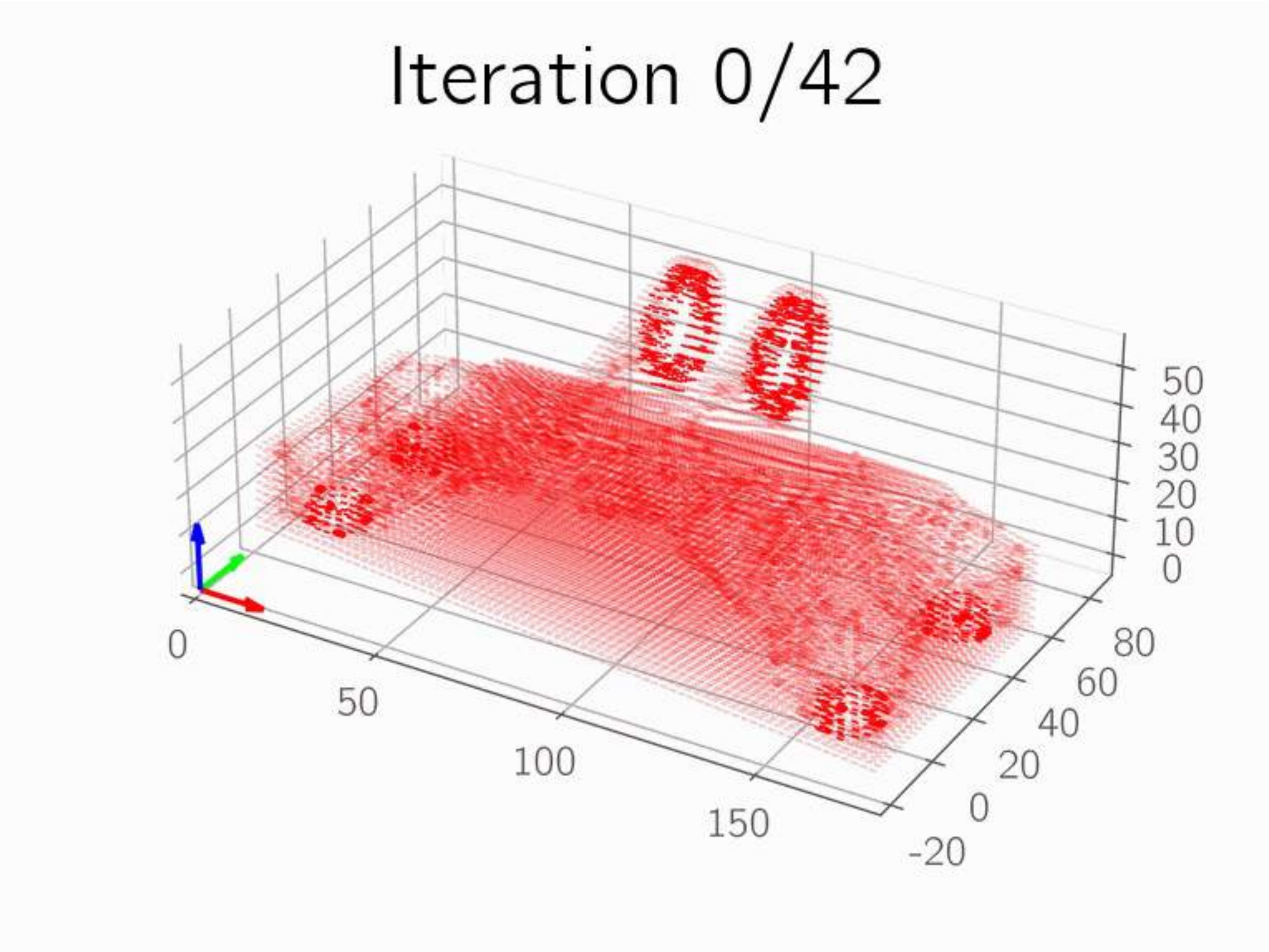
Figure 10: Isosurfaces of the optimal designs for each printing direction.

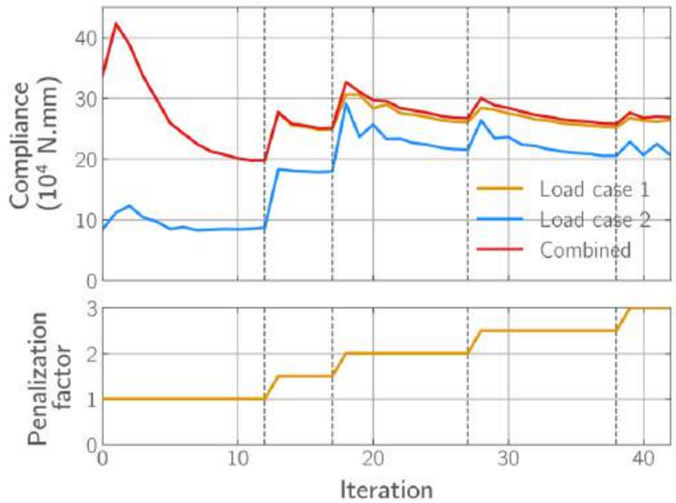
https://github.com/mid2SUPAERO/SOMP_Ansys

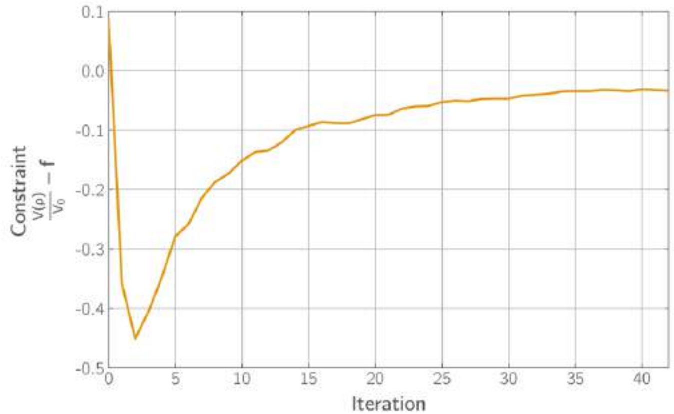
Iteration 1/42






Iteration 0/42
0
50
100
150
-20
0
20
40
60
80
0
10
20
30
40
50


Compliance (10^4 N.mm)
Load case 1
Load case 2
Combined
Penalization factor
Iteration


Constraint $\frac{V(\rho)}{V_0} - f$
Iteration

Add Ecomaterial selection, printability

Results

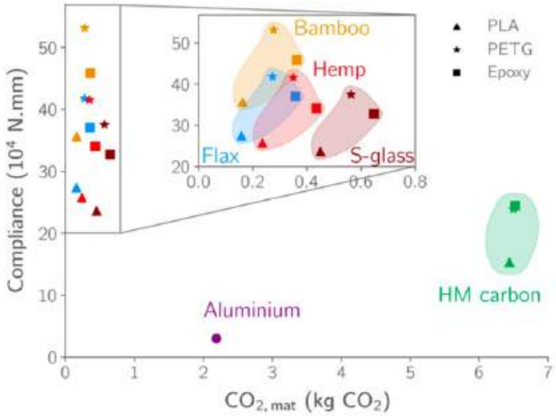


Figure 7: Compliance versus material production footprint of the optimal designs, grouped by fiber.

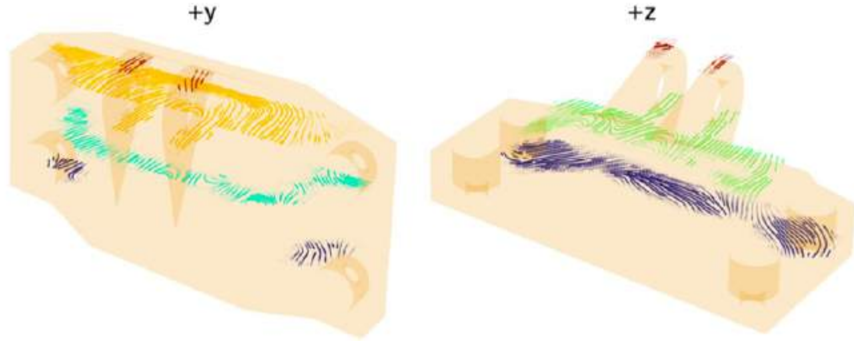


Figure 11: Examples of fiber distribution on slices of the optimal designs.

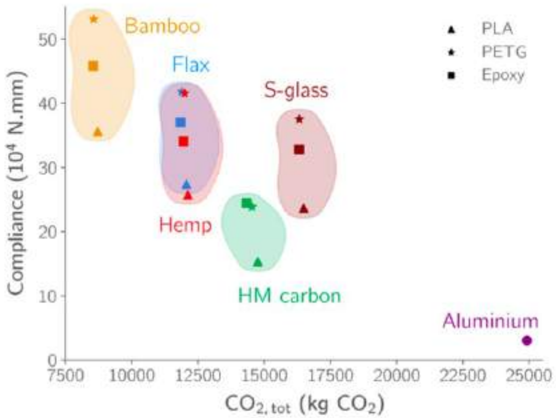


Figure 8: Compliance versus total footprint of the optimal designs, grouped by fiber.

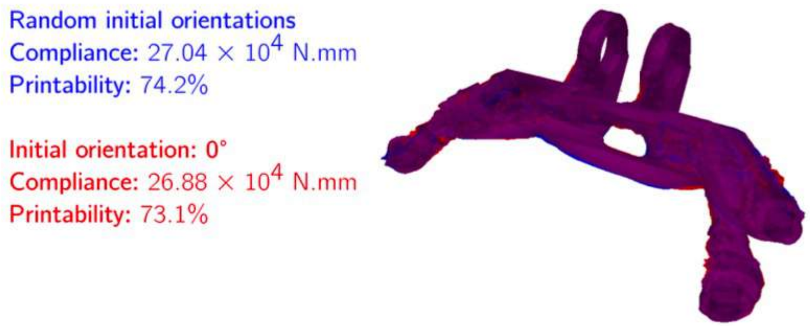
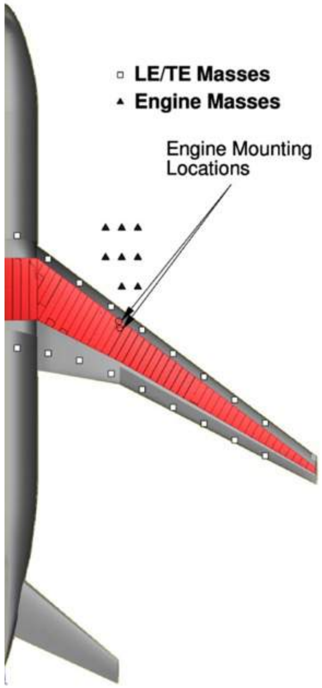


Figure 16: Isosurfaces of the optimal designs for random and 0° initial orientations.

https://github.com/mid2SUPAERO/SOMP_Ansys

Full wingbox concept

- Proof of concept of greener aerostructures with lattice wingbox
- Material as Design variable open new solutions:
- Who is the best?



Wingspan, m : 58.76
MTOW, t : 297,55

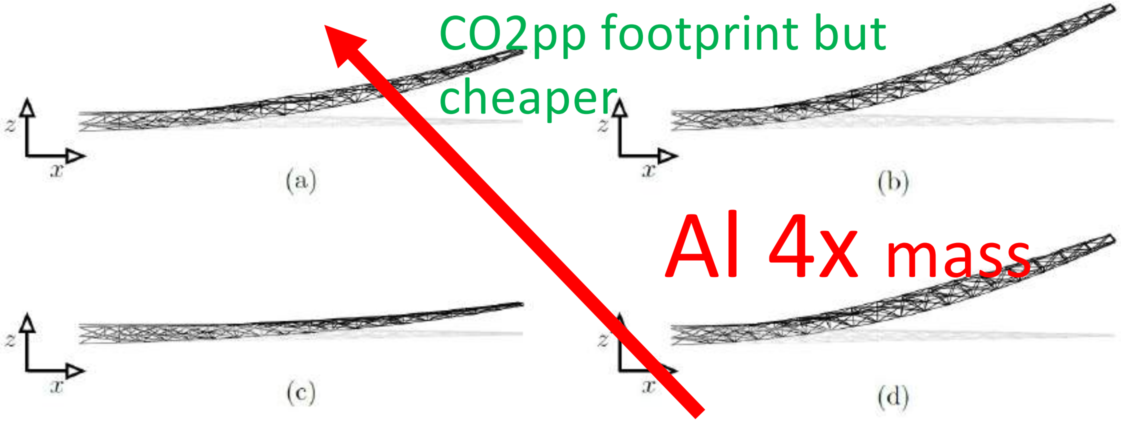
3 load cases:
- +2.5 g manouver
- -1 g manouver
- Cruise with gust (+1.3 g)

$$
\begin{aligned}
\min_{\substack{\boldsymbol{a},\boldsymbol{q}^0,\ldots,\boldsymbol{q}^{N_p},\\ \boldsymbol{U}^0,\ldots,\boldsymbol{U}^{N_p}}} \quad & V = \boldsymbol{\ell}^T\boldsymbol{a} & \\
\text{s.t.} \quad & \boldsymbol{B}\boldsymbol{q}^p = \boldsymbol{f}^p & \forall p \in [0,\ldots,N_p] \\
& \boldsymbol{q}^p = \frac{\boldsymbol{a}E}{\boldsymbol{\ell}}\boldsymbol{b}^T\boldsymbol{U}^p & \forall p \in [0,\ldots,N_p] \\
& \boldsymbol{q}^p \geq -\frac{s\boldsymbol{a}^2}{\boldsymbol{\ell}^{*2}} & \forall p \in [0,\ldots,N_p] \\
& -\sigma_c\boldsymbol{a} \leq \boldsymbol{q}^p \leq \sigma_t\boldsymbol{a} & \forall p \in [0,\ldots,N_p] \\
& 0 \leq \boldsymbol{a} \leq \frac{4\pi\boldsymbol{\ell}^2}{\lambda_{\max}}. &
\end{aligned}
$$

Material	Aluminium	Titanium	Steel	Pultruted CFRP
E	69 GPa	120 GPa	210 GPa	150 GPa
σ_c, σ_t	±270 MPa	±880 MPa	±355 MPa	+1200, −880 MPa
ρ	2.7 g cm^{-3}	4.5 g cm^{-3}	7.8 g cm^{-3}	1.6 g cm^{-3}

Aluminum
M = 21.34t

Titanium
M = 20.37t

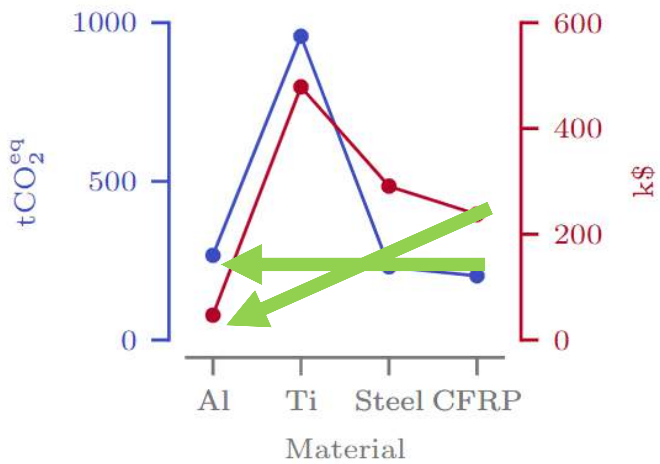


Steel
M = 46.16t

CFRP
M = 5.86t

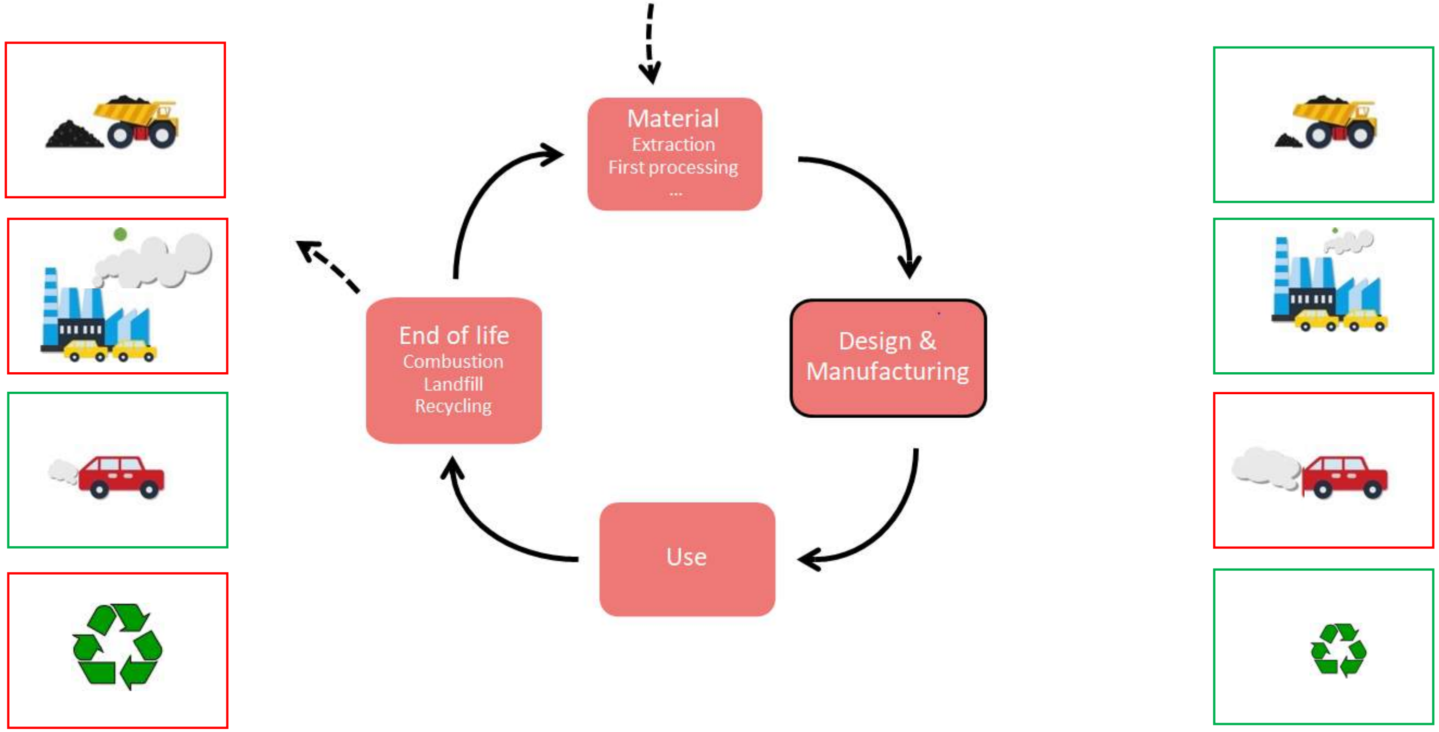
But finally
Al has approx same CO2pp footprint but cheaper

Al 4x mass



Hypothesis 2

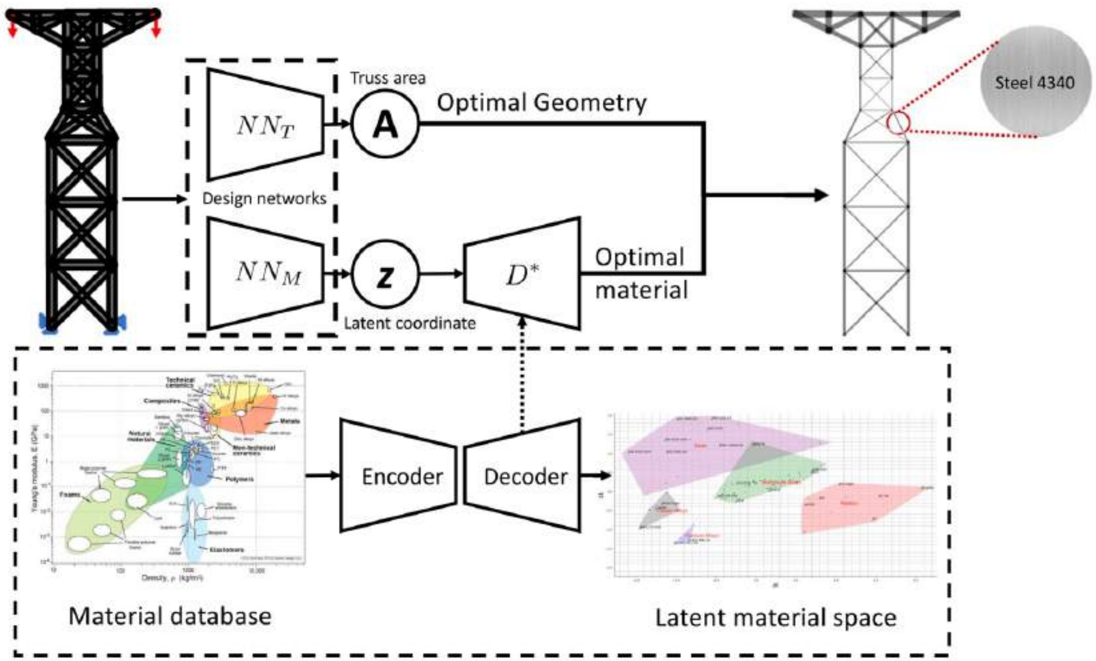
- $\color{red}{Not\ only\ CO_2\ \ldots .}$



Collaboration with UW-ERSL


Home > Engineering with Computers > Article
Integrating material selection with design optimization via neural networks
Original Article | Published: 16 September 2022
Volume 38, pages 4715–4730, (2022) Cite this article
Engineering with Computers


Home > Structural and Multidisciplinary Optimization > Article
A hybrid machine learning and evolutionary approach to material selection and design optimization for eco-friendly structures
Research Paper | Published: 11 May 2024
Volume 67, article number 69, (2024) Cite this article
Structural and Multidisciplinary Optimization



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

VAE used for a continuous mapping

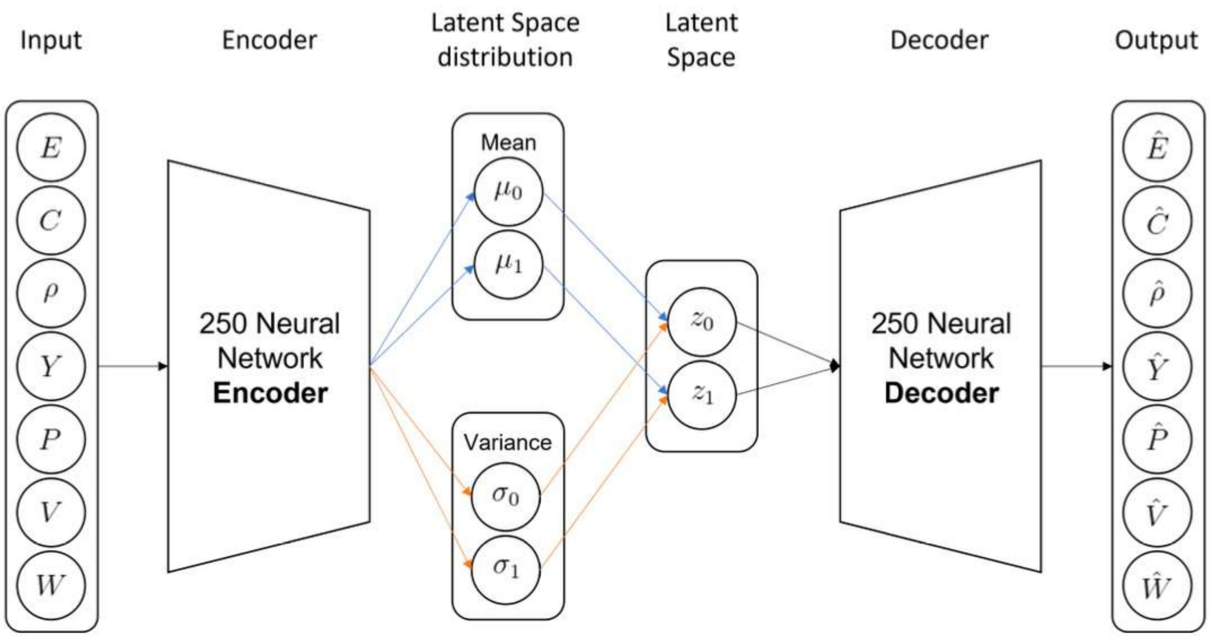


Fig. 1: Architecture of the Variational Autoencoder

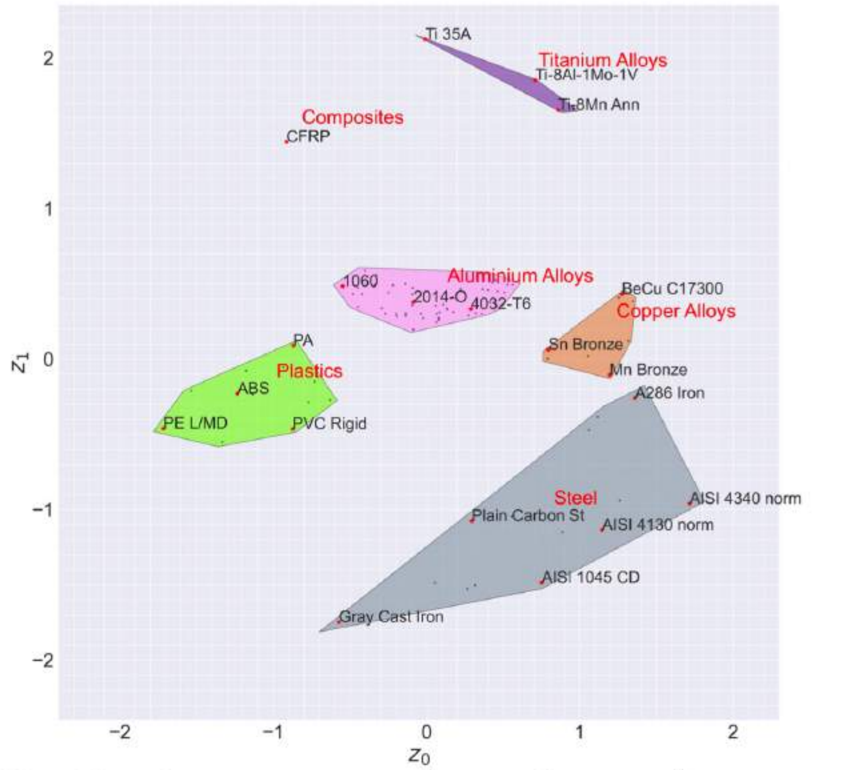


Fig. 2: Material representation in a two-dimensional latent space (7 properties considered)

A differentiable material representation

$$
\begin{aligned}
\min_{A_i \in \mathbf{A}, z_0, z_1} \quad & \psi(A_1, \dots, A_N, z_0, z_1) \\
\text{subject to} \quad & \mathbf{K}(A_1, \dots, A_N, z_0, z_1)\mathbf{u} = \mathbf{f} \\
& g(A_1, \dots, A_N, z_0, z_1) \leq 0 \\
& A_{min} \leq A_i \leq A_{max} \\
& z_{0_{min}} \leq z_0 \leq z_{0_{max}} \\
& z_{1_{min}} \leq z_1 \leq z_{1_{max}}
\end{aligned}
$$

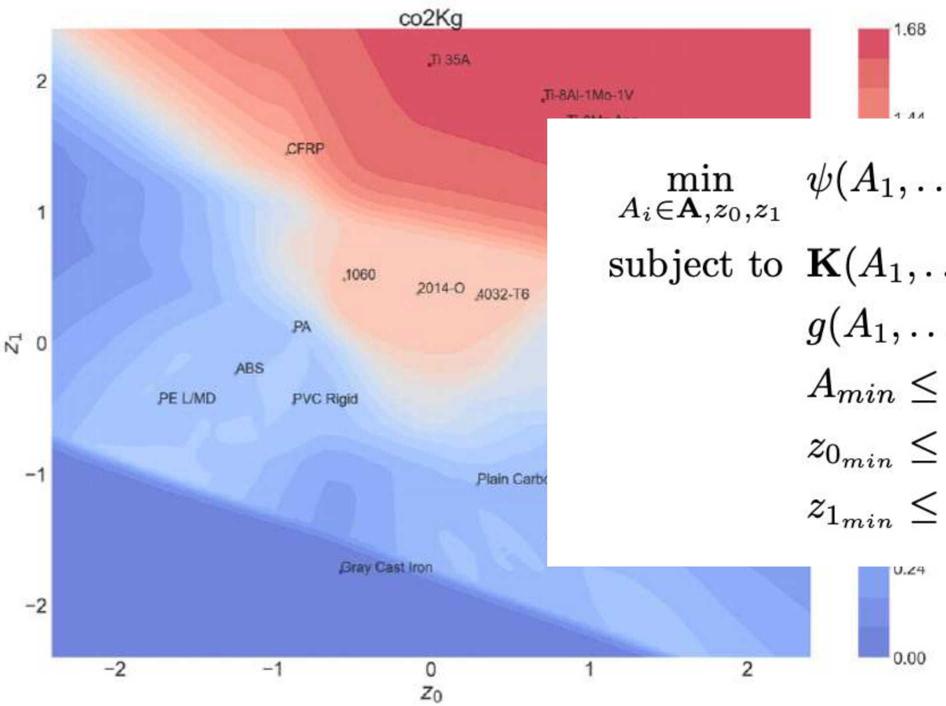


Fig. 3: CO_2 per kilogram colormap over the latent space

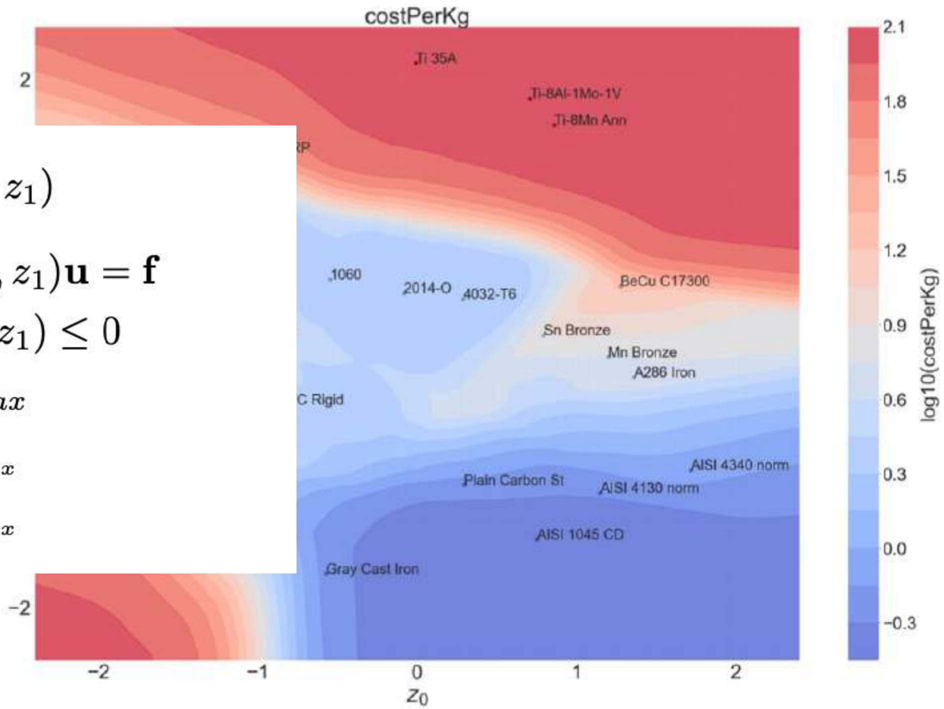
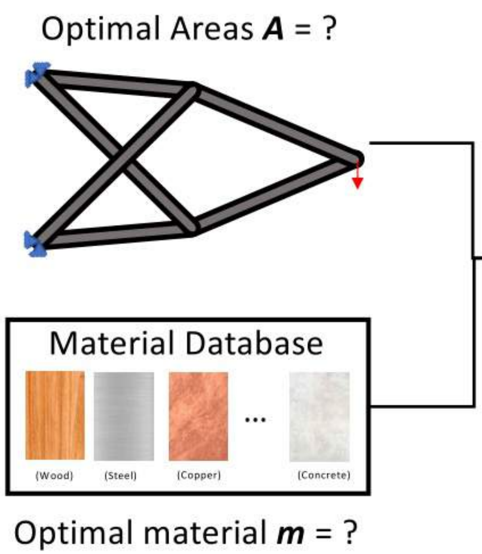
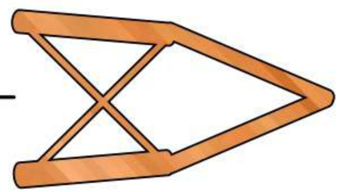


Fig. 4: Cost per kilogram per kilogram colormap over the latent space

Extension to new eco-objectives





Objective	Equation
Compliance	$\mathbf{f}^\intercal \mathbf{u}(\mathbf{A}, \hat{E})$
Mass	$\hat{\rho} \sum_{k=1}^{N} A_k L_k$
Cost	$\hat{\rho}\hat{C} \sum_{k=1}^{N} A_k L_k$
CO2	$\hat{\rho}\hat{P} \sum_{k=1}^{N} A_k L_k$
Energy	$\hat{\rho}\hat{V} \sum_{k=1}^{N} A_k L_k$
Water	$\hat{\rho}\hat{W} \sum_{k=1}^{N} A_k L_k$

Table B2: Available objective functions

$$\underset{\boldsymbol{A}=\{A_1,A_2,\ldots A_N\},z_0,z_1}{\text{minimize}} \quad J = \boldsymbol{f}^{\mathrm{T}}\boldsymbol{u}(\boldsymbol{A}, \hat{E})$$

$$\text{subject to} \quad [K(\boldsymbol{A}, \hat{E})]\boldsymbol{u} = \boldsymbol{f}$$

$$g_c := \left(\frac{\hat{\rho}\hat{C}}{C^*} \sum_{k=1}^{N} A_k L_k \right) - 1 \leq 0$$

$$g_b := \max_k \left(\frac{-4 P_k L_k^2}{\pi^2 \hat{E} A_k^2} \right) - \frac{1}{F_s} \leq 0$$

$$g_y := \max_k \left(\frac{P_k}{\hat{Y} A_k} \right) - \frac{1}{F_s} \leq 0$$

$$\boldsymbol{A}_{\min} \leq \boldsymbol{A} \leq \boldsymbol{A}_{\max},$$

Extension to eco-database

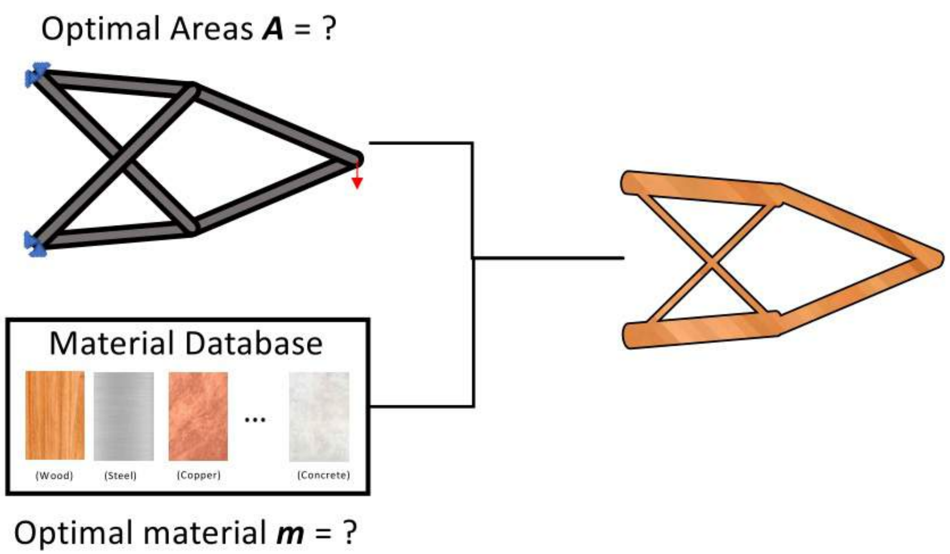


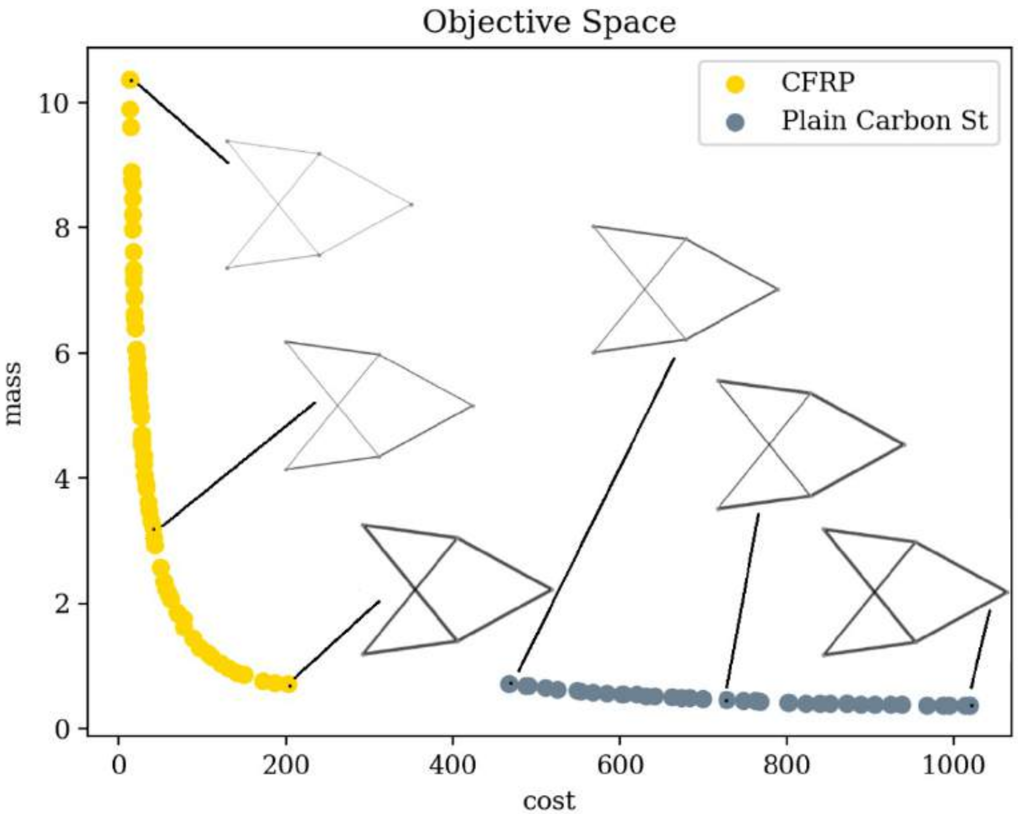
Table 1 A curated subset of materials and their properties used in the training

Material	Class	E [Pa]	Cost C [\$/kg]	ρ [kg/m^3]	Y [Pa]
A286 iron	Steel	2.01E+11	5.18E+00	7.92E+03	6.20E+08
AISI 304	Steel	1.90E+11	2.40E+00	8.00E+03	5.17E+08
Gray cast iron	Steel	6.62E+10	6.48E−01	7.20E+03	1.52E+08
3003-H16	Al alloy	6.90E+10	2.18E+00	2.73E+03	1.80E+08
5052-O	Al alloy	7.00E+10	2.23E+00	2.68E+03	1.95E+08
7050-T7651	Al alloy	7.20E+10	2.33E+00	2.83E+03	5.50E+08
Acrylic	Plastic	3.00E+09	2.80E+00	1.20E+03	7.30E+07
ABS	Plastic	2.00E+09	2.91E+00	1.02E+03	3.00E+07
PE HD	Plastic	1.07E+09	2.21E+00	9.52E+02	2.21E+07

Name	Property	Units
E_m	Young's modulus	Pa
C_m	Cost per unit mass	\$/kg
ρ_m	Mass density	kg/m^3
Y_m	Yield strength	Pa
P_m	CO_2 produced per unit mass	kg/kg
V_m	Energy required per unit mass	J/kg
W_m	Water required per unit mass	L/kg

Table 1: Material properties

Solve a MOO at fixed topology



Obviously, the material that guarantees the minimum in both properties is the CFRP (left). However to continue reducing the compliance, it is necessary to make a jump in the total mass of the system and use a denser material such as Gray Carbon.

MOO → Multi Objective Optimization

$$\begin{aligned} \min \quad & f_m(x) && m = 1, .., M \\ \text{s.t.} \quad & g_j(x) \leq 0 && j = 1, .., J \\ & h_k(x) = 0 && k = 1, .., K \\ & x_i^L \leq x_i \leq x_i^U && i = 1, .., N \\ & x \in \Omega \end{aligned} \tag{6}$$

Where $f_m(x)$ can be each $\psi(\mathbf{A}, \zeta_m)$ described in B3, $g_j(x)$ can be any set of constraints (i.e. feasibility constraints such as yield strength and buckling constraints), $h_j(x)$ can be the equilibrium $\mathbf{K}(\mathbf{A}, E_m)\mathbf{u} = \mathbf{f}$ and x_i are bounds for both continuous and discrete variables $\mathbf{A}$ and ζ_m.

Our framework uses the state of the art in multi-objective optimization pymoo [15] to solve Equation 6. It is worth noting the fact that most of the objectives we are considering (CO_2, cost...) are proportional to the mass by the factor of the associated property (CO_2 per kilogram, \$ per kilogram...). Then, for each material, there is only one optimal configuration that minimizes the mass, and this one provides a minimum value of CO2, cost, water... Therefore, the optimal value of each material in these targets translates into a single point in the objective space.

Solve a MOO at fixed topology

MOO with compliance is different !
since this value decreases as mass increases and vice versa
→ continuous range of optimal values in terms of mass and compliance.
There is:
→ a minimum area configuration (limited by yield strength and buckling constraints) that guarantees minimum mass but maximum compliance
→ A maximum mass configuration limited by the upper limit of the areas that will provide minimum compliance.

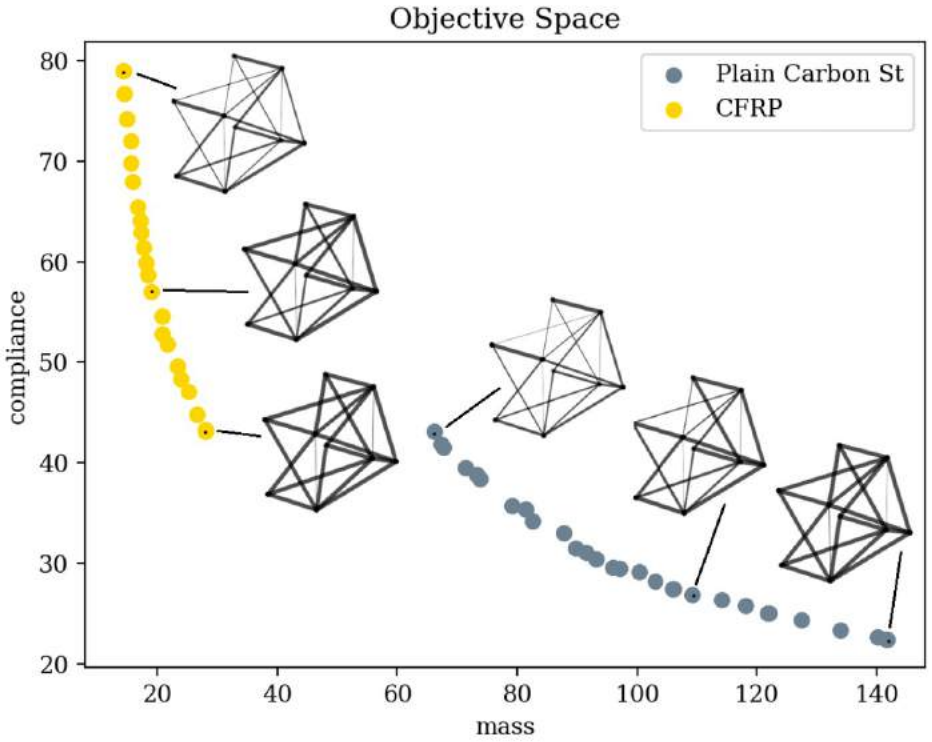
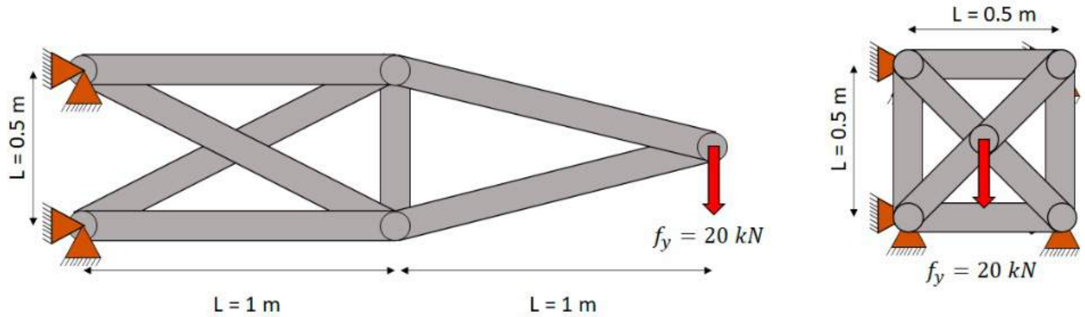


Fig. 21: Pareto front of mass vs compliance, depicting the geometry evolution (three-dimensional case)

Environmentally friendly 3D truss

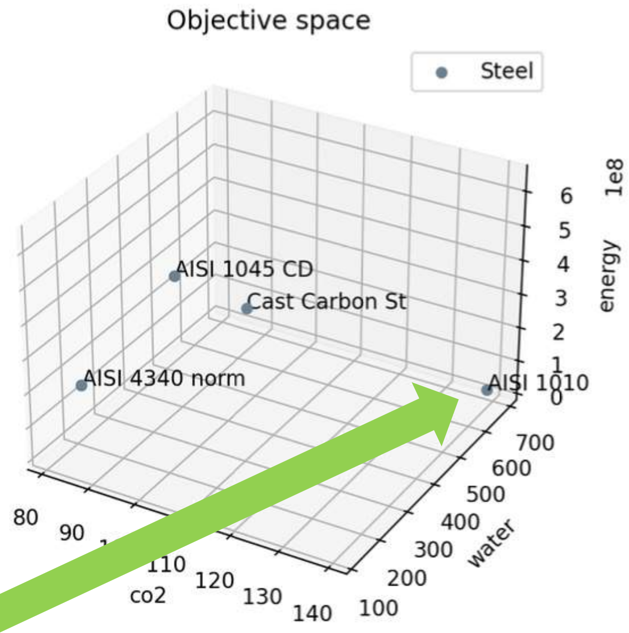


Being P_{min}, W_{min} and V_{min} the minimum value of CO_2, water and energy achievable respectively, the index is defined as:

$$H = \frac{1}{3}\frac{P - P_{min}}{P_{min}} + \frac{1}{3}\frac{W - W_{min}}{W_{min}} + \frac{1}{3}\frac{V - V_{min}}{V_{min}} \quad (7)$$

In such a way that the perfect material with minimum consumption would yield $H = 0$. To take into account the cost of the structure as well, both values were calculated for each solution and presented in Table 10.

Material	Cost	Env. Consumption
AISI 1045 CD	18.63 \$	9.60 [-]
Cast Carbon St	28.68 \$	7.85 [-]
AISI 4340 norm	31.91 \$	2.28 [-]
AISI 1010	24.04 \$	1.73 [-]



Au programme

- Engineering optimization
- Eco friendly structures
- **Design acceleration through SMT**

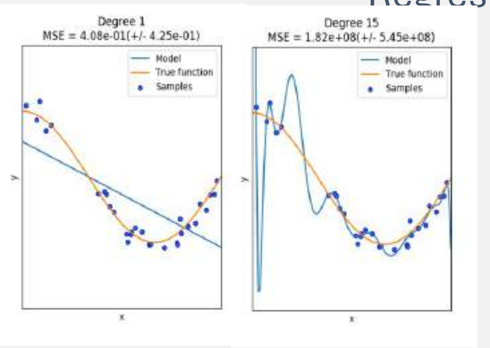
Learning using data

: $y = f(X)$

And more to come with Pram and ITB !!

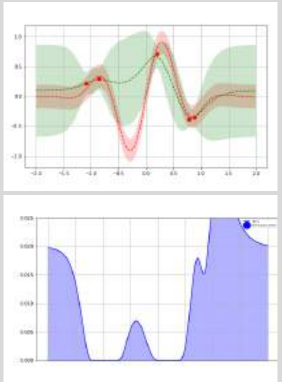
PROs and CONs (Thanks MonolithAI)

Linear and polynomial Regressions



- ? Some of the most basic models: fitting a polynomial to the data
- − They might not capture all the complexity that is in the data
- + They are explainable (e.g. via equations), which make it really attractive to some industries
- Main parameters: degree of polynomial (finding the "right compromise")

Gaussian Process Regressions



- ? More complex statistical process that fits a smooth function through the points, based on gaussian distributions
- − Doesn't scale well with large data sets
- + Work well with small data sets
  Simple to train, less prone to overfitting
  Always return uncertainty
- Main parameters: kernels (e.g. RBF, defines the smoothness of the model)

GAUSSIAN PROCESS (GP)

OPTIMIZATION AT FIXED BUDGET ++ (FOR EXPENSIVE CODE)

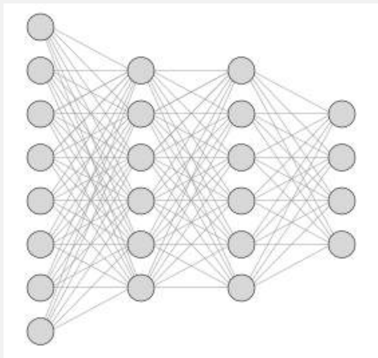
ENRICHMENT (INFILL) ++

MULTIFIDELITY (COKRIGING) ++

UNCERTAINTIES ESTIMATION ++ → LEAD TO BAYESIAN OPTIMIZATION & UQ

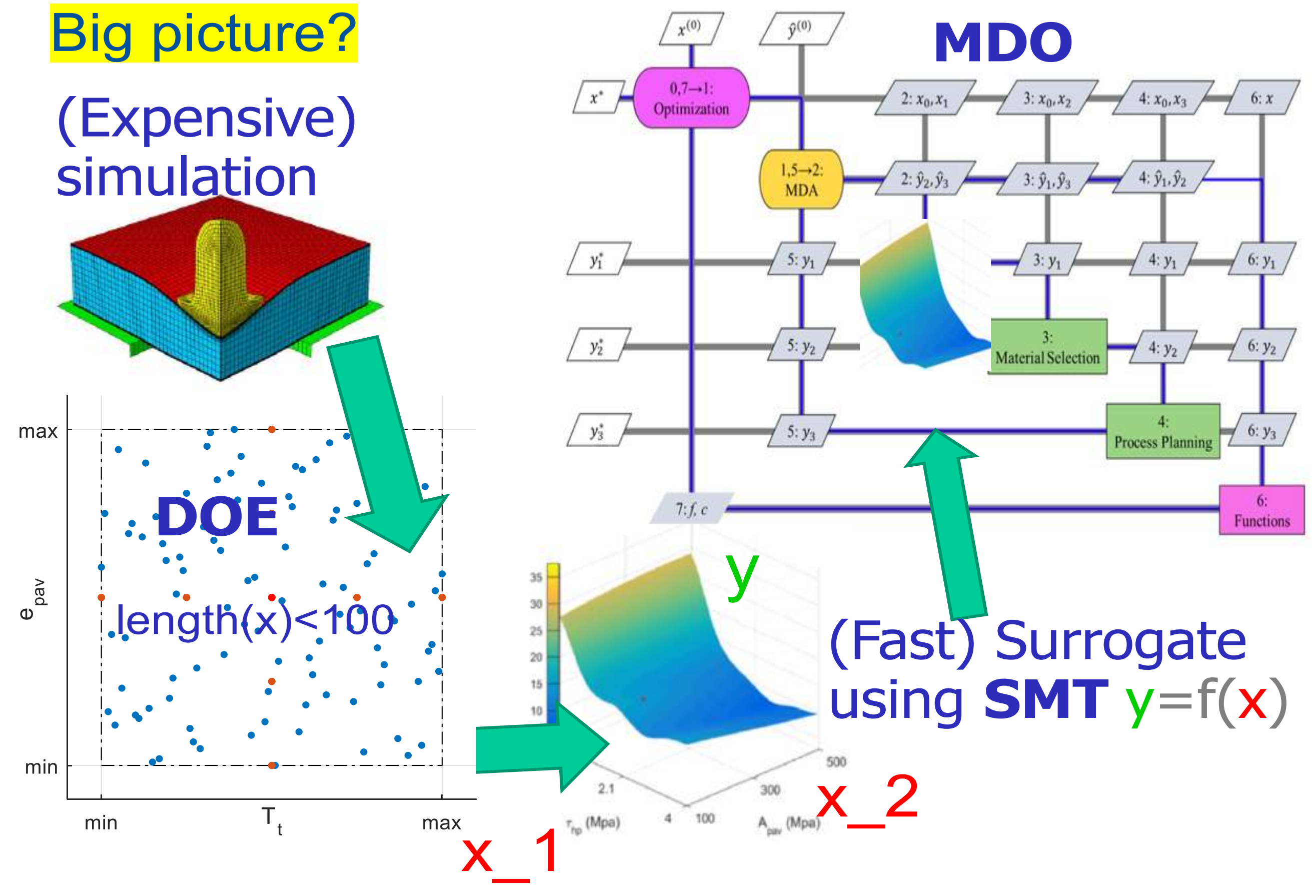
EXPLAINABILITY

Neural Networks



- ? Algorithms based on a system of neurons, based on biological neural network (brain)
- − Could return uncertainty but requires work
  Very flexible: prone to overfit
  Not very good on small data sets
- + Very good to tackle very large data sets
  Flexible: can fit most data set if big enough
  Handle non-linearity well
- Main parameters: architecture (number of layers, neurons), number of training steps

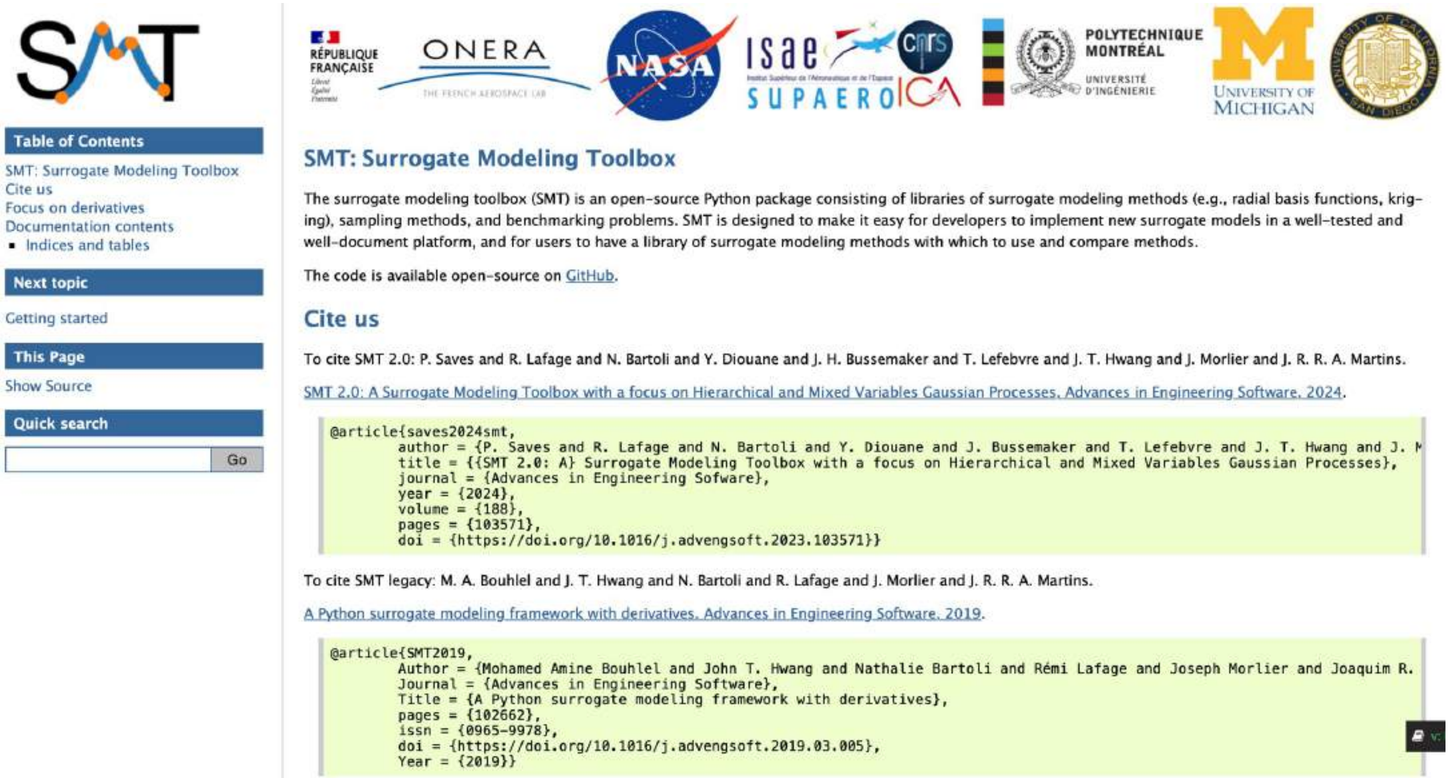
Main Idea

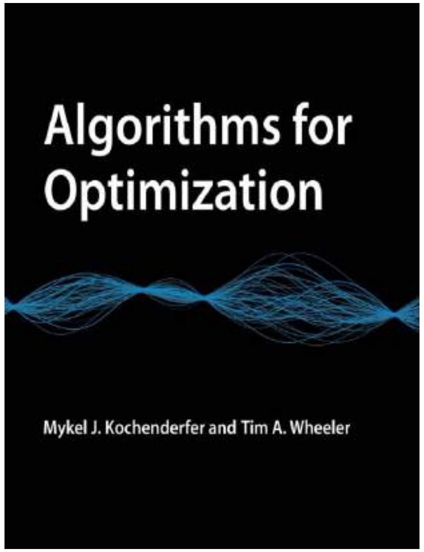

Big picture?
(Expensive) simulation
DOE
length(x)<100
max
min
e_pav
T_t
min
max
x_1
x_2
y
MDO
0,7→1: Optimization
1,5→2: MDA
3: Material Selection
4: Process Planning
6: Functions
7: f, c
(Fast) Surrogate using SMT y=f(x)

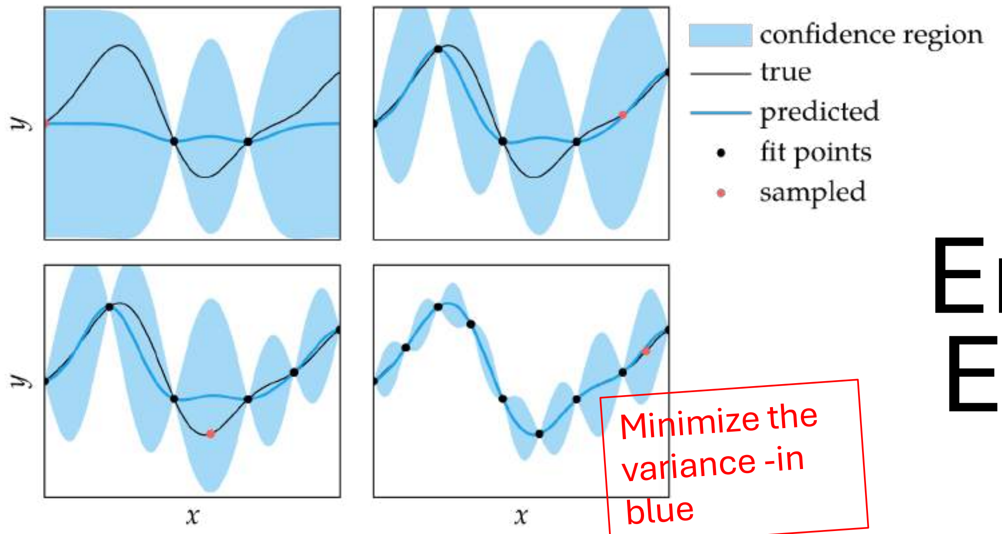
X_0 in practice
Since 2017

https://smt.readthedocs.io/en/latest

https://github.com/SMTorg/smt







I want the most precise surrogate

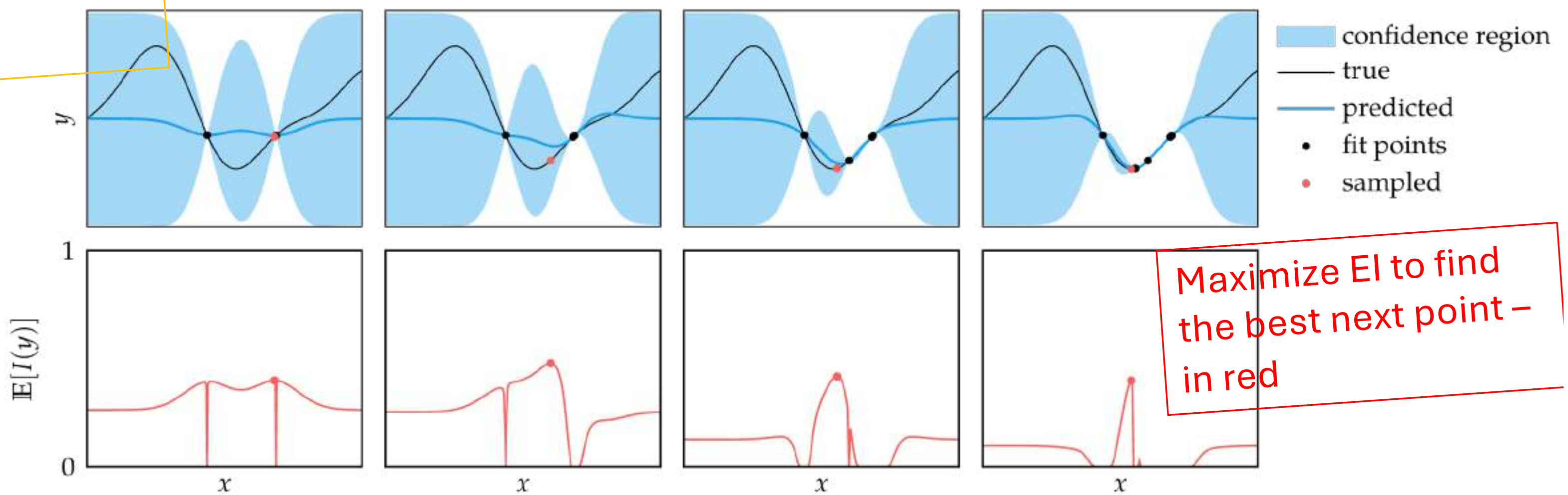
Error-Based Exploration

Minimize the variance -in blue

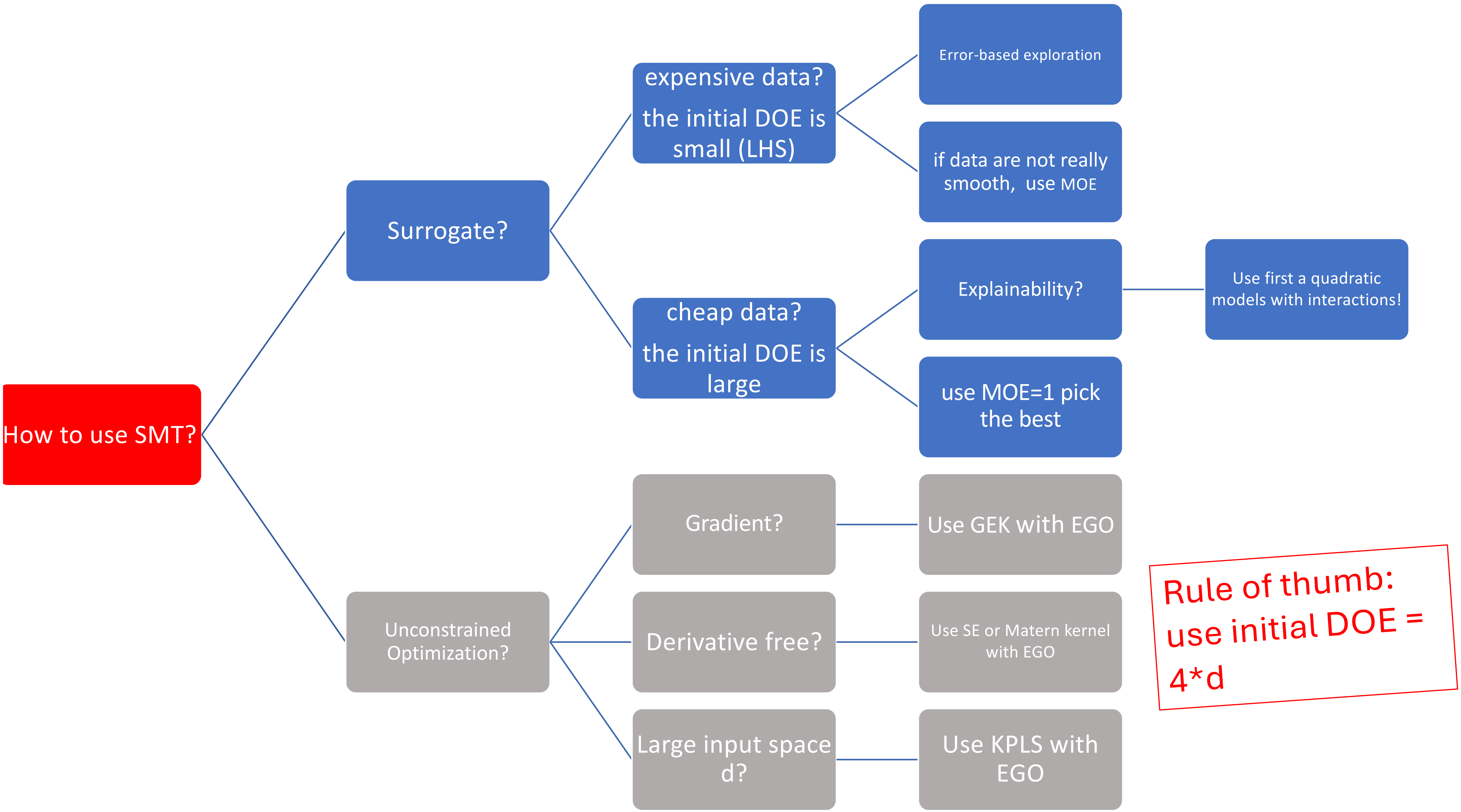
VS

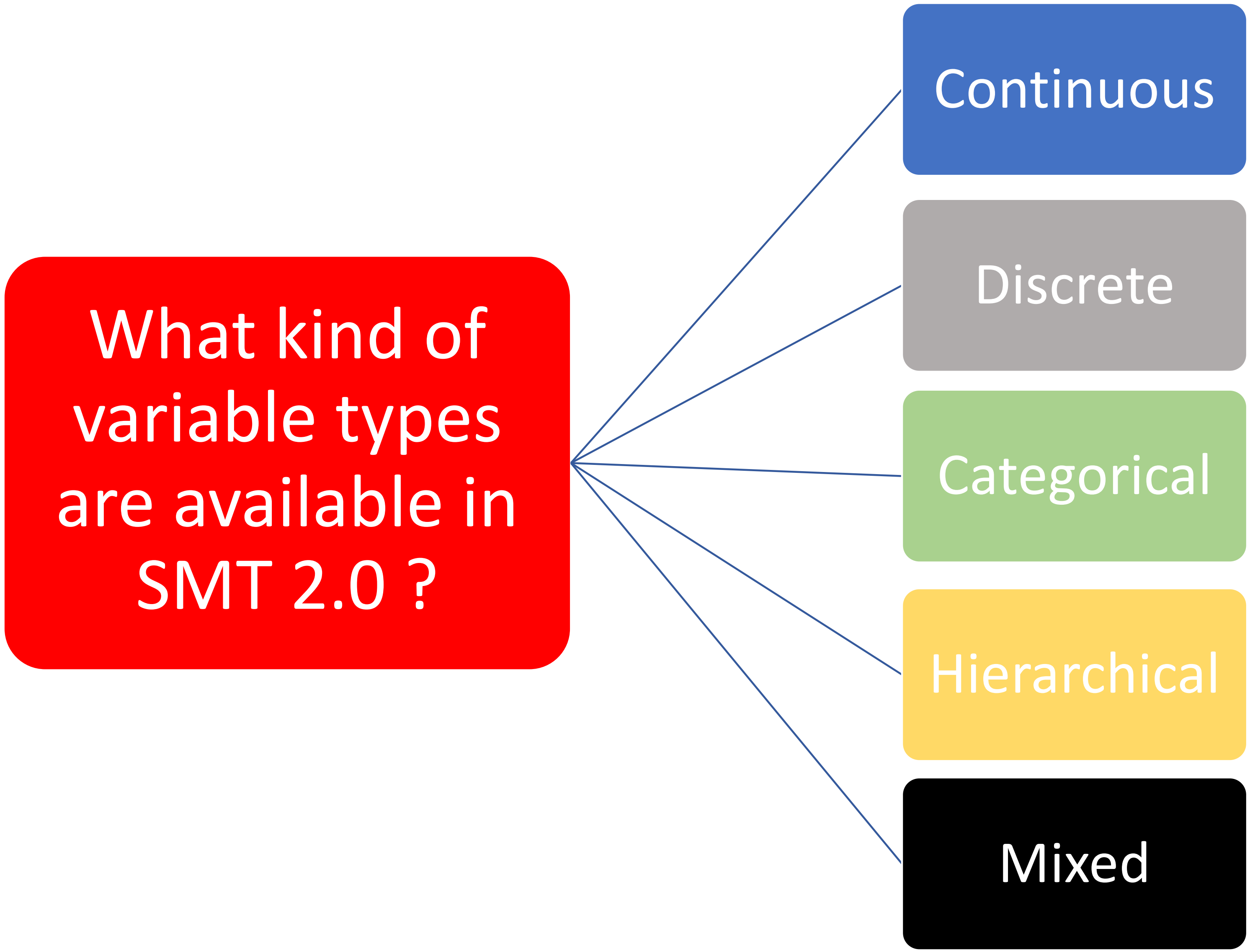
I want a global optimum at fixed budget

Efficient Global Optimization



Maximize EI to find the best next point – in red


How to use SMT?
Surrogate?
expensive data?
the initial DOE is small (LHS)
Error-based exploration
if data are not really smooth, use MOE
cheap data?
the initial DOE is large
Explainability?
Use first a quadratic models with interactions!
use MOE=1 pick the best
Unconstrained Optimization?
Gradient?
Use GEK with EGO
Derivative free?
Use SE or Matern kernel with EGO
Large input space d?
Use KPLS with EGO
Rule of thumb: use initial DOE = 4*d


What kind of variable types are available in SMT 2.0 ?
Continuous
Discrete
Categorical
Hierarchical
Mixed

Tutorials

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

Open in Colab

Noisy Gaussian process

Open in Colab

Multi-Fidelity Gaussian Process

Without noise

Open in Colab

With noise

Open in Colab

LHS sampling (initial and expanded)

Open in Colab

Gaussian Process Trajectory Sampling

Open in Colab

Bayesian Optimization - Efficient Global Optimization to solve unconstrained problems

Open in Colab

Proper Orthogonal Decomposition and Interpolation

Open in Colab

Mixed-integer and mixed-hierarchical surrogate models

Specific notebook associated to the SMT 2.0 Journal Paper (submitted) with a focus on mixed integer and mixed hierarchical surrogate models (continuous, discrete, categorical)

Open in Colab

DesignSpace to variables (continuous, discrete, categorical, hierarchical)

Open in Colab

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

Open in Colab

Mixed-Integer Gaussian Process and Bayesian Optimization for Engineering application

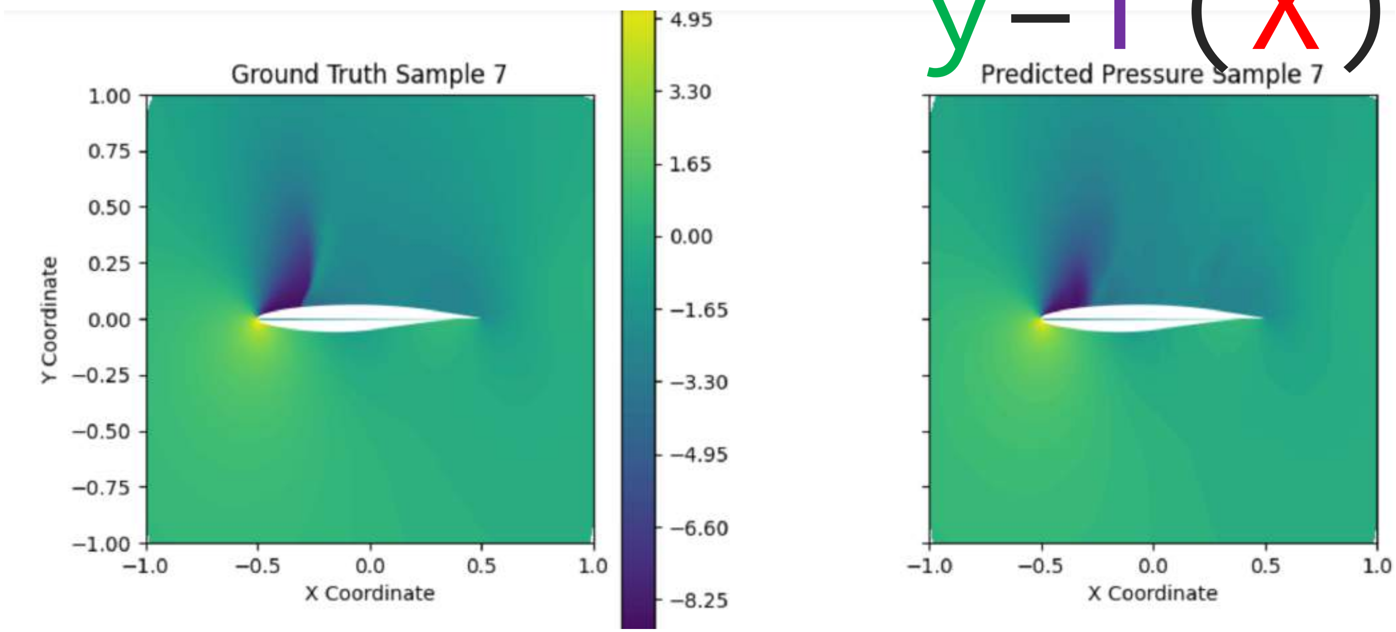
Open in Colab

Data Loading and Processing for Transonic Airfoil Analysis (soon online)

A dataset with more than 2.000 RANS simulations at various angles of attack and Mach numbers has been created

https://zenodo.org/records/12700680?token=eyJhbGciOiJIUzUxMiJ9.eyJpZCI6IjQyNzI4M2NmLWIwYjktNDc1Ny1hYjA5LTliYjU4YjY4MjFmNCIsImRhdGEiOnt9LCJyYW5kb20iOiI5ZjY5MWIzNWQ5MTRmNGE4ZDdjNmY4ZjI4MTY1NDAyMiJ9._BqW0JKCMiI89PjbTmNOtbvYO6iCBx-hjP4WRPGepV2ufmAlqk_SEmAgbPfqkW9YvjOsh67lHn2jGQ7cg_n1nw

$y = f(x)$



Battery Engineering

Example in Battery Engineering Agrawal, D., **Crystal System Properties for Li-ion batteries**, Properties of Li-ion silicate to predict the crystal system class of the battery, Kaggle, March 2020.

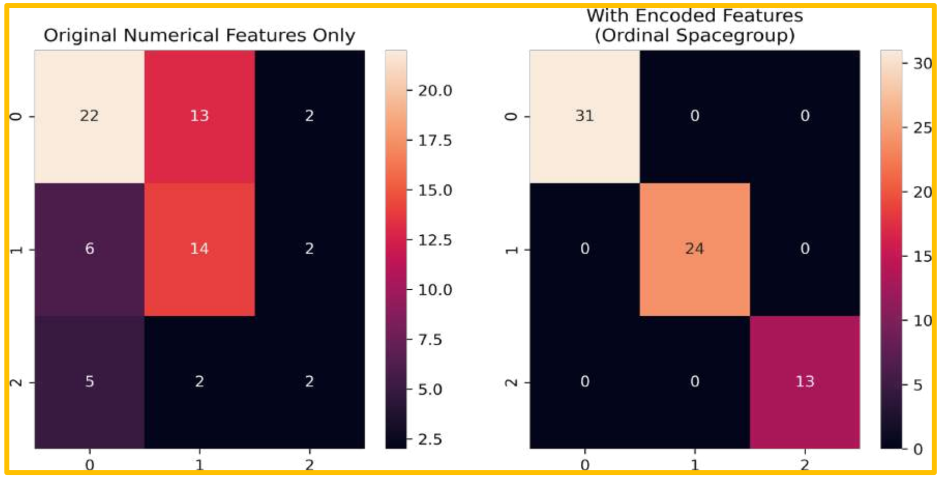
Materials Id	Formula	Spacegroup	# Formation Ene...	# E Above Hull (...	# Band Gap (eV)	# Nsites	# Density (gm/cc)	# Volume	✓ Has Bandstruc...
The unique ID of the material as stated on materialsproject.org	Chemical formula of the material	Spacegroup	Formation Energy	Energy if decomposition of material into most stable ones	Band Gap (in eV)	Number of atoms in the unit cell of the crystal	The density of bulk crystalline materials	The unit cell volume of the material	Boolean variable for bandstructure
339 unique values	LiFeSiO4 12% LiCoSiO4 9% Other (268) 79%	P1 21% P21/c 9% Other (235) 69%	-2.98 – -2.0	0 – 0.19	0 – 3.82	10 – 132	2.2 – 4.2	123 – 1.52k	true 274 81% false 65 19%

Crystal System	
The predicted column. This column contains 3 classes which your model will learn to classify.	
monoclinic	41%
orthorhombic	38%
Other (72)	21%

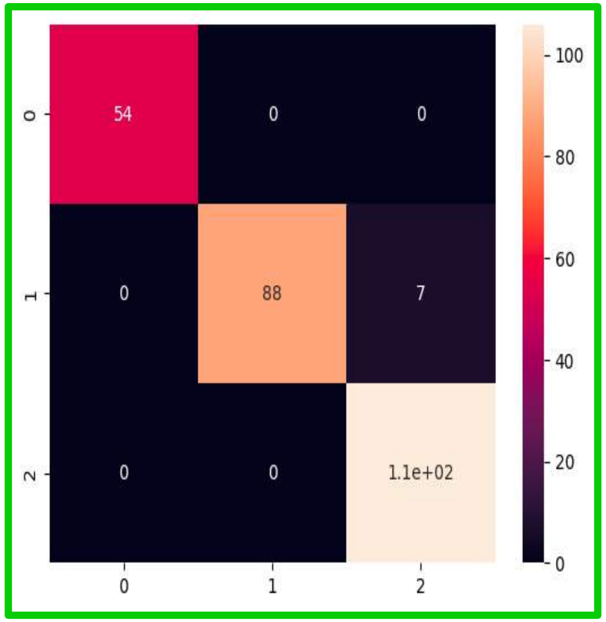
$$y=f(X)$$

y=f(X)

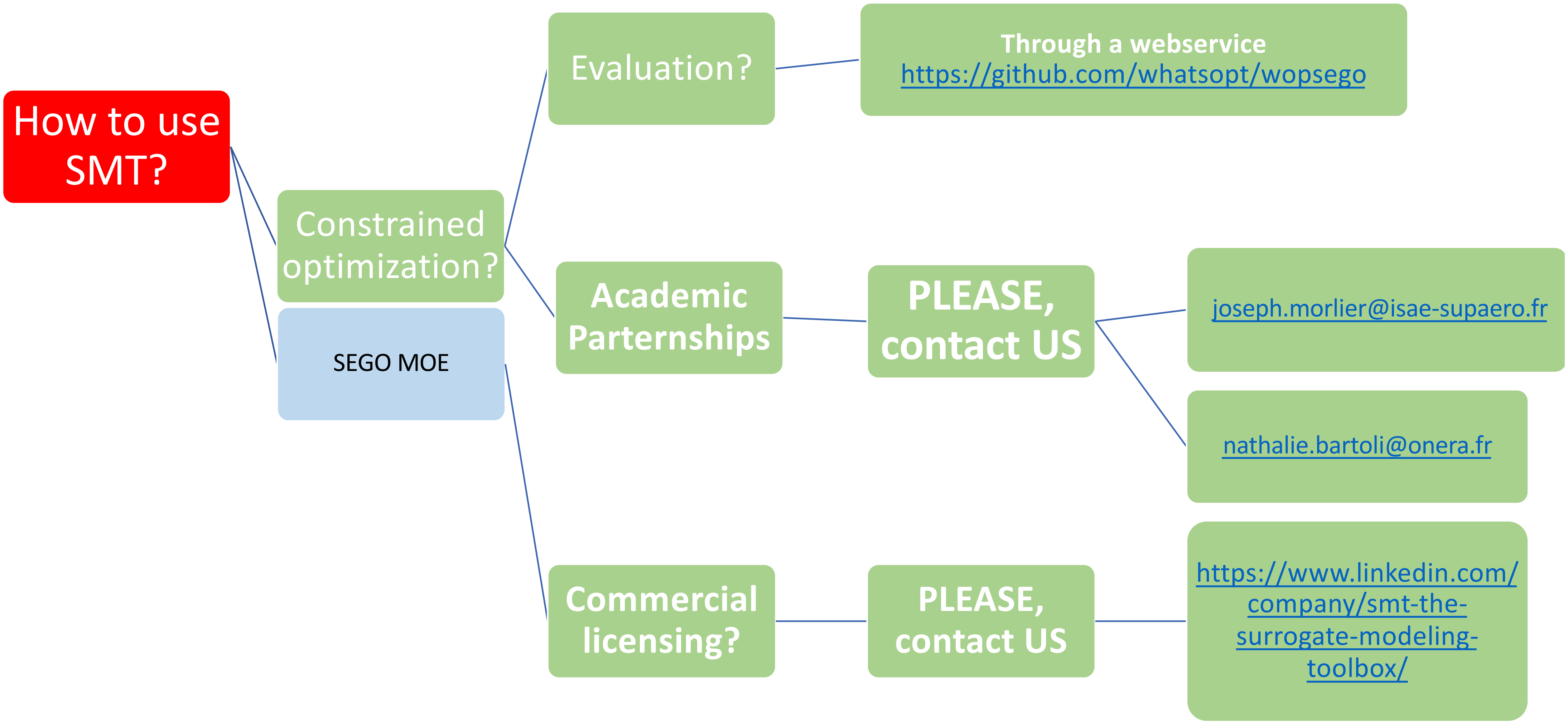
Predict y the crystal structure type (monoclinic, orthorhombic, triclinic)
from X Lithium-ion physical and chemical compound information
i.e. learn from learning database y=f(x)



scikit-learn with 80/20 dtree w/wo specific features (*sf*)



SMT with 10/90 (!!) wo sf


How to use SMT?
Constrained optimization?
SEGO MOE
Evaluation?
Through a webservice
https://github.com/whatsopt/wopsego
Academic Parternships
PLEASE, contact US
joseph.morlier@isae-supaero.fr
nathalie.bartoli@onera.fr
Commercial licensing?
PLEASE, contact US
https://www.linkedin.com/company/smt-the-surrogate-modeling-toolbox/

Au programme

- Engineering optimization
- Eco friendly structures
- Design acceleration through SMT
- **Conclusions**

Conclusions (1)

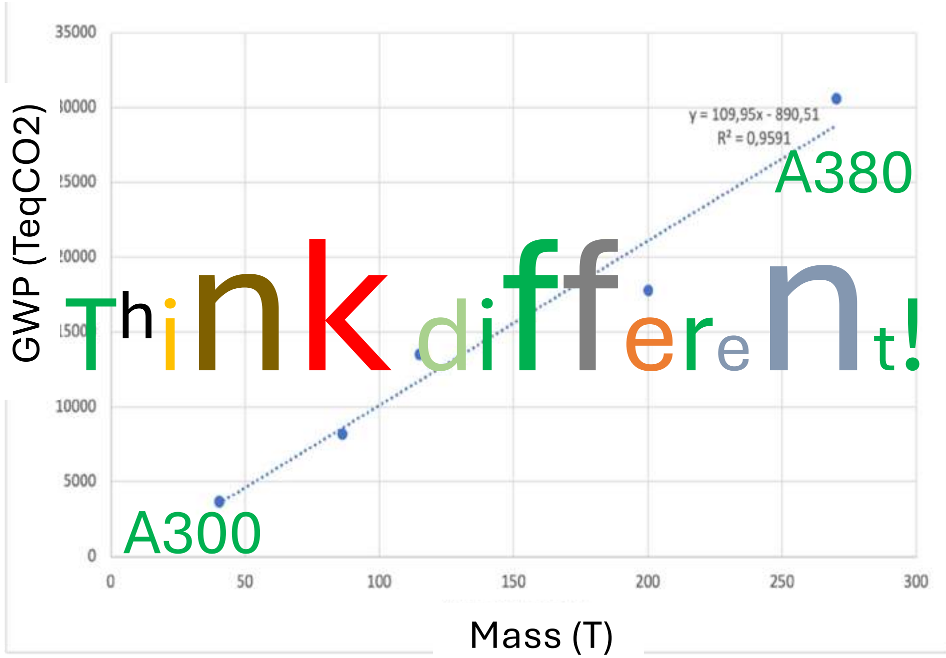
In Aircraft Design:

min {mass} is proportional to min {CO_2PP}

Manufacturing <1% of total aircraft emissions

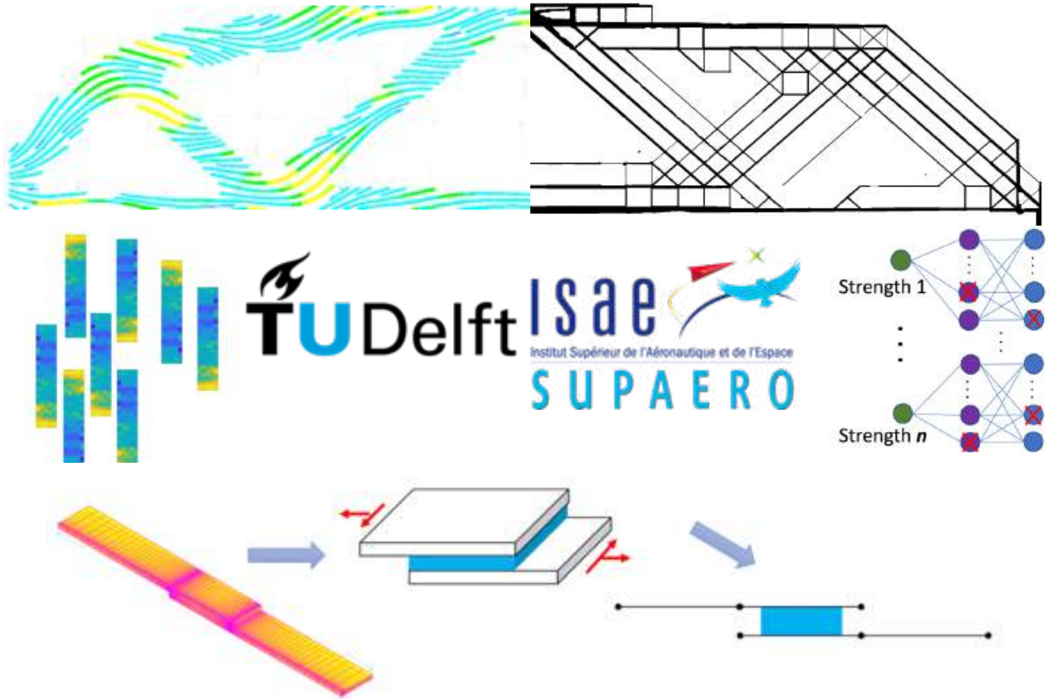
But what about others flying vehicules?

Integrating Ecomaterial selection and/or LCA in MDAO opens possibilities for better eco-optimisation



Conclusions (2)

- Proof of concept of greener aerostructures
- Design acceleration through SMT2.0
- Link between education and research in the topic of sustainable aerostructures



→I hope we can construct together an integrated MsC+PhD in cotutelle agreement like we did with TUD

Opensource initiatives

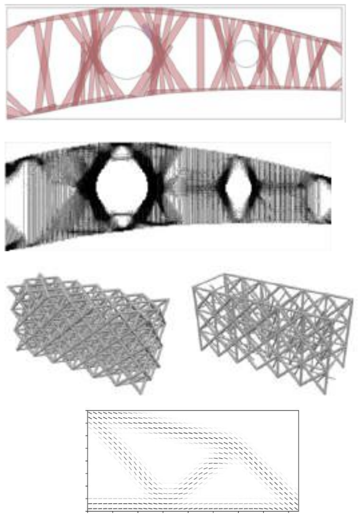
https://github.com/topggp/blog

https://github.com/mid2SUPAERO/EMTO

https://github.com/mid2SUPAERO/TTO

https://github.com/mid2SUPAERO/SOMP_Ansys

https://github.com/mid2SUPAERO/LCA4MDAO



https://github.com/SMTorg/SMT

Advances in Engineering Software
Volume 135, September 2019, 102662

A Python surrogate modeling framework with derivatives

Mohamed Amine Bouhlel [a], John T. Hwang [b], Nathalie Bartoli [c], Rémi Lafage [c], Joseph Morlier [d], Joaquim R.R.A. Martins [a]

https://doi.org/10.1016/j.advengsoft.2019.03.005

Advances in Engineering Software
Volume 188, February 2024, 103571

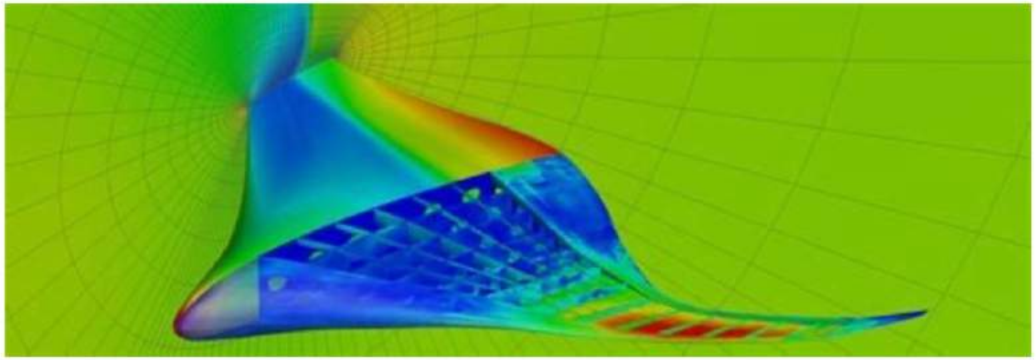
Research paper

SMT 2.0: A Surrogate Modeling Toolbox with a focus on hierarchical and mixed variables Gaussian processes

Paul Saves [a b 1], Rémi Lafage [a 1], Nathalie Bartoli [a 1], Youssef Diouane [c 1], Jasper Bussemaker [d 1], Thierry Lefebvre [a 1], John T. Hwang [e 1], Joseph Morlier [f 1], Joaquim R.R.A. Martins [g 1]

https://doi.org/10.1016/j.advengsoft.2023.103571

https://smt.readthedocs.io/en/latest/



joseph.morlier@isae-supaero.fr

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

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

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

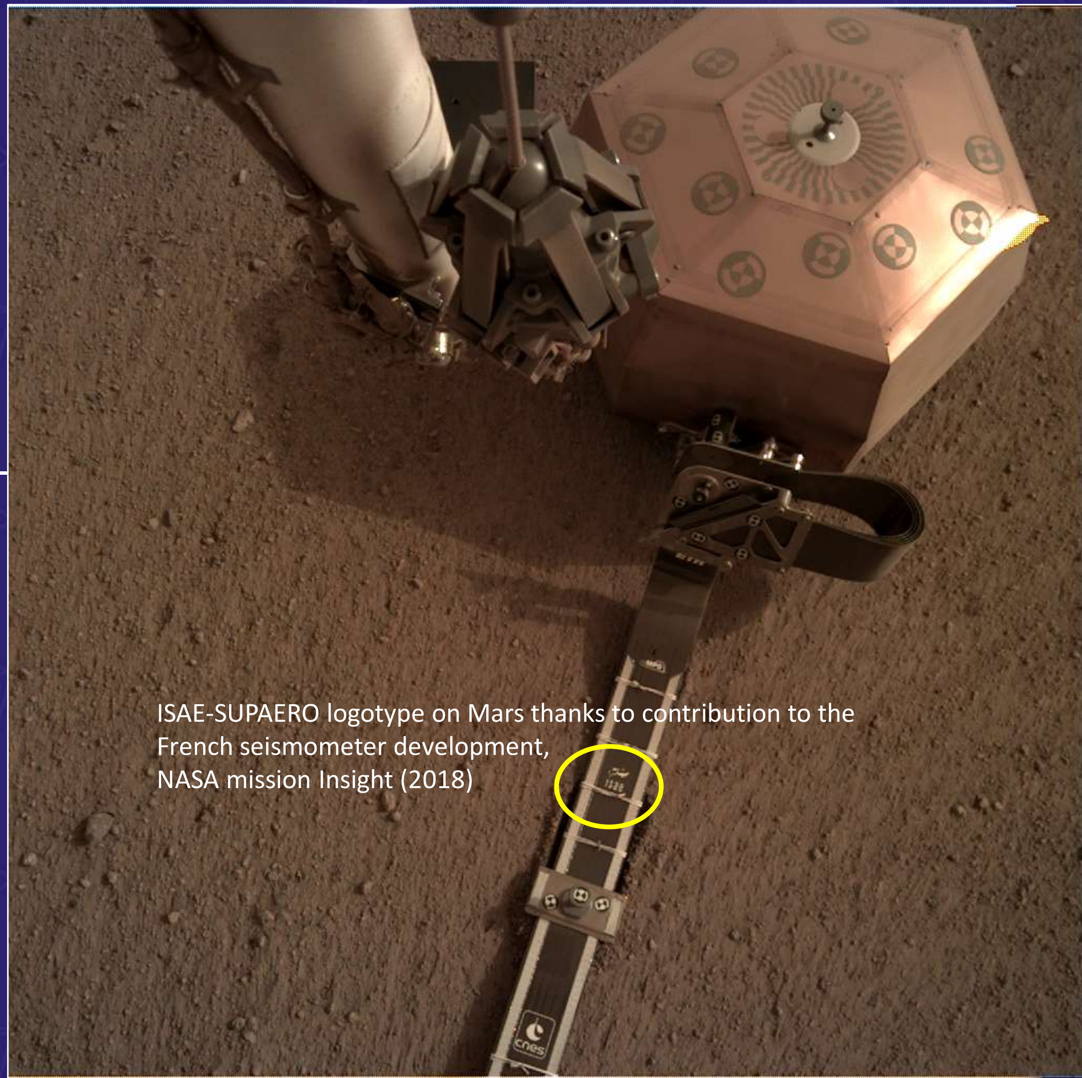
Is it possible to build an aircraft wing in LEGO® ?

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

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

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

Thank you
for your attention



ISAE-SUPAERO logotype on Mars thanks to contribution to the French seismometer development,
NASA mission Insight (2018)