Multidisciplinary Optimization and Machine Learning for Engineering Design

19 July 2021 – 5 August 2021

https://mdoml2021.ftmd.itb.ac.id/

Jointly organized by

香港科技大學
THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

Design for Additive Manufacturing: Topology Optimization

Prof. Joseph Morlier

Multidisciplinary Optimization and Machine Learning for Engineering Design

19 July 2021 – 5 August 2021

https://mdoml2021.ftmd.itb.ac.id/

Jointly organized by

Part 4

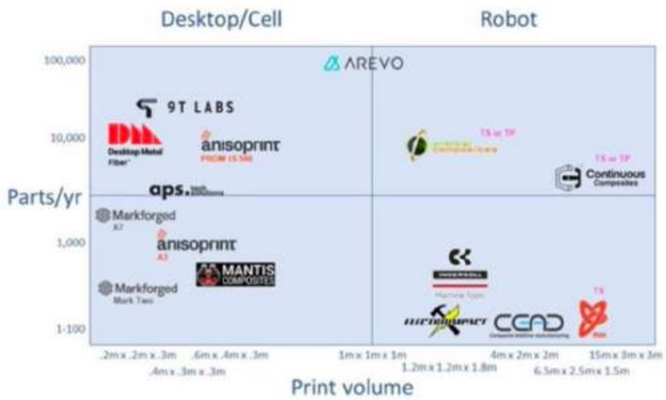
Ecoptimization for Computational Fabrication

Can we **Click and Print** greener & lighter aerostructures?

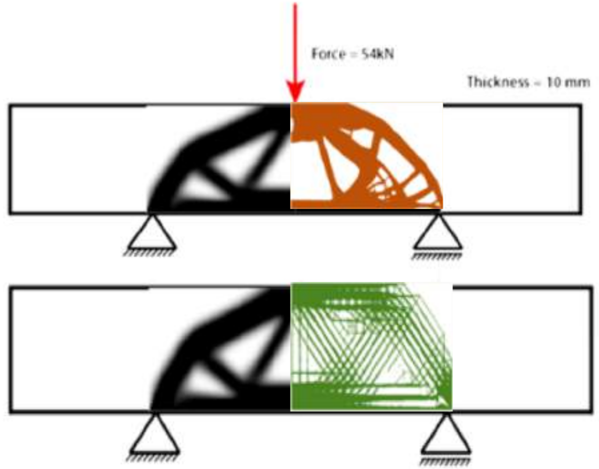
Definitely the answer is **NO**!

but…in few years?

Click and Print i.e.
CAD→CAE→OPTIM **and** GCODE→3DPRINTER



Current problems: Software, geometrical tolerence, mechanical performance, structural size, layer monitoring, post-curing, chemical support removal etc.



AGENCE NATIONALE DE LA RECHERCHE ANR

EcoDD project :Print it , test it !

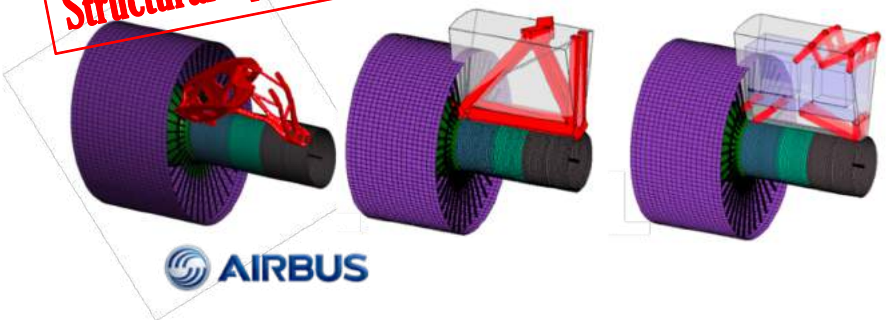
My Research Group

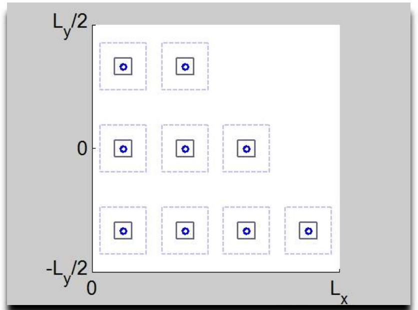
https://ica.cnrs.fr/author/jmorlier/

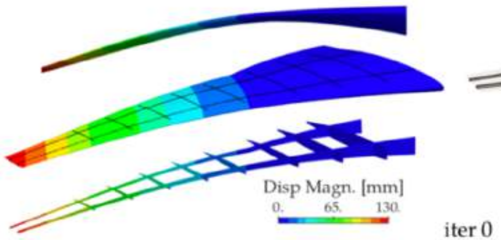
- 5 PhDs, 3 MsCs

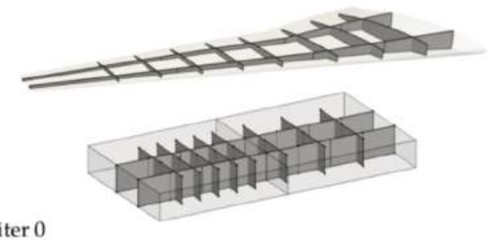
$$\min\ w(\boldsymbol{a}, \boldsymbol{c})$$
$$\boldsymbol{a} \in \mathbb{R}^{10}$$
$$\boldsymbol{c} \in \Gamma^{10}$$
$$s.t.\ \ s(\boldsymbol{a}, \boldsymbol{c}) \le 0$$
$$d(\boldsymbol{a}, \boldsymbol{c}) \le 0$$
$$\underline{a} \le \boldsymbol{a} \le \overline{a}$$

Structural Optimization

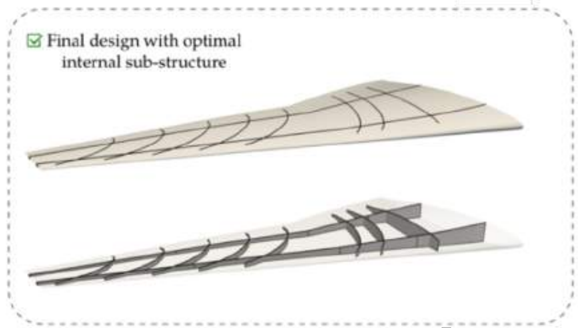




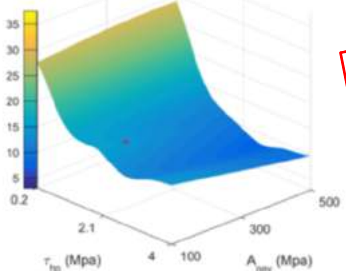




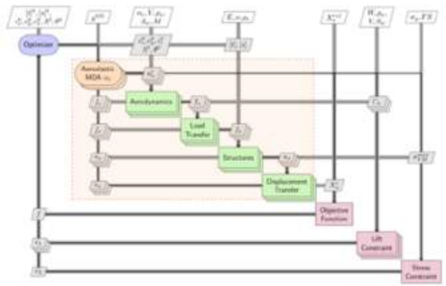
→ EcoMaterial selection

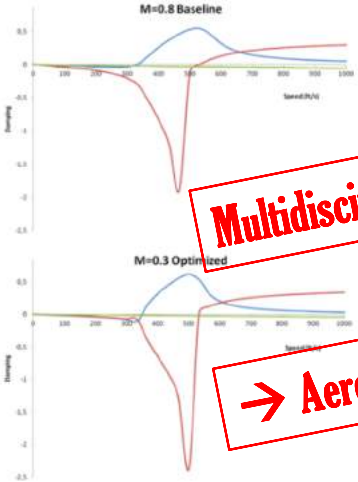


My Research Group (Joint research with ONERA on MDO)



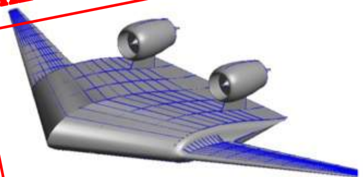
#AI4E
Artificial Intelligence For Engineers

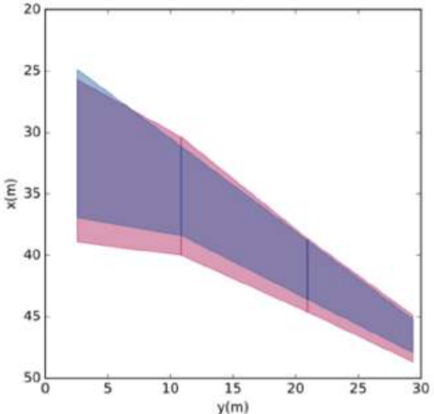




Multidisciplinary Design Optimization.

→ Aeroelasticity



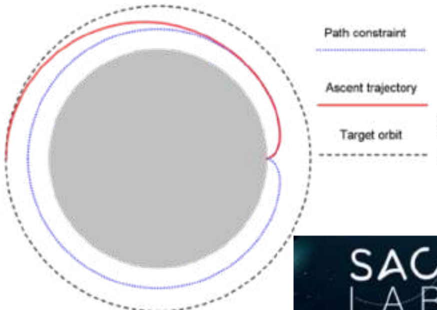


AEROSPACE ENGINEERING

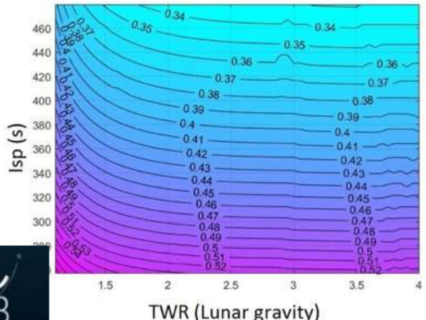
AIRBUS

CHAIR FOR ECO DESIGN OF AIRCRAFT

ONERA
THE FRENCH AEROSPACE LAB



SAC LAB



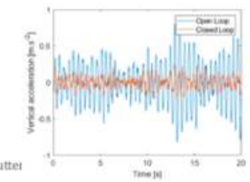
→ New disciplines such as trajectory or control

minimize $f(x) = w_1 k_h + w_2 \bar{h}_{max}(t, V_f^{CL})$

with $x = (k_h, Q, R)^{[4]}$

subject to $\begin{cases} V_f^{CL} > 1.2\, V_{f x_0}^{OL} \\ |\beta_{max}(t, V_f^{CL})| < \beta_{ref} \\ f_{max}^i < 3 f_{max\, x_0}^i \end{cases}$

where V_f^{XL} is the open loop (OL) or closed loop (CL) flutter
β_{ref} is the maximum control surface deflection
f_{max}^i is the maximum frequency of mode i
$V_{f x_0}^{OL}$ is the open-loop flutter velocity at the starting point
Q, R are the LQR weight matrix to compute K



AIRBUS

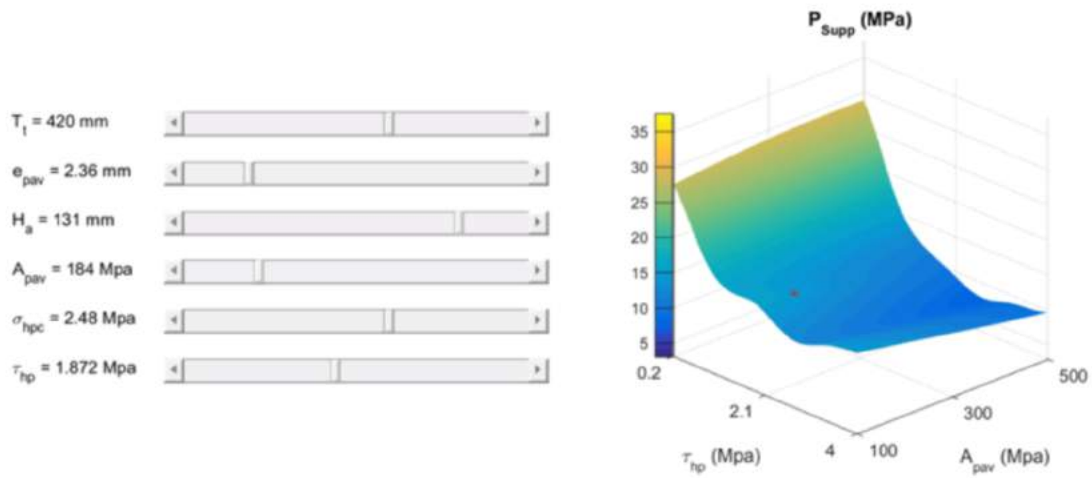
«Costly code» reduction with GP

joseph morlier ▪▪▪
Professor in Structural and Multidisciplinary Design Optimization, ... any i...
2 j

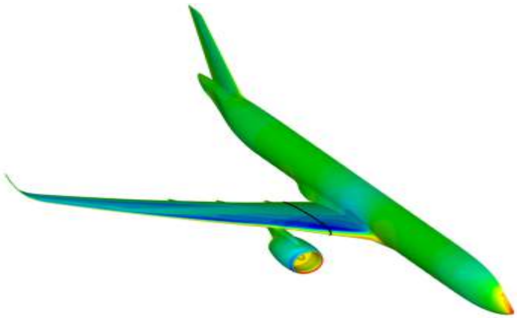
#ML

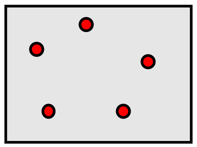
Have a look to one of our 2018 paper, where Machine Learning or Surrogate modelling technics help to understand Complex mechanical behaviour (impact on sandwich shield)

https://lnkd.in/dr_WSqA



Surrogate modeling Recipes

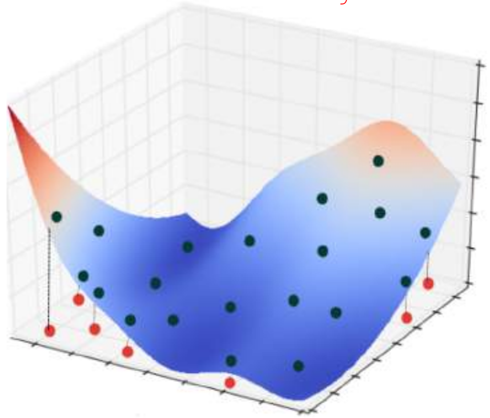


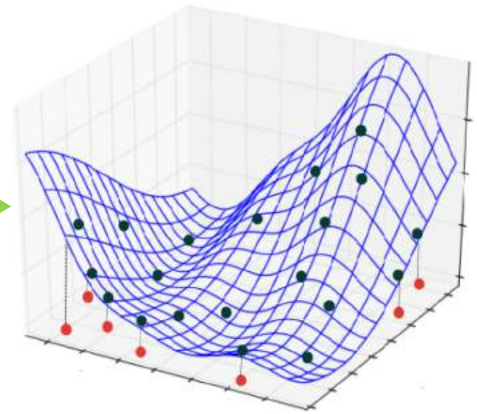


DOE

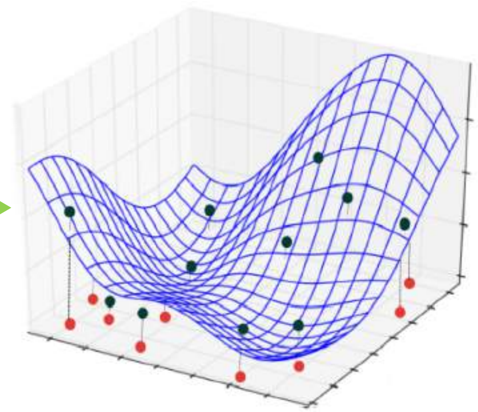
True Function Evaluation

This is costly!





Interpolant model



Regression model

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

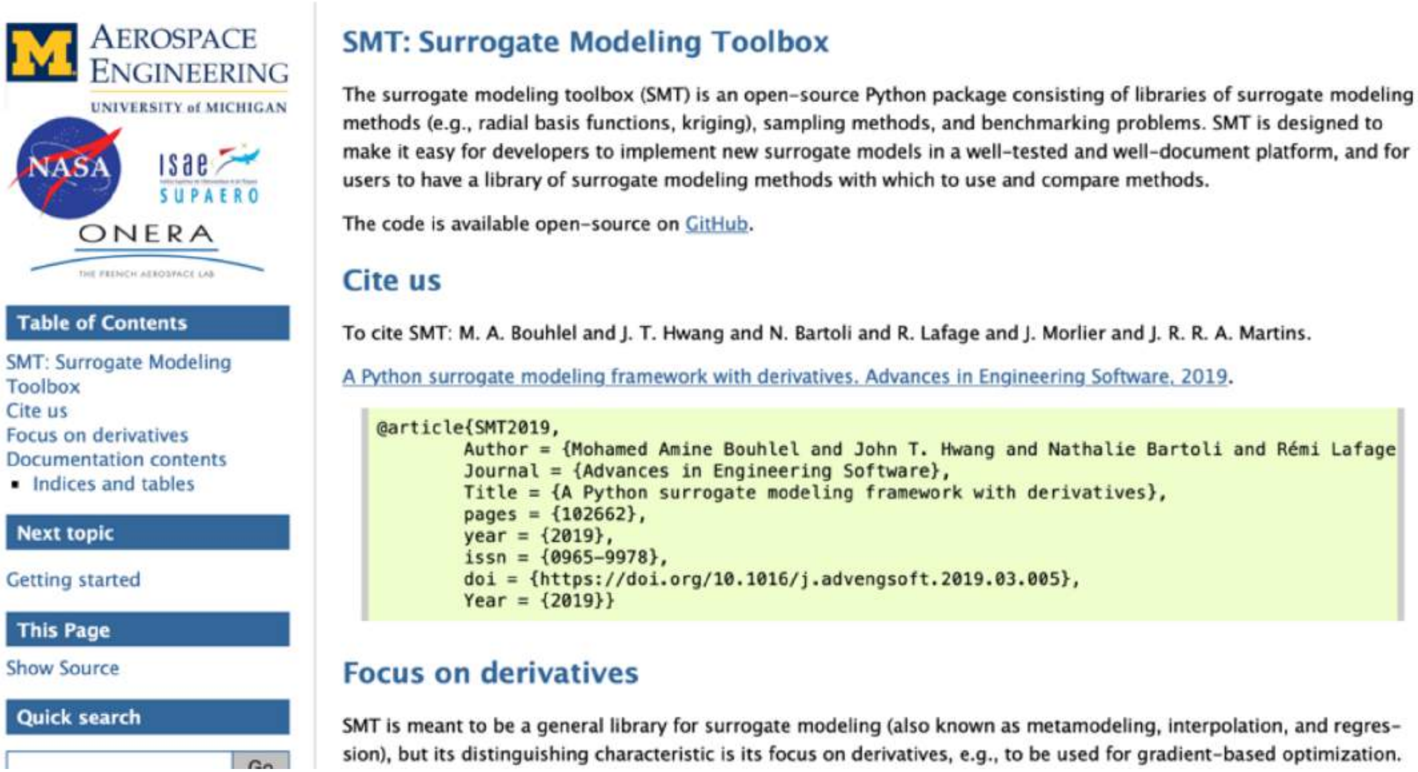
$$LOF = \frac{MSE}{Var(y)}$$

$\boldsymbol{n}$ is the number of samples

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

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

Use SMT for your own apps



AEROSPACE ENGINEERING
UNIVERSITY of MICHIGAN

Table of Contents

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

Next topic

Getting started

This Page

Show Source

Quick search

SMT: Surrogate Modeling Toolbox

The surrogate modeling toolbox (SMT) is an open-source Python package consisting of libraries of surrogate modeling methods (e.g., radial basis functions, kriging), sampling methods, and benchmarking problems. SMT is designed to make it easy for developers to implement new surrogate models in a well-tested and well-document platform, and for users to have a library of surrogate modeling methods with which to use and compare methods.

The code is available open-source on GitHub.

Cite us

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

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

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

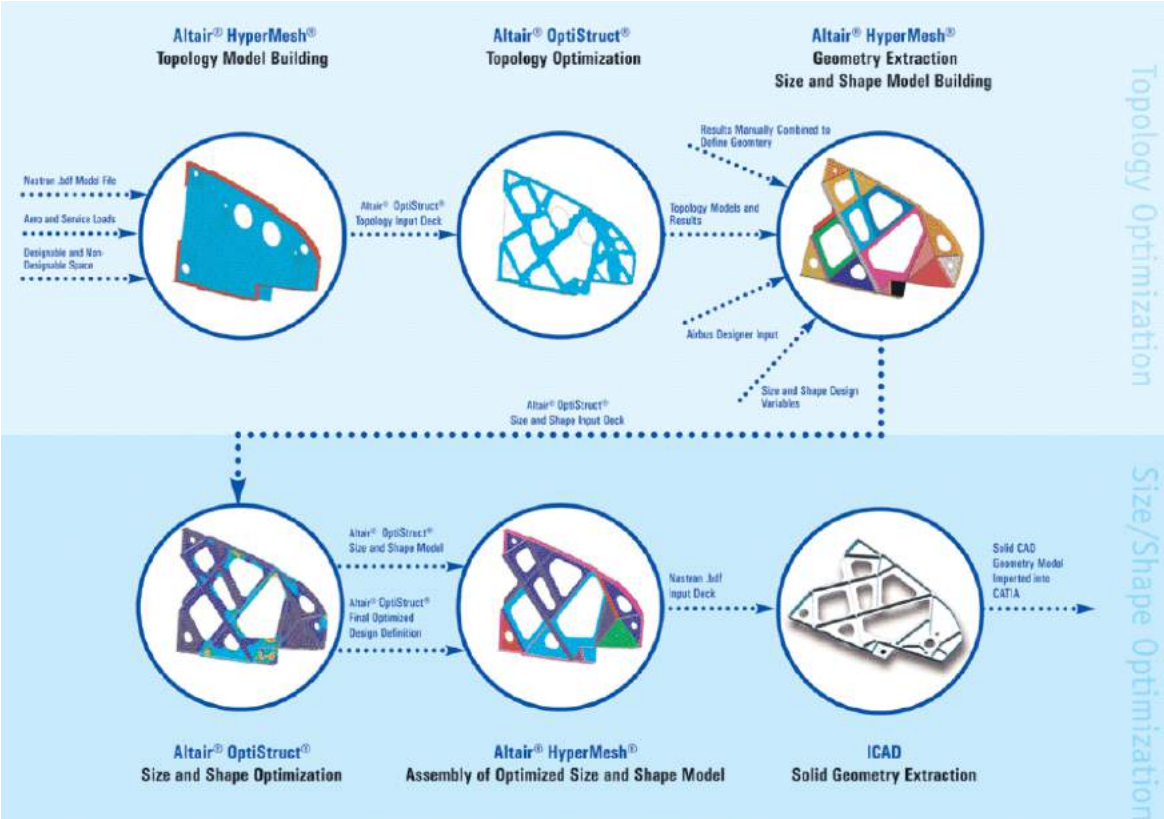
Focus on derivatives

SMT is meant to be a general library for surrogate modeling (also known as metamodeling, interpolation, and regression), but its distinguishing characteristic is its focus on derivatives, e.g., to be used for gradient-based optimization.

and please cite us…

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.

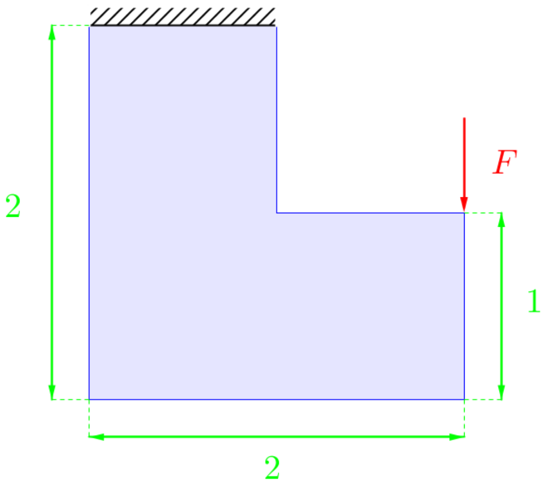
« LOW SPEED » INDUSTRIAL DESIGN

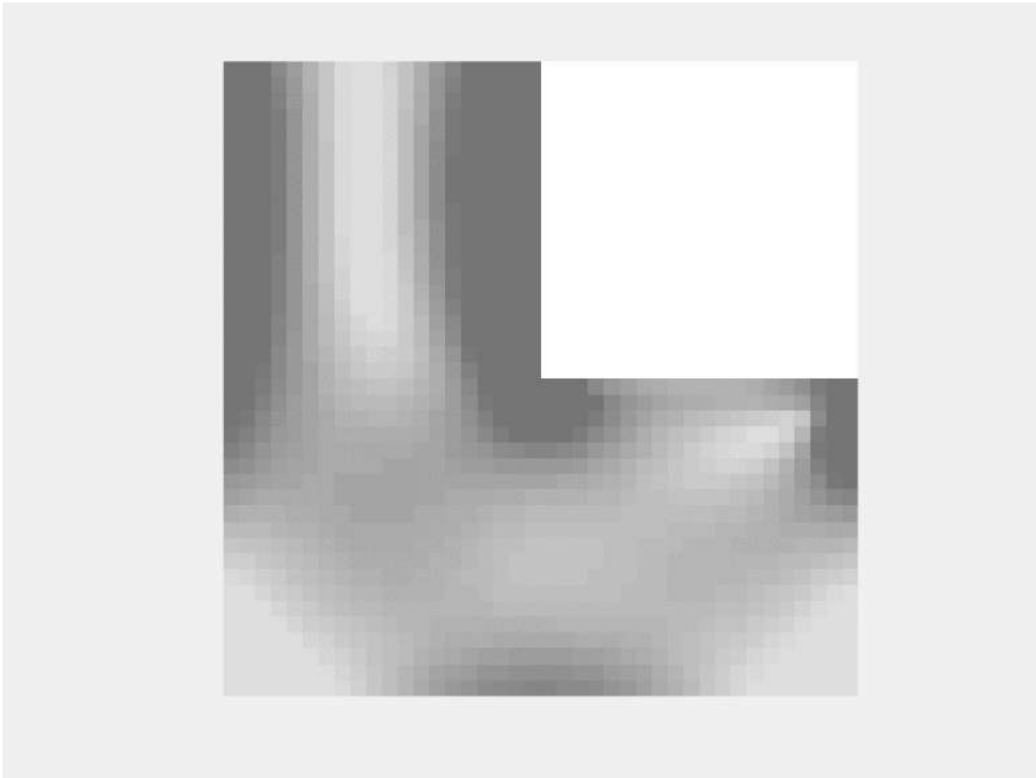


Schematic Representation of Enhanced Rib Design Process

Altair Engineering

Results SIMP nelx=nely=40→ 1600 design variables minC wrt Volfrac=0.25 , Ku=f



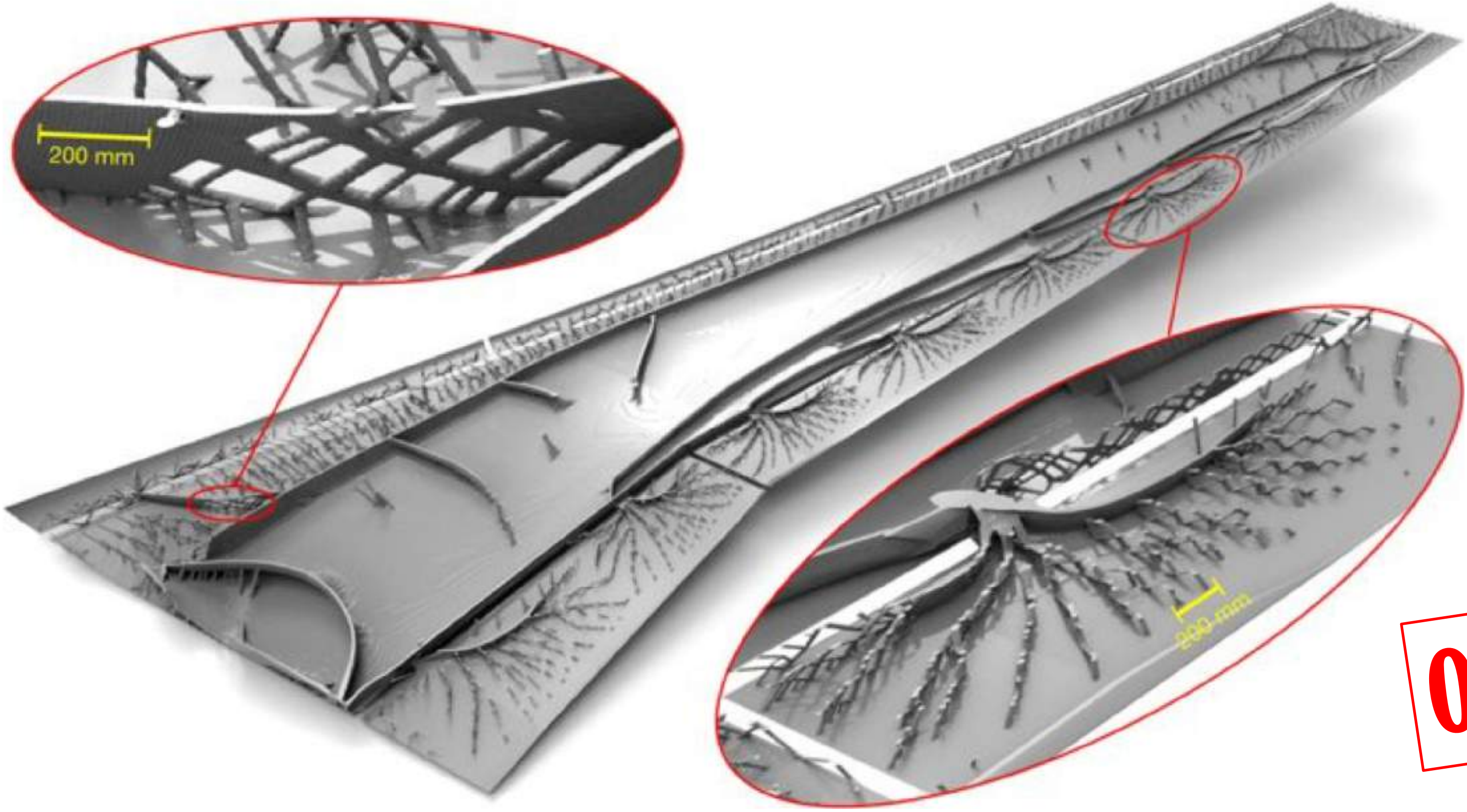


Andreassen, E., Clausen, A., Schevenels, M., Lazarov, B. S., & Sigmund, O. (2011). Efficient topology optimization in MATLAB using 88 lines of code. Structural and Multidisciplinary Optimization, 43(1), 1-16.

http://www.topopt.mek.dtu.dk

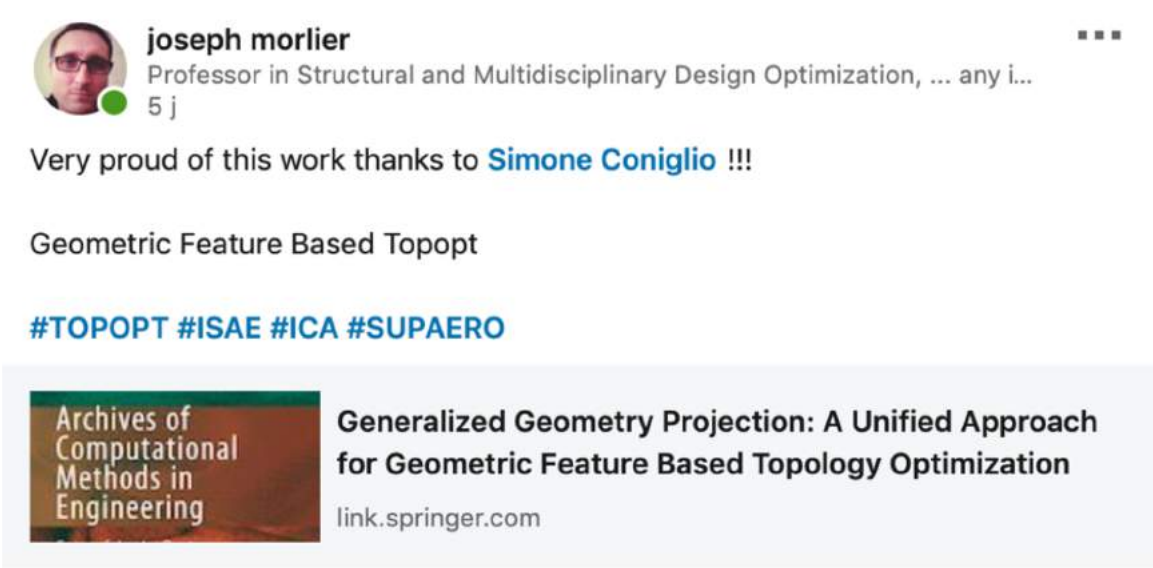
Use HPC and lot of time

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

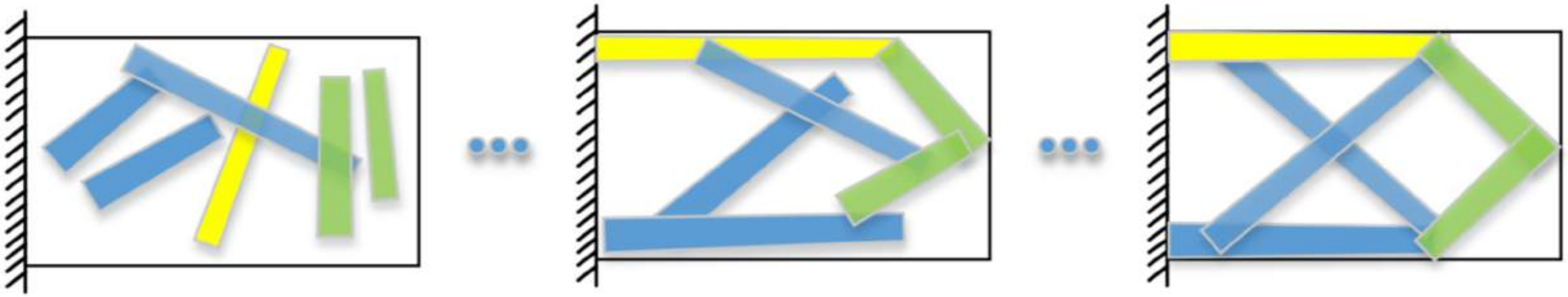


Or ...

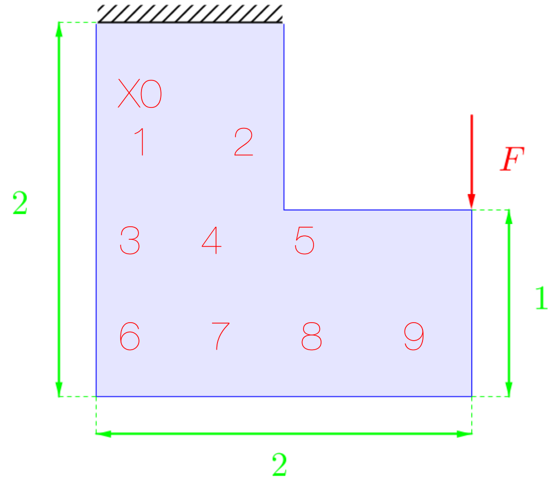
Explicit TopOpt

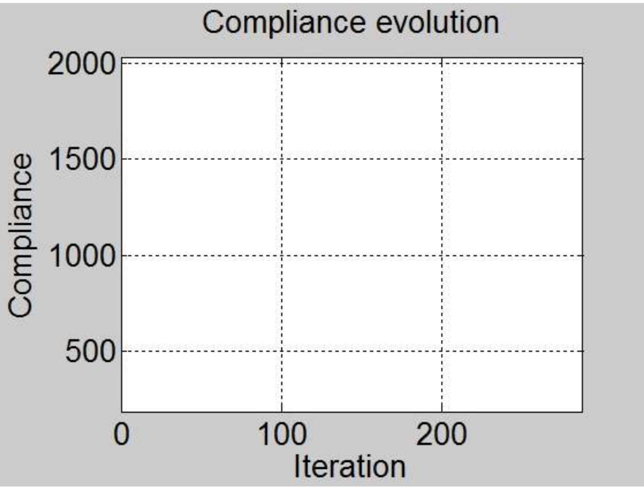


https://github.com/topggp/blog



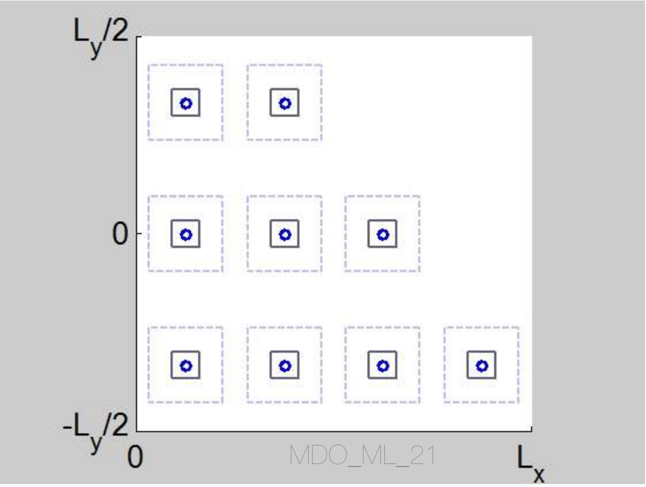
Results MNA, 9*5=45 design variables
minC wrt Volfrac=0.25 , Ku=f

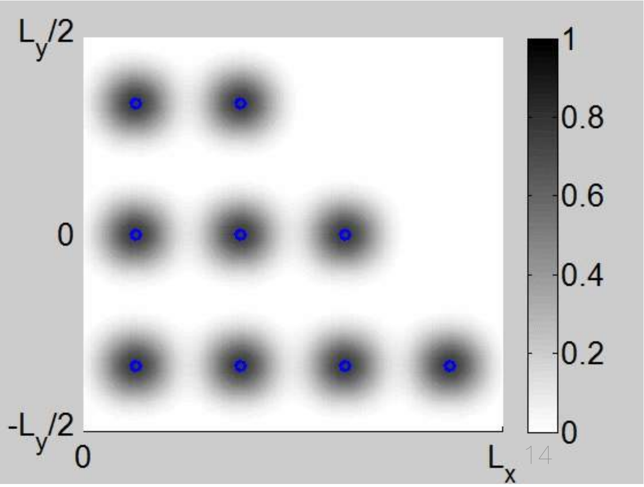




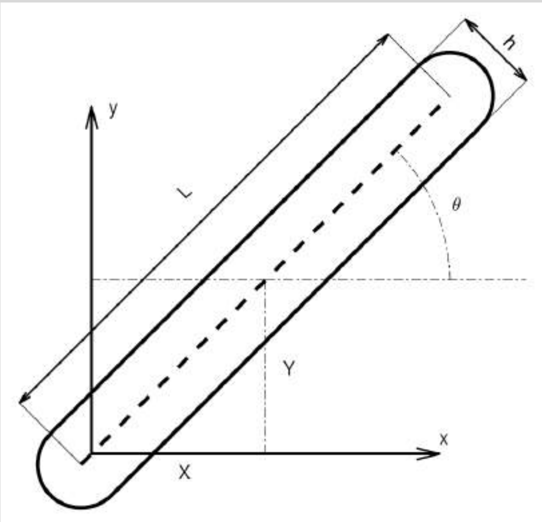
At the end, explicit assembly of beams!

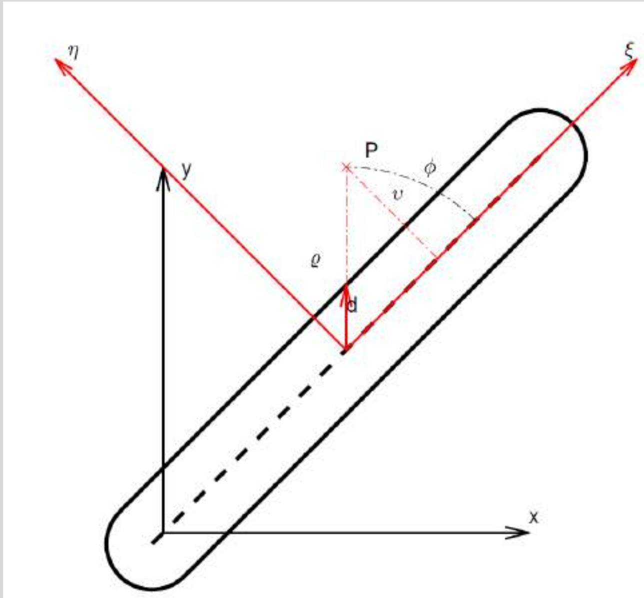
Raze, G., & Morlier, J. (2021). Explicit topology optimization through moving node approach: beam elements recognition. arXiv preprint arXiv:2103.08347..





Common Geometric Primitive Description





Configuration vector

$$\{x_i\} = \{X_i, Y_i, L_i, h_i, \theta_i, m_i\}^T$$

Polar coordinates computation

$$\varrho(x, y, X, Y) = \sqrt{(x-X)^2 + (y-Y)^2}$$

$$\phi(x, y, X, Y, \theta) = \begin{cases} \arctan\left(\frac{y-Y}{x-X}\right) - \theta & \text{if } x \neq X, \\ \frac{\pi}{2}\text{sign}(y-Y) - \theta & \text{if } x = X. \end{cases}$$

Bar axis distance computation

$$\upsilon(\varrho, \phi, L, h) = \begin{cases} \sqrt{\varrho^2 + \frac{L^2}{4} - \varrho L|\cos\phi|} & \text{if } \varrho^2 \cos\phi^2 \geq \frac{L^2}{4}, \\ \varrho|\sin\phi| & \text{otherwise} \end{cases}$$

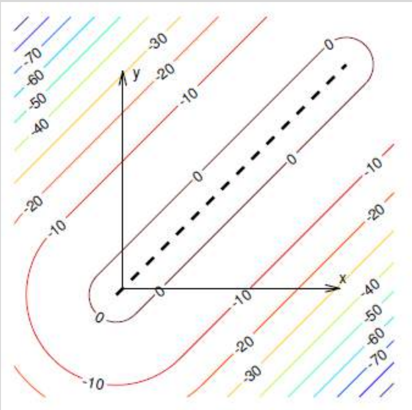
Moving **M**orphable **C**omponent**s (MMCs)** with Esartz Material model [7]

Adapted to round ended bar components

Topology Description Function Computation

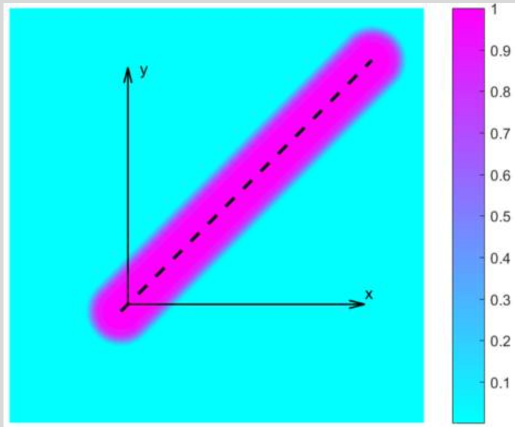
$$\begin{cases} \chi_i > 0 & \text{if } \{X_g\} \in \omega_i, \\ \chi_i = 0 & \text{if } \{X_g\} \in \partial\omega_i, \\ \chi_i < 0 & \text{if } \{X_g\} \in D\backslash\omega_i. \end{cases}$$

$$\chi_i = 1 - \left(\frac{4v_i^2}{h_i^2}\right)^{\alpha} \quad \text{with } \alpha \geq 1$$



Smooth Heaviside Function application

$$H_\epsilon(x) = \begin{cases} 1, & \text{if } x > \epsilon, \\ \frac{3(1-\beta)}{4}\left(\frac{x}{\epsilon} - \frac{x^3}{3\epsilon^3}\right) + \frac{1+\beta}{2} & \text{if } -\epsilon \leq x \leq \epsilon, \\ \beta & \text{otherwise.} \end{cases}$$

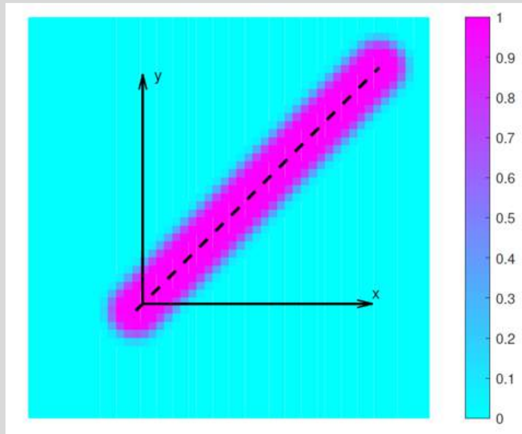


$H_\epsilon(\chi(\{X_g\}))$

Element Material update

$$E^{el} = \frac{E\left(\sum_{j=1}^{4}(H_\epsilon(\chi_j^{el}))^q\right)}{4}$$

$$\rho^{el} = \frac{\sum_{j=1}^{4}(H_\epsilon(\chi_j^{el}))}{4}$$

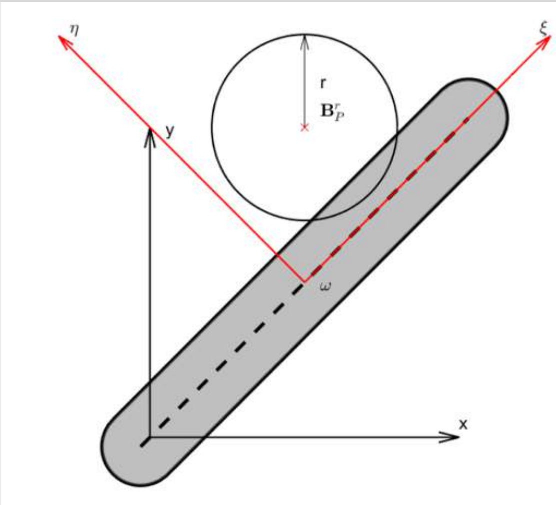


$\frac{E^{el}}{E}$

[7] Zhang, Weisheng, et al. "A new topology optimization approach based on Moving Morphable Components (MMC) and the ersatz material model." Structural and Multidisciplinary Optimization 53.6 (2016): 1243-1260.

Geometry Projection Method [10]

Signed distance computation



$$\varsigma(v,h) := v - \frac{h}{2}$$

Local volume fraction computation

$$\delta_i^{el} = \frac{|\mathbf{B}_P^r \cap \omega_i|}{|\mathbf{B}_P^r|}$$

$$\delta_i^{el} \approx \begin{cases} 0 & \text{if} \quad \varsigma > r, \\ \frac{1}{\pi r^2}\left[r^2 \arccos\left(\frac{\varsigma}{r}\right) - \varsigma\sqrt{r^2 - \varsigma^2}\right] & \text{if} \quad -r \leq \varsigma \leq r, \\ 1 & \quad \text{otherwise.} \end{cases}$$

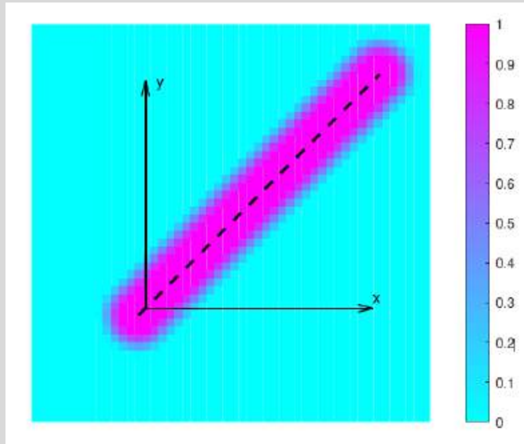
Element Material update

$$\tilde{\delta}_i^{el} = \delta_{min} + (1 - \delta_{min})\delta_i^{el}$$

$$\hat{\delta}_i^{el}(m_i, \gamma) = \tilde{\delta}_i^{el} m_i^{\gamma}$$

$$\rho^{el}(\gamma_v, \kappa) = \Pi(\{\hat{\delta}^{el}(\{m\}, \gamma_v)\}, \kappa)$$

$$E^{el} = \rho^{el}(\gamma_c, \kappa)E$$



$$\frac{\boldsymbol{E}^{el}}{\boldsymbol{E}}$$

[10] Zhang, Shanglong, et al. "A geometry projection method for the topology optimization of plate structures." Structural and Multidisciplinary Optimization 54.5 (2016): 1173-1190.

Moving **N**ode **A**pproach (MNA) [11]

Smooth characteristic function computation

$$w(v,h,\varepsilon) = \begin{cases} 1 & \text{if} \quad v \le l, \\ a_3 v^3 + a_2 v^2 + a_1 v + a_0 & \text{if} \quad l < v < u, \\ 0 & \text{otherwise.} \end{cases}$$

$$l = \frac{h}{2} - \frac{\varepsilon}{2}$$
$$u = \frac{h}{2} + \frac{\varepsilon}{2}$$
$$a_3 = \frac{2}{\varepsilon^3}$$
$$a_2 = -\frac{3h}{\varepsilon^3}$$
$$a_1 = 3\frac{(h^2 - \varepsilon^2)}{\varepsilon^3}$$
$$a_0 = -\frac{(h+\varepsilon)^2(h-2\varepsilon)}{4\varepsilon^3}$$

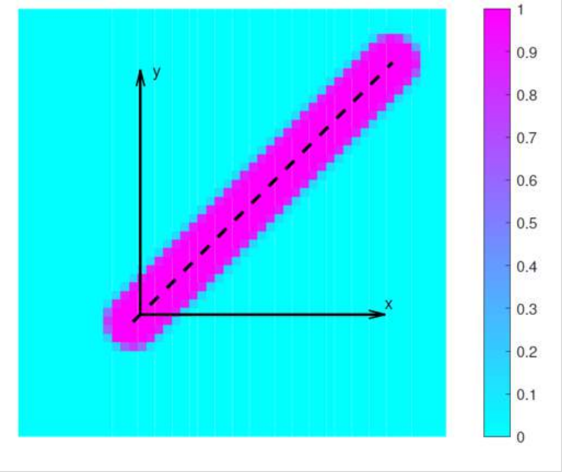
Local density computation

$$\delta_i^{el} = m_i^\gamma w(v_i^{el}, h_i, \varepsilon_i) = m_i^\gamma w_i^{el}$$

Element Material update

$$\rho^{el} = \Pi(\{\delta\}_v^{el}, \kappa)$$

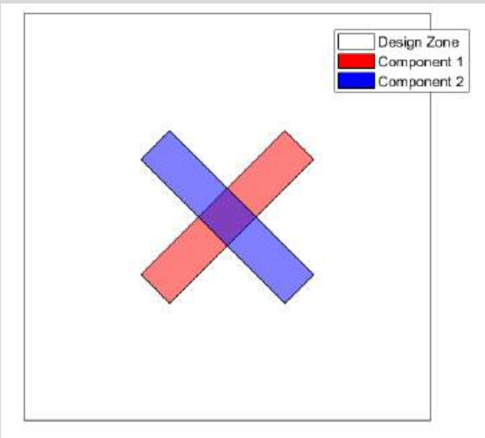
$$E^{el} = E_{min} + (E - E_{min})(\Pi(\{\delta\}_c^{el}, \kappa))^{p_b}$$

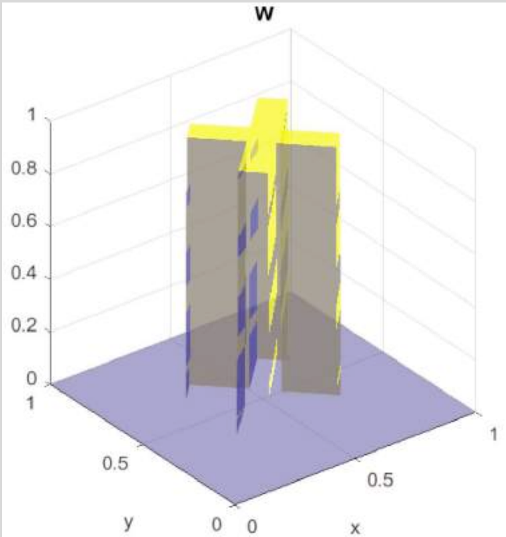


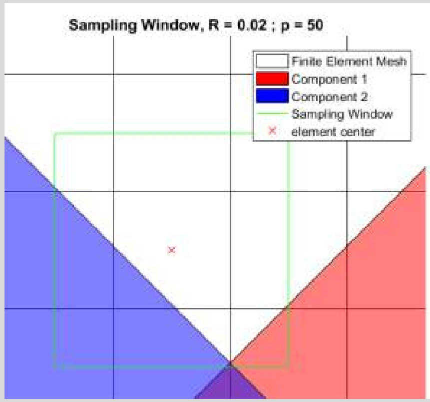
[11] Overvelde, Johannes TB. "The Moving Node Approach in Topology Optimization." (2012).

Generalized Geometry Projection (GGP)

Geometric features → Characteristic functions → Generalized Geometry Projection → Fixed mesh model update

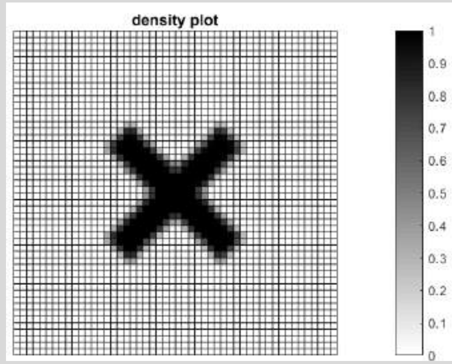






$$\mathbf{D}(\{X_g\},p,R) = \{\{X\} \in \mathbb{R}^{d_g} \mid \|\{X\} - \{X_g\}\|_{2p} \le R\}$$

$$\delta_i^{el}(W_i,p,R) = \frac{\int_{\mathbf{D}(\{X_g^{el}\},p,R)} W_i(\{X\},\{X_i\},\{r\})d\Omega}{\int_{\mathbf{D}(\{X_g^{el}\},p,R)} d\Omega}$$



$$E^{el} = \mathbb{M}(\{\delta^{el}\}_c, E, E_{min}, \kappa)$$

$$\rho^{el} = \mathbb{V}(\{\delta^{el}\}_v, \kappa)$$

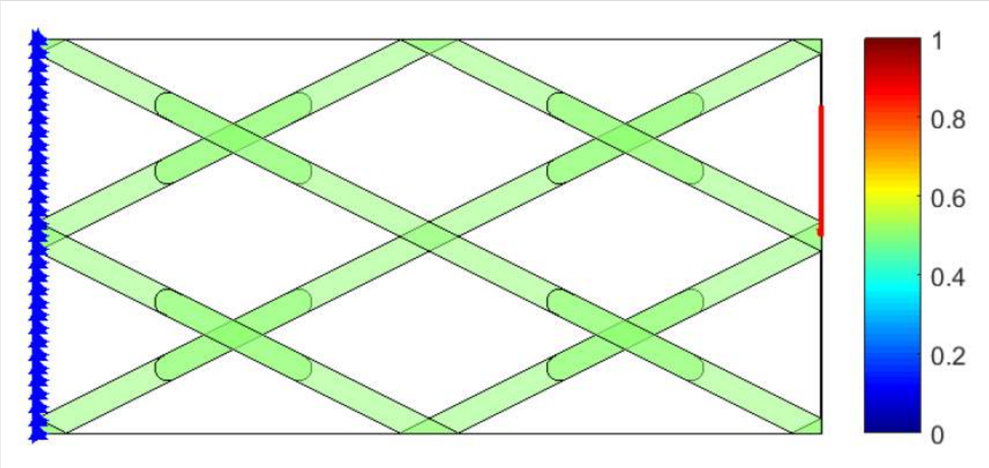
Generalized **G**eometry **P**rojection (GGP)

Table 1: Choice to be made to recover all other approaches using Generalized Geometric Projection

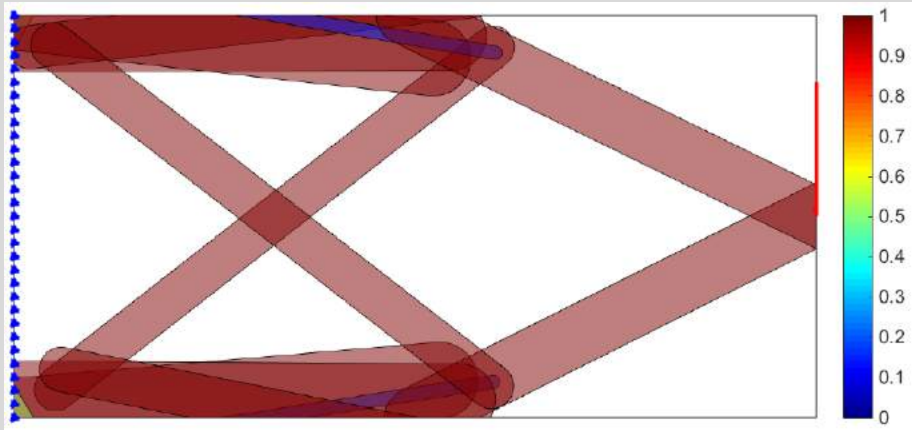
Method	MMC	GP	MNA
W^c	$H_\epsilon(\chi^{el})^q$	$\tilde{\delta}_i^{el} m_i^{\gamma_c}$	$m_i^{\gamma_c} w_i^{el}$
W^v	$H_\epsilon(\chi^{el})$	$\tilde{\delta}_i^{el} m_i^{\gamma_v}$	$m_i^{\gamma_v} w_i^{el}$
p	∞	∞	∞
R	$\frac{\sqrt{3}}{2} dx$	$\frac{1}{2} dx$	$\frac{1}{2} dx$
N_{GP}	4	1	1
$\mathbb{V}$	$\frac{\sum_{j=1}^{4} H_\epsilon(\chi_j^{el})}{4}$	$\Pi(\left\{\hat{\delta}^{el}\right\}_v, \kappa)$	$\Pi(\{\delta^{el}\}_v, \kappa)$
$\mathbb{M}$	$\frac{\sum_{j=1}^{4} (H_\epsilon(\chi_j^{el}))^q}{4}$	$\Pi(\left\{\hat{\delta}^{el}\right\}_c, \kappa) E$	$E_{min} + (E - E_{min}) \Pi(\{\delta^{el}\}_c, \kappa)^{p_b}$

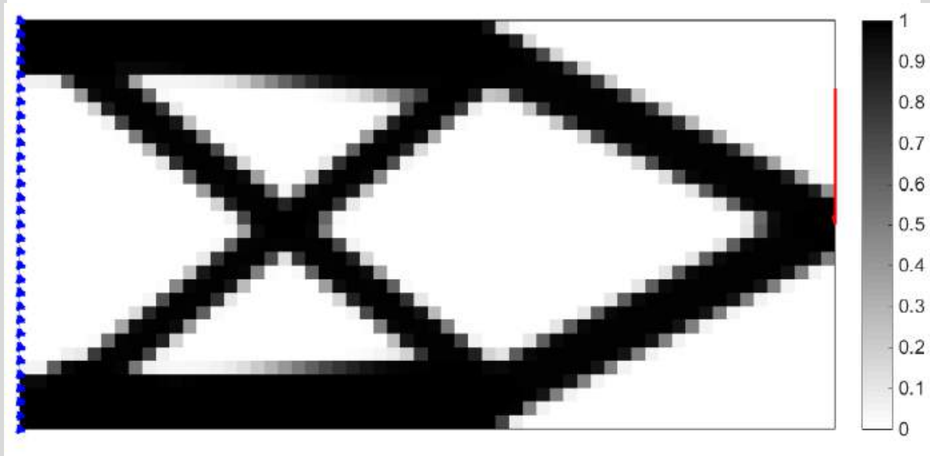
- All reviewed approach can be represented as a special case of Generalized Geometry Projection
- One can moreover change sampling window size (R),shape (p), Gauss Points number (N_{GP})
- Changing the number of Gauss point one can avoid optimization saddle points induced by the projection

Generalized **G**eometry **P**rojection (GGP)



$$
\begin{cases}
\min_{\{x\}} C = \{U\}^T\{F\} \\
s.t. \\
V = \frac{\sum_{el=1}^{N} \rho^{el}}{N} \leq V_0 \\
\{l_b\} \leq \{x\} \leq \{u_b\}
\end{cases}
$$





Continuation strategy for MNA approach and stress allowable update

- Try to achieve improved local optima
- Sequentially increasing the problem non-convexity evolving hyper parameters:
  - p_b is initially set to 2 increased of 1 every 300 iterations or after reaching convergence stopped at 3
  - ε is initially set to 6-12 elements is decreased of 1-2 elements every 300 iterations or after reaching convergence stopped at 3 elements
  - Limit stress for stress constraints is updated every 20 iteration to account of KS function maximum approximation

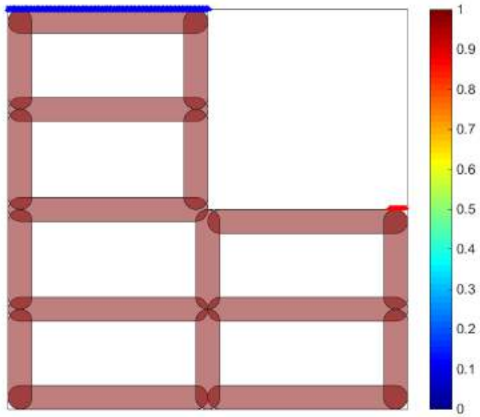
$$\begin{cases} \min \{|\Omega_{el}|\}^T \{x\} \\ s.t. \\ \{l_b\} \leq \{x\} \leq \{u_b\} \\ G_{KS}^l \leq 0 \end{cases}$$

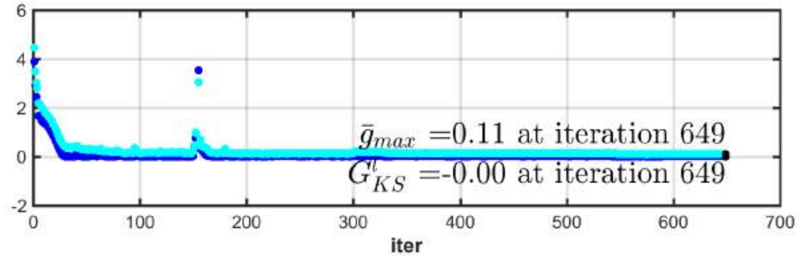
$$\sigma_{max} = C\sigma_{lim}$$

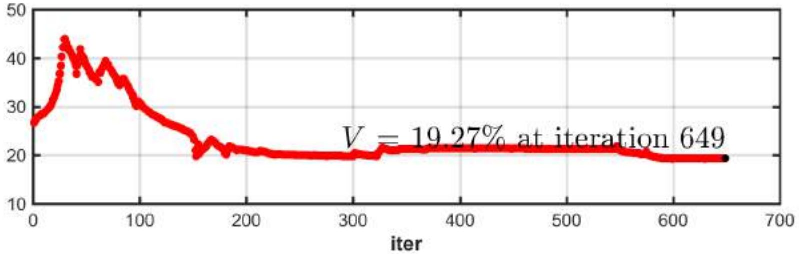
$$(\sigma_{lim})_{(n+1)k} = \frac{1}{C}\sigma_{alw} = \frac{(\sigma_{lim})_{nk}}{(\sigma_{max})_{nk}}\sigma_{alw}$$

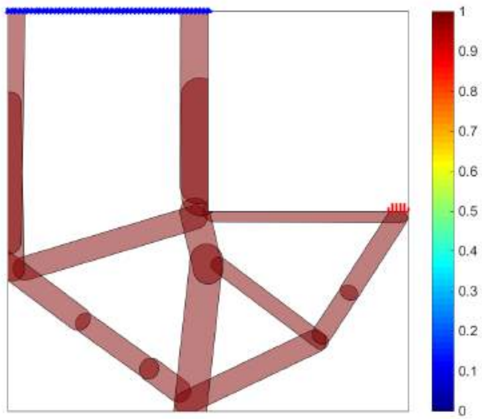
$$|\sigma_{alw} - \sigma_{max}| < tol_\sigma$$

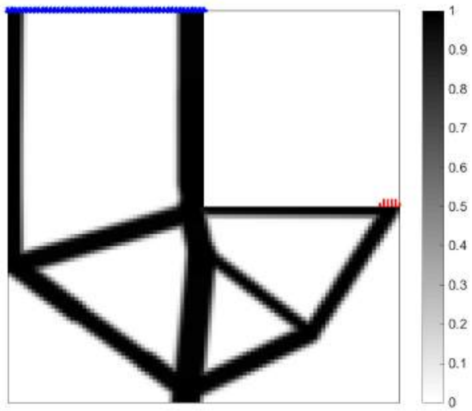
L-shape stress based Explicit TO

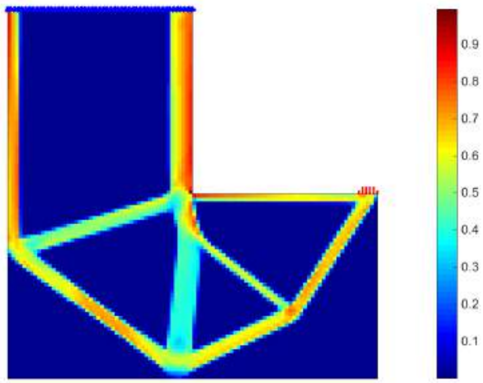








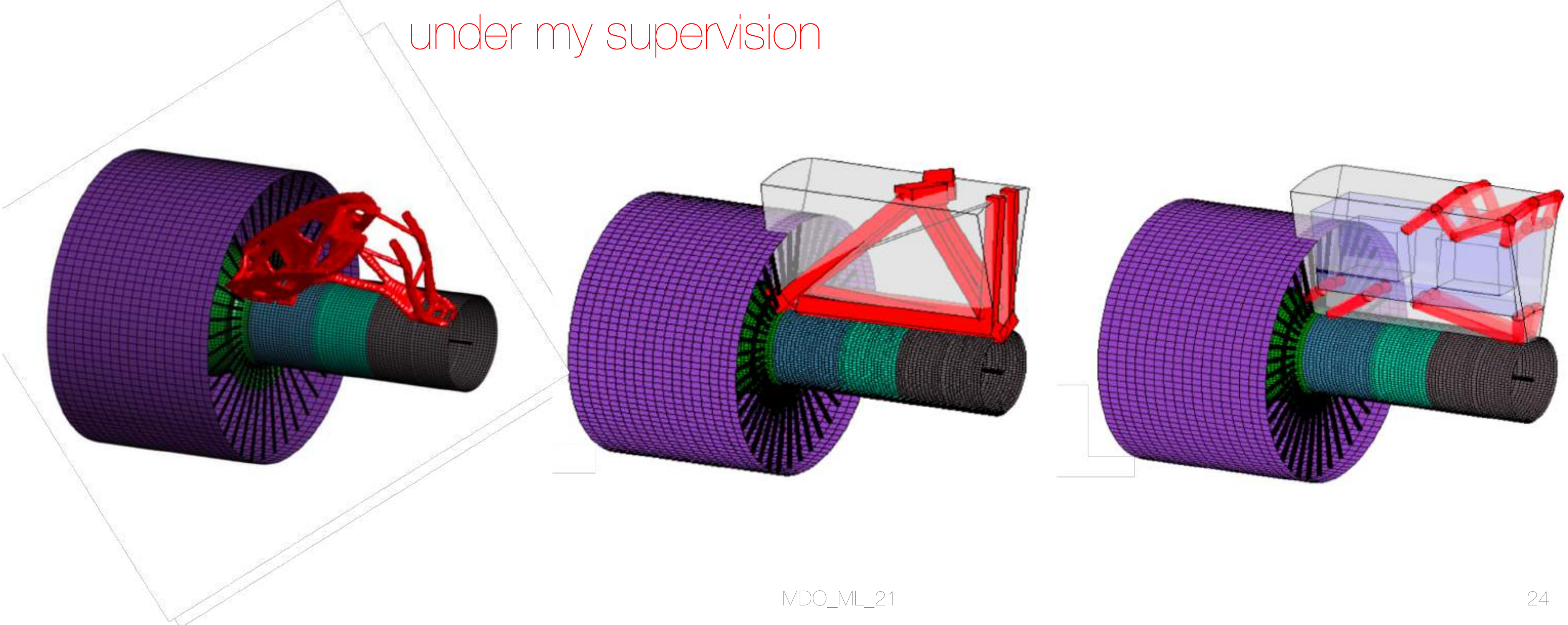




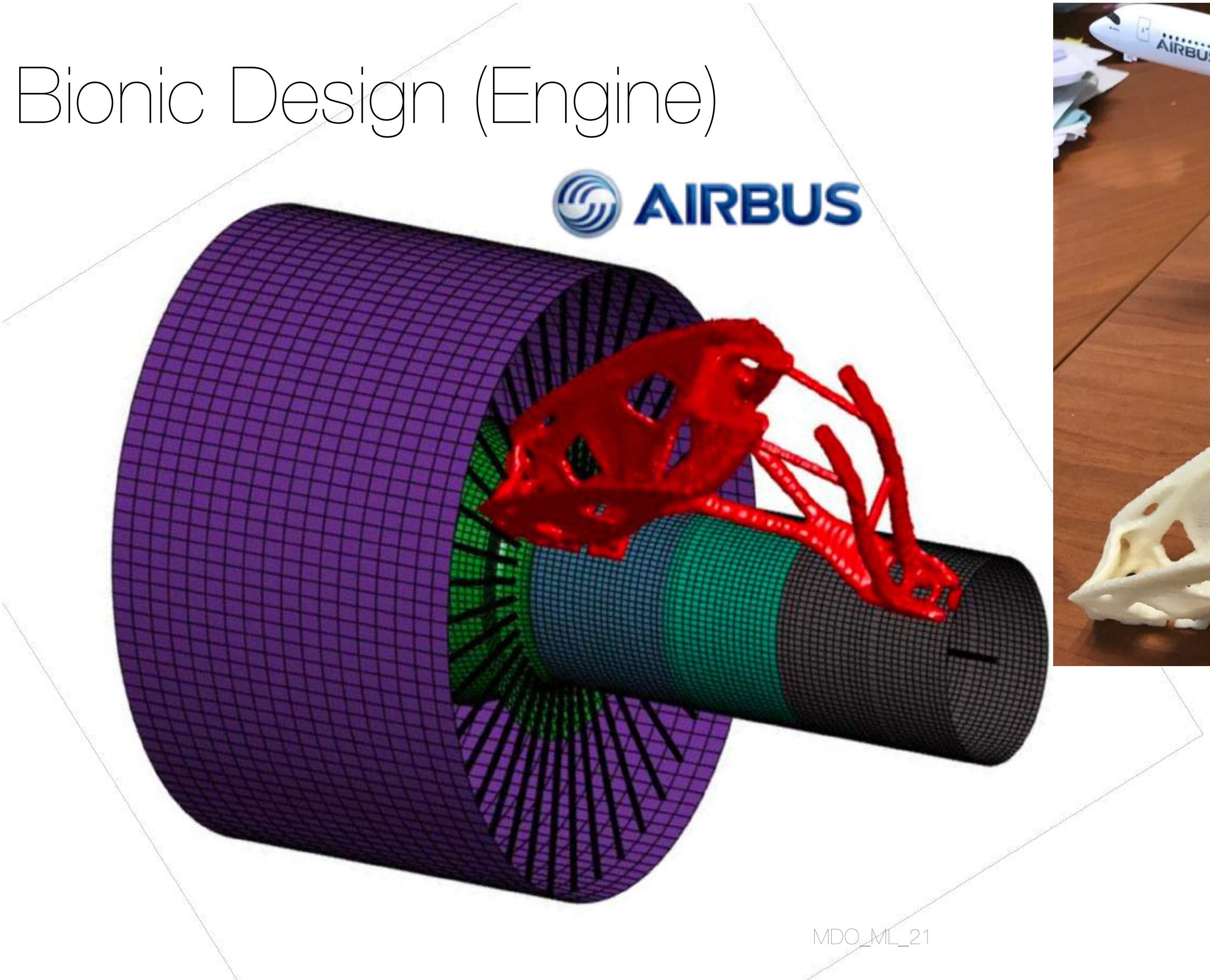
Bionic SIMP vs EXP TRUSS vs EXP WINGBOX

RESULTS OF SIMONE CONIGLIO's PHD at AIRBUS

under my supervision



Bionic Design (Engine)



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

Prof. Joseph Morlier, Vilas Bhat* (MAE 2019), Edouard Duriez (X-SUPAERO 2018), Enrico Stragiotti (Polito 2020, Onera)

Simone Coniglio, Gabriele Capasso Airbus, Prof. C. Gogu (ICA)

#Multiscale aerostructures

#Reasoned HPC

#AI4E

#MDO including Ecodesign. of Materials & Process, 3Dprinting, SHM …

*

ONERA
THE FRENCH AEROSPACE LAB

ICA
INSTITUT CLÉMENT ADER

AGENCE NATIONALE DE LA RECHERCHE
ANR

l'X
ÉCOLE POLYTECHNIQUE
IP PARIS

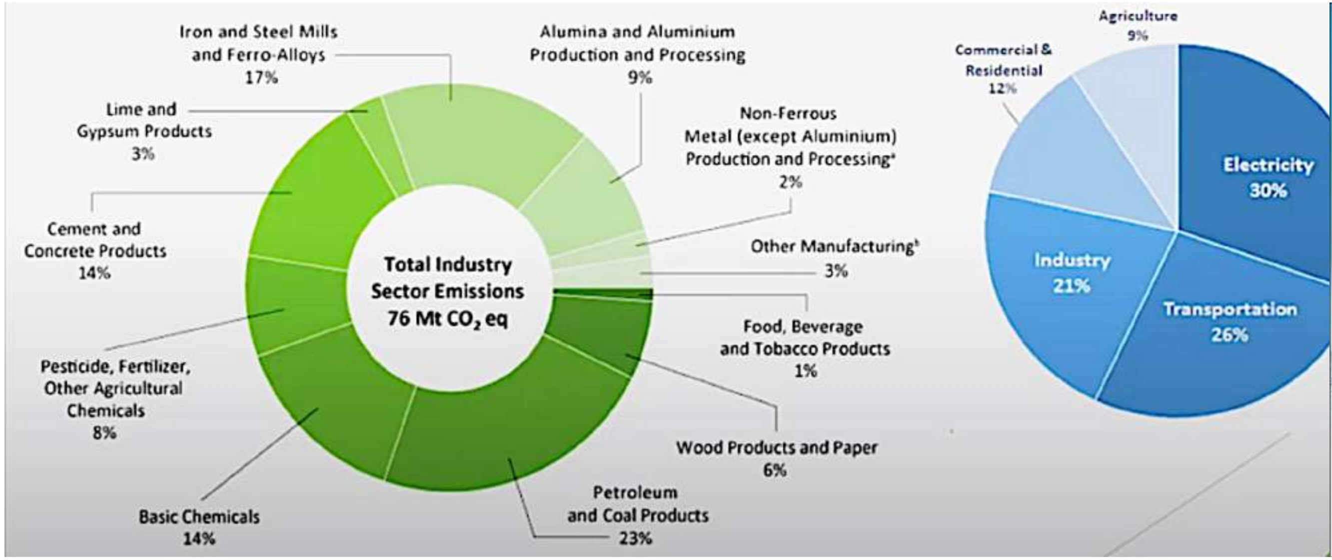
isae
Institut Supérieur de l'Aéronautique et de l'Espace
SUPAERO

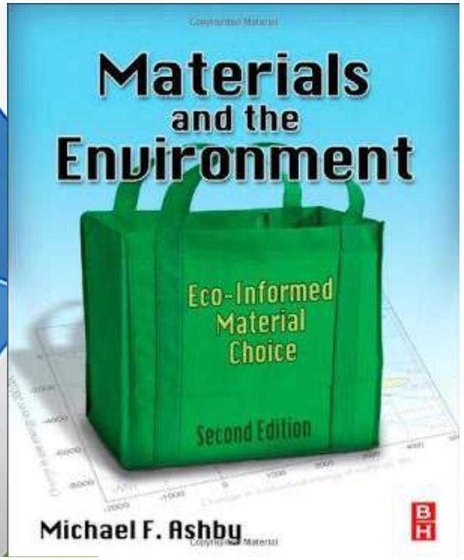
How to **ECO**design tomorrow's structures?

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

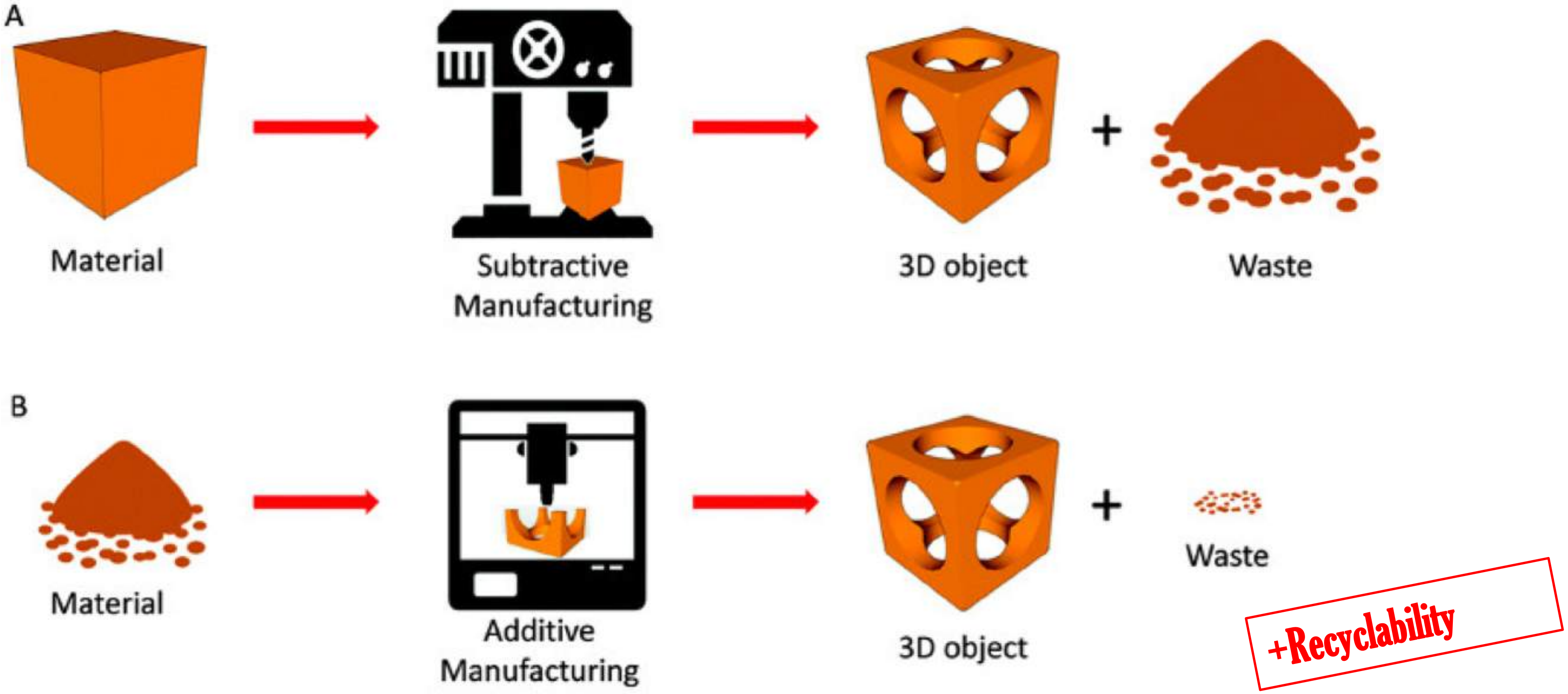
#The essential technologies for the transition, in particular green energy, will translate into considerable demand for metals that have become strategic.

#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. !!!

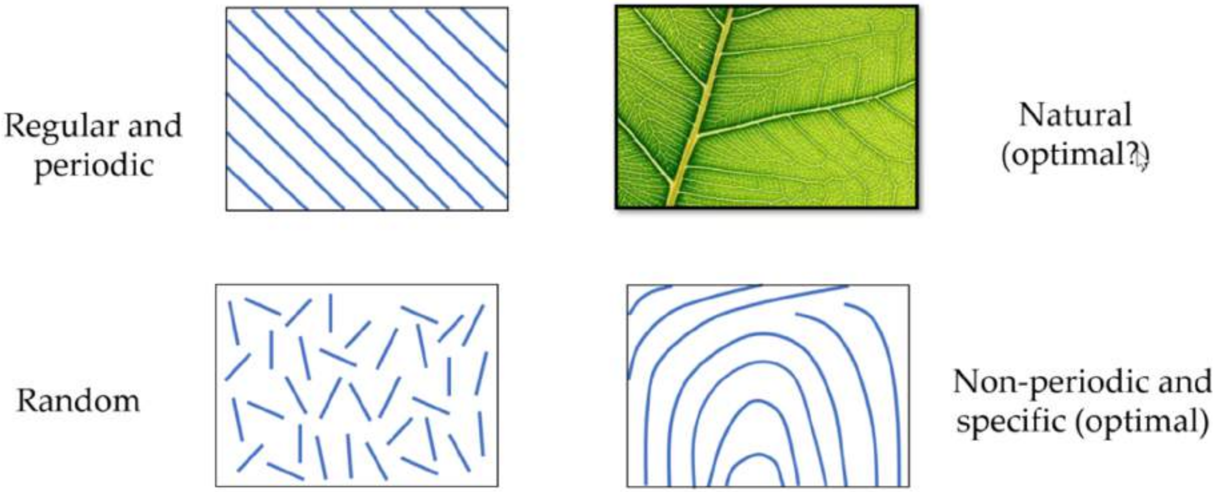




Why Metallic 3D printing?

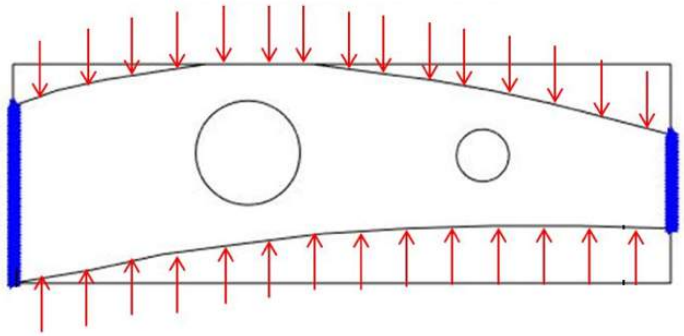


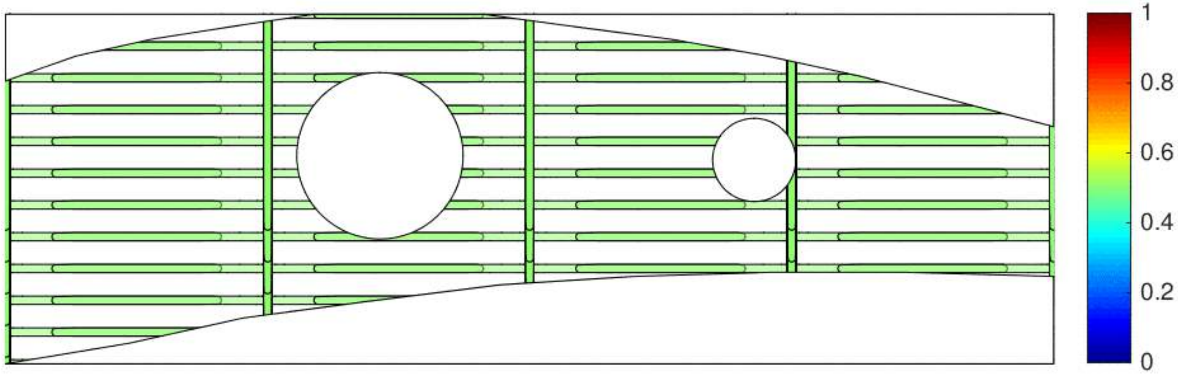
Why Composites 3D printing?



+ Automatic Fiber Placemen t

A typical Aerostructures example



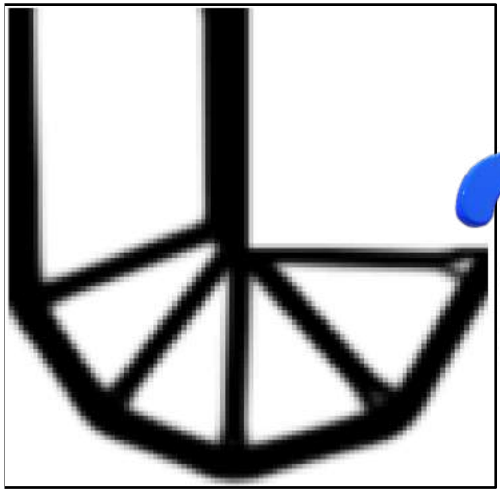


use GGP

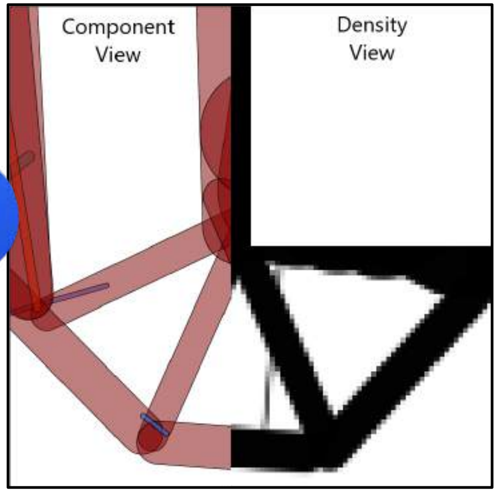
https://github.com/topggp/blog

GGP For ALM?

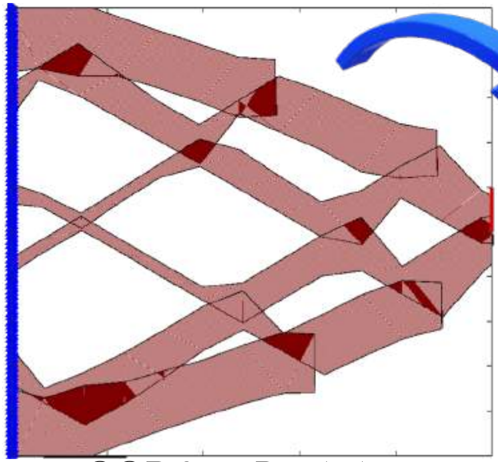
Prof, How can I do that?



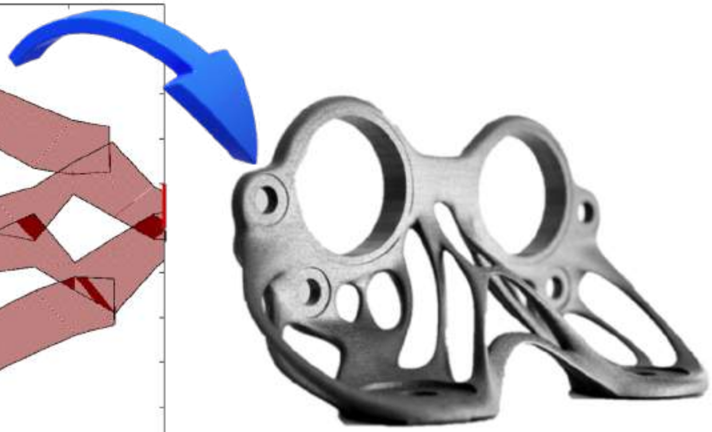
SIMP



GGP



GGP for 3D printing

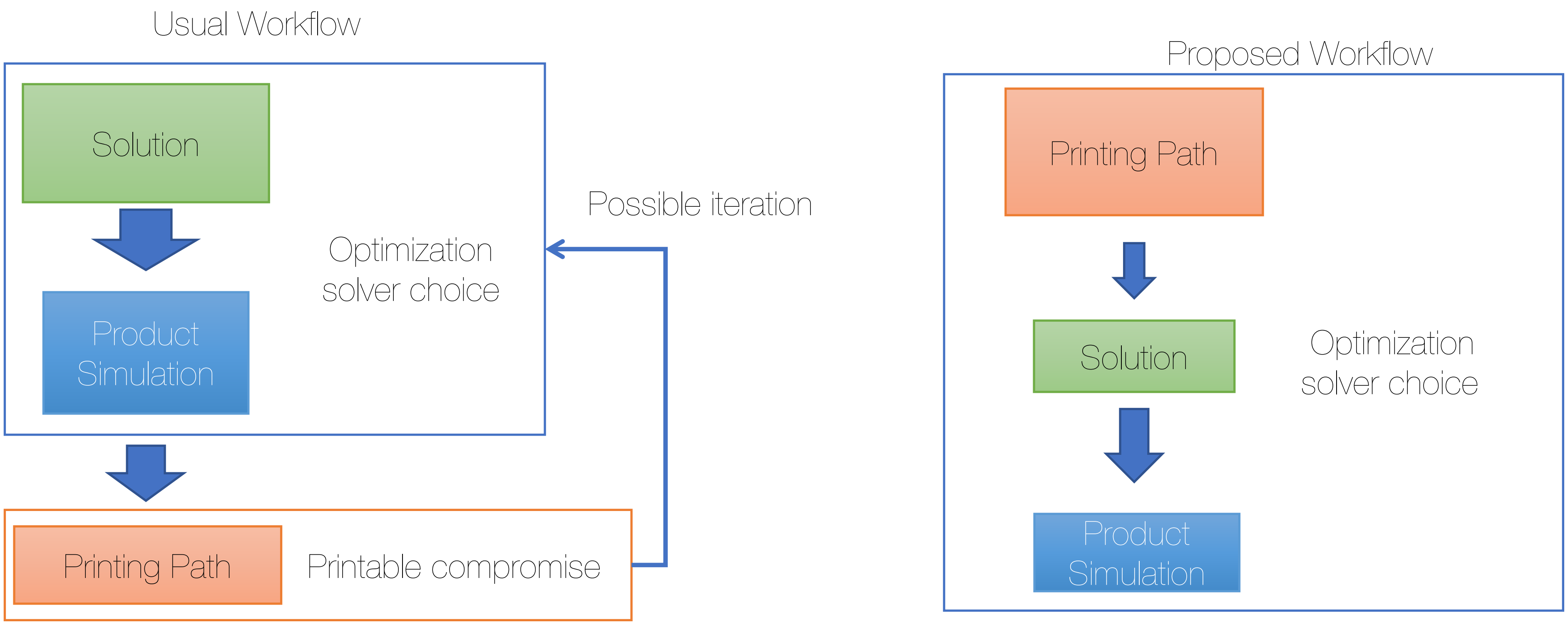


3D Printed part

S. Coniglio, J. Morlier, C. Gogu, An introduction to Generalized Geometry Projection, a unified framework for feature-based topology optimization methods, WCCM-ECCOMAS 2020

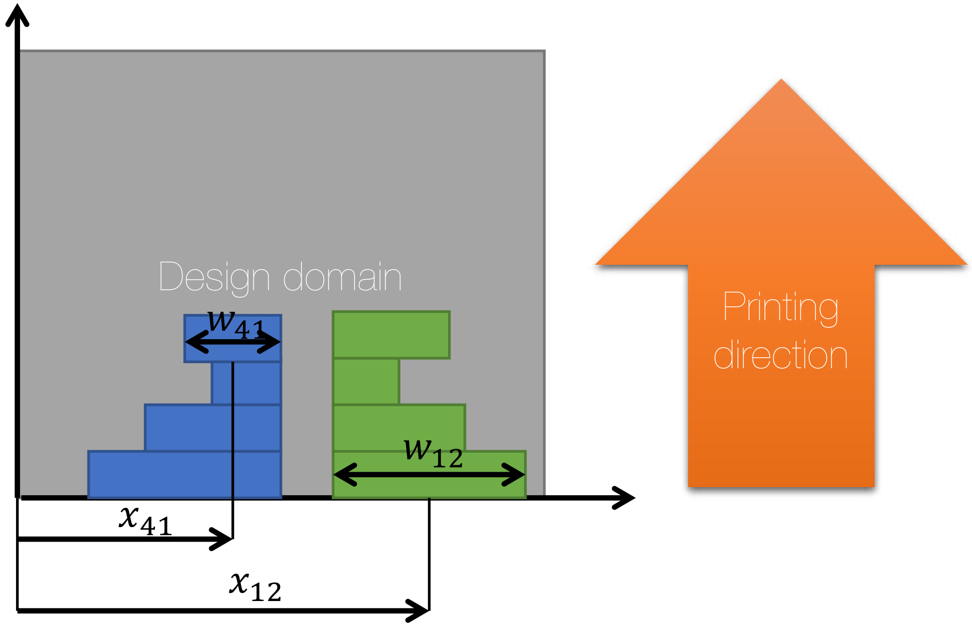
G. Capasso, V. Bhat, S. Coniglio, J. Morlier, C. Gogu, Topology Optimization of Additive Layer Manufacturing products using Generalized Geometric Projection, WCCM-ECCOMAS 2020

ALM based GGP

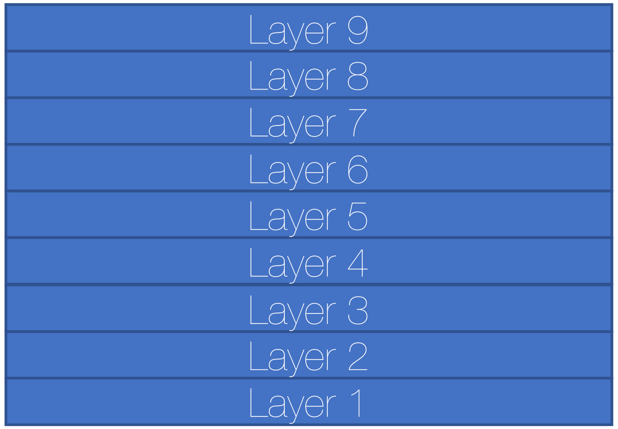


ALM based GGP

A solution is determined by its manufacturing process: (in this case printing path)



Printing process is discretized in n_l layers



- MNA Components are replaced by printed branches
- Design variables will be printed branch position and width per layer: x_{li}, w_{li}
- For each layer a projection is made to get the solid model modulus

ALM based GGP

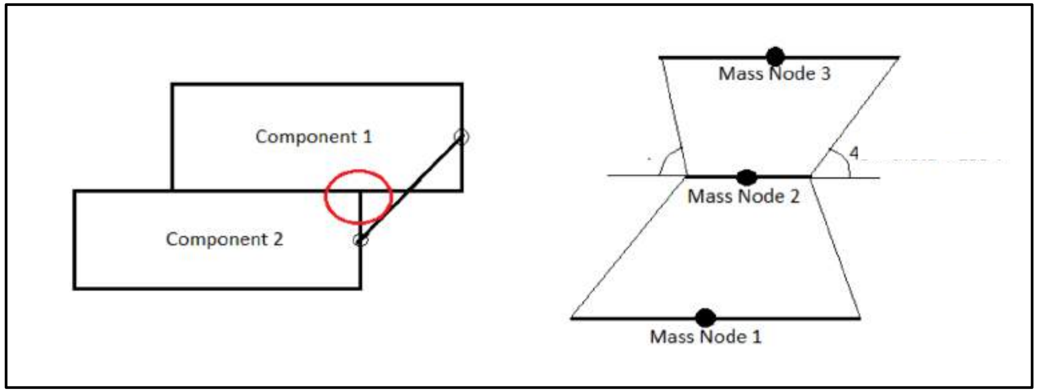
Optimization formulation

$$\begin{cases} \min\limits_{X} c = F^T \cdot U \\ \qquad s.t. \\ \sum\limits_{i=1}^{N} \rho_i - v_f N \leq 0 \\ \theta_l \leq \theta \quad \leq \pi - \theta_l \end{cases}$$

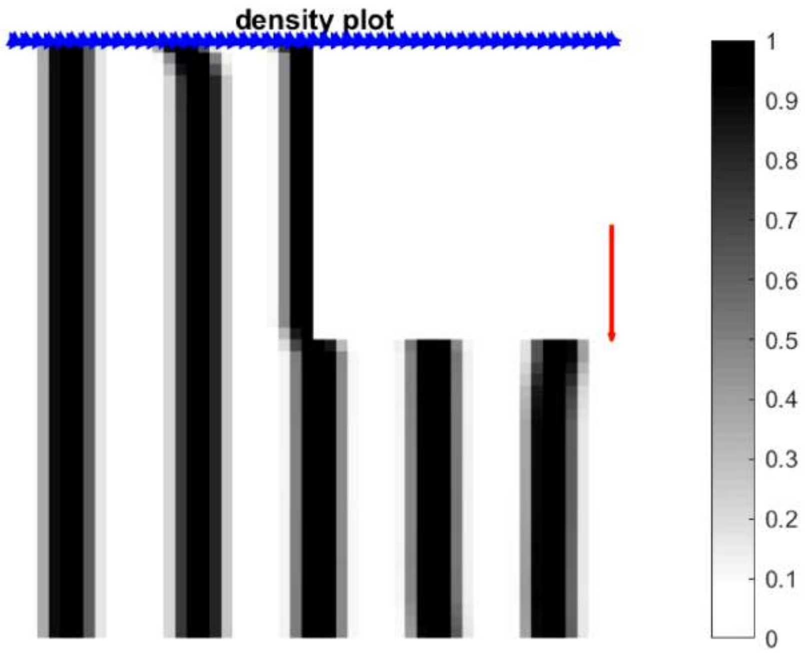
External forces work

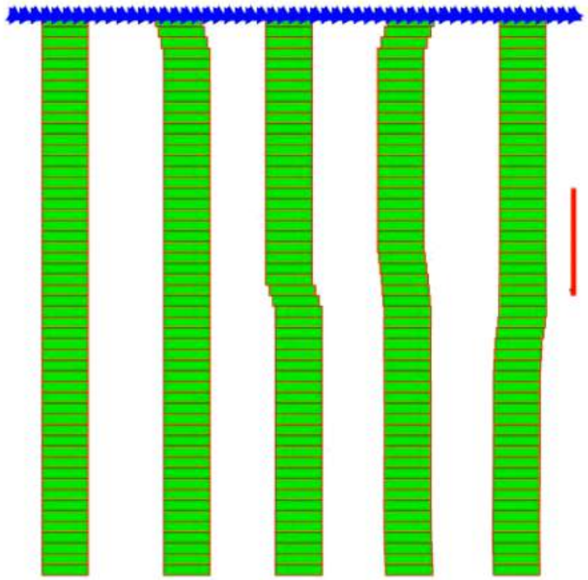
Mass constraint

Overhang angle constraint



ALM based GGP: Very First Results



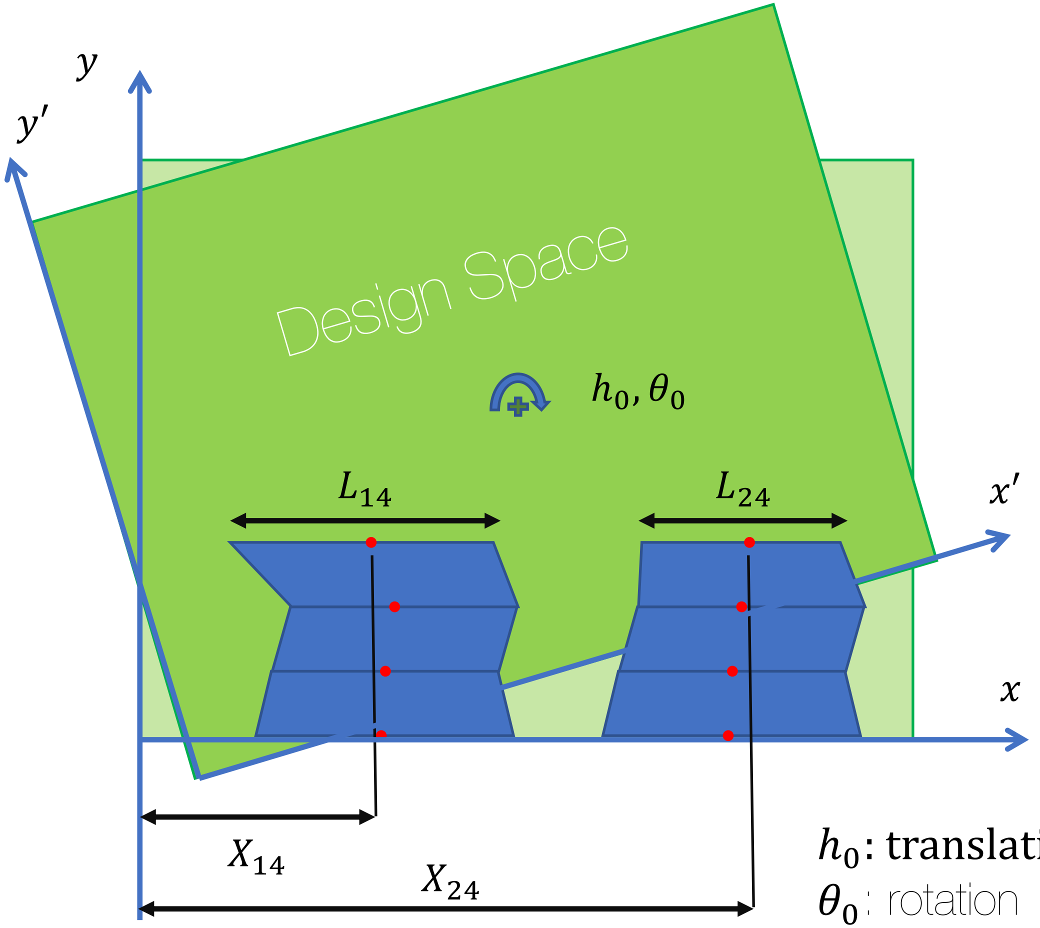


$N_x = N_y = 52$
$v_f = 0.4$
$5\ printing\ components$
$18\ printing\ intervals$
$5{\times}18{\times}2\ design\ variables$

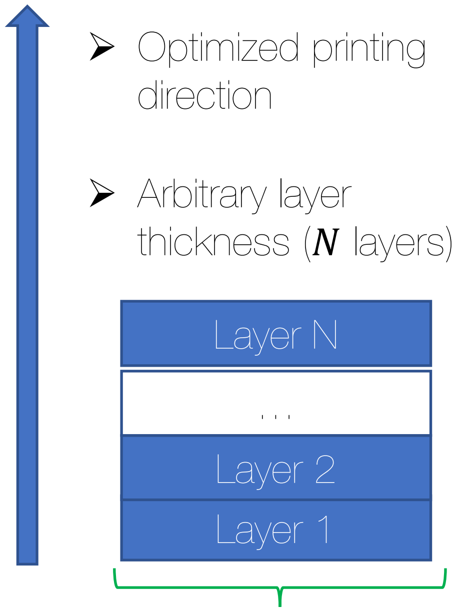
Current approaches

	Check on	Overhang **angle**	Bridge **length**	Optimal **printing plane**	Comment
SIMP [Leary et al. 2014]	Boundaries	Yes	No	No	Additional **iterations**
AM Filter (SIMP-**based)** [Langelaar 2015]	Densities	Yes	No	No	One **constraint per element**
Level-set [Allaire et al. 2017]	Boundaries	Yes	Yes	No	Implicit **constraints**
MMV [Guo et al. 2017]	Boundaries	Yes	No	No	
MMC [Xian et al. 2019]	Components **angles**	Yes	No	Yes	Difficult **quality check**

ALM based GGP: Last Results



h_0: translation
θ_0: rotation



- Optimized printing direction
- Arbitrary layer thickness ($\boldsymbol{N}$ layers)

Component j

Problem Statement

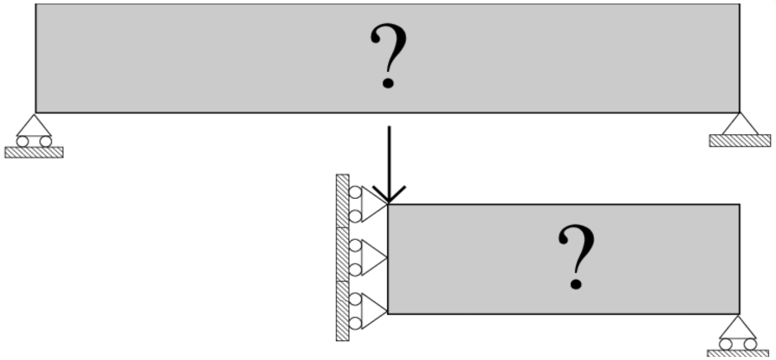
$$\begin{cases} min & & C(X, U_f) \\ s.t.: & & V \le V_0 \\ & \theta_{ij} \le \theta_{max} & \forall\, i = 1, \dots, N \quad j = 1, \dots, M \\ & BL_{ij} \le BL_{max} & \forall\, i = 1, \dots, N \quad j = 1, \dots, M \end{cases}$$

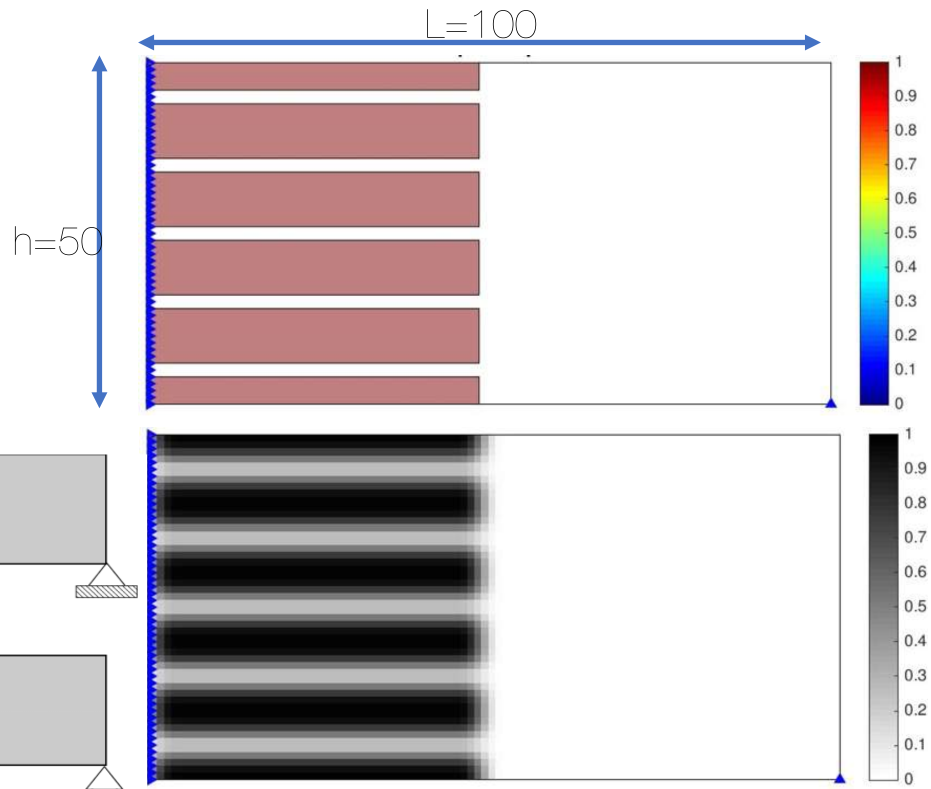
- N layers per component
- N+1 segments per component
- M components
- 2 features per segment (X_k, L_k)
- 2 features per component (h_j, m_j)
- 2 global features (h_0, θ_0)

$\Rightarrow$ $2M(N+2)+2$ design variables

MBB Results: convergence

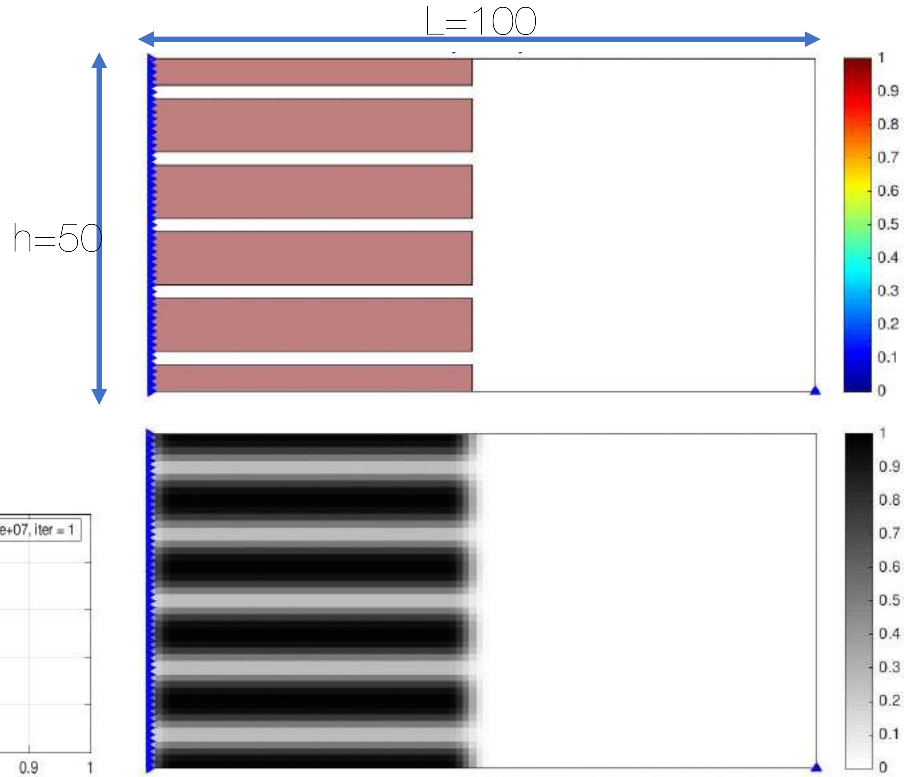
Parameter	Quantity
Mesh	50×100
V_0	0.3
θ_{max}	$45°$
$BL_{max}/2$	25
N (layers)	18
M (components)	6
Design variables	242

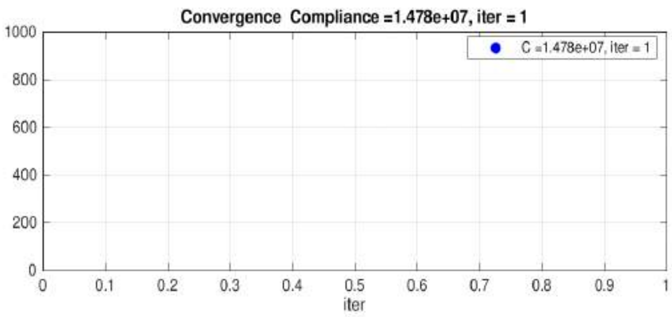




MBB Results: convergence

Parameter	Quantity
Mesh	50×100
V_0	0.3
θ_{max}	45°
$BL_{max}/2$	25
N (layers)	18
M (components)	6
Design variables	242



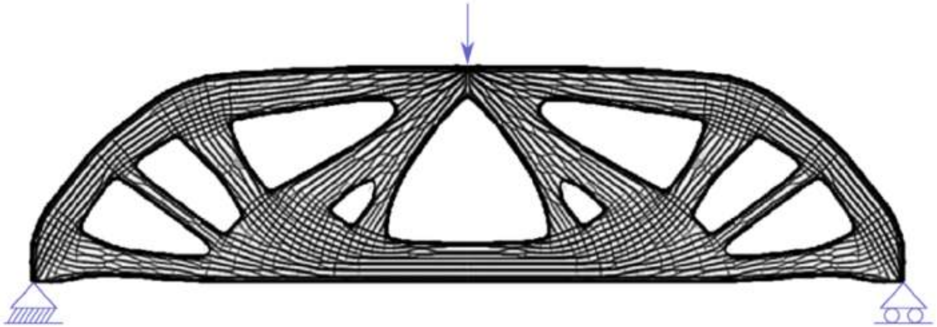


And your Click and Print question?

Prof. Joseph Morlier, Enrico Stragiotti, Frederic Lachaud

#Our very First Results

#Fiber Placement



Formulation of the optimization problem

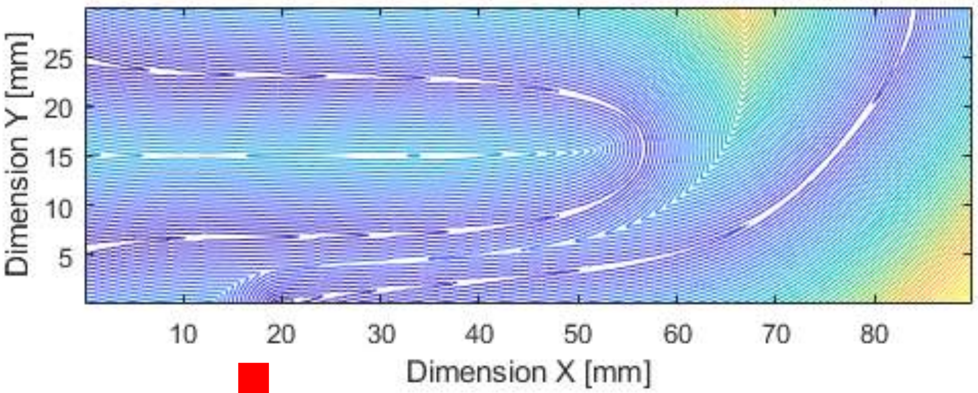
$$\text{minimize} : J = \frac{1}{2} q^T K(\theta(x,y)) q$$

$$\text{subject to} : \begin{cases} f = K(\theta(x,y))q \\ -\pi/2 \leq \theta(x,y) \leq \pi/2 \end{cases}$$

- The algorithm is implemented in MATLAB and it features **Multistart and Parallel** computation.
- Spatial filter used to **achieve fiber continuity**
- Hybrid formulation that use Tsai and Pagano Parameters.

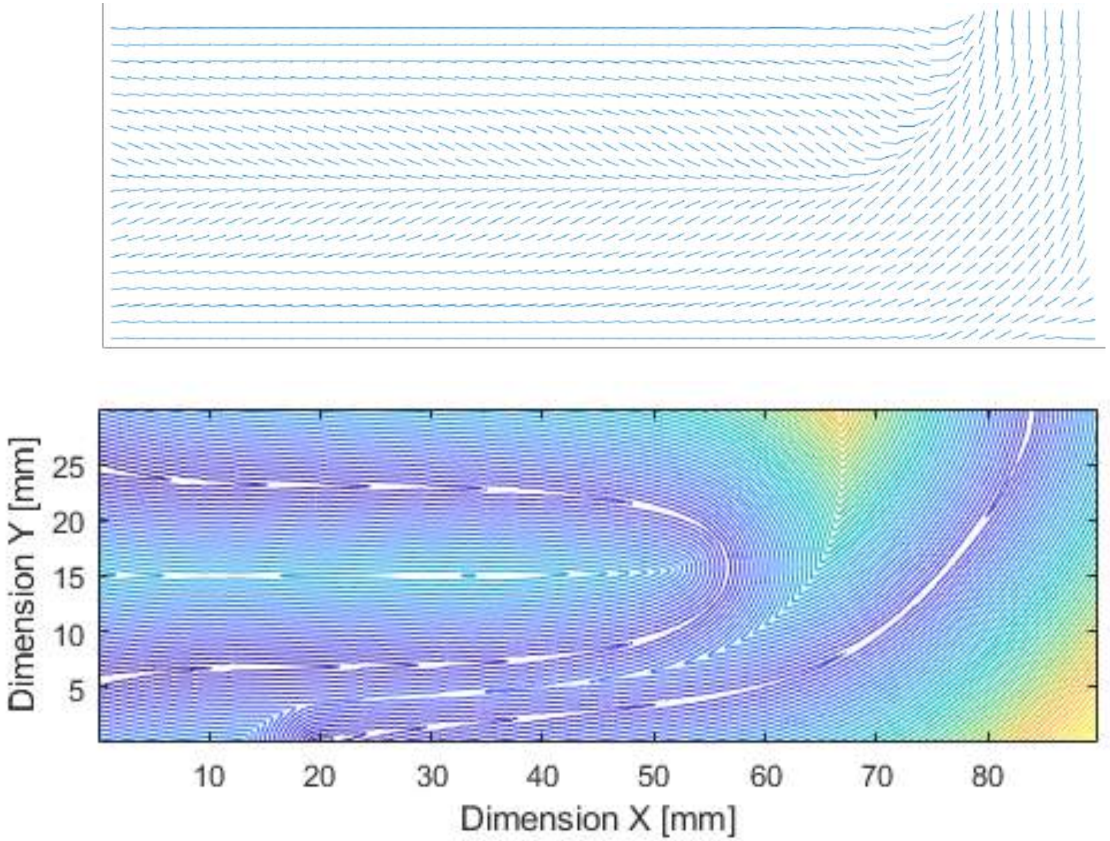
https://github.com/mid2SUPAERO/FCFAO-with-manufacturing-constraints

G-Code and 3D printing



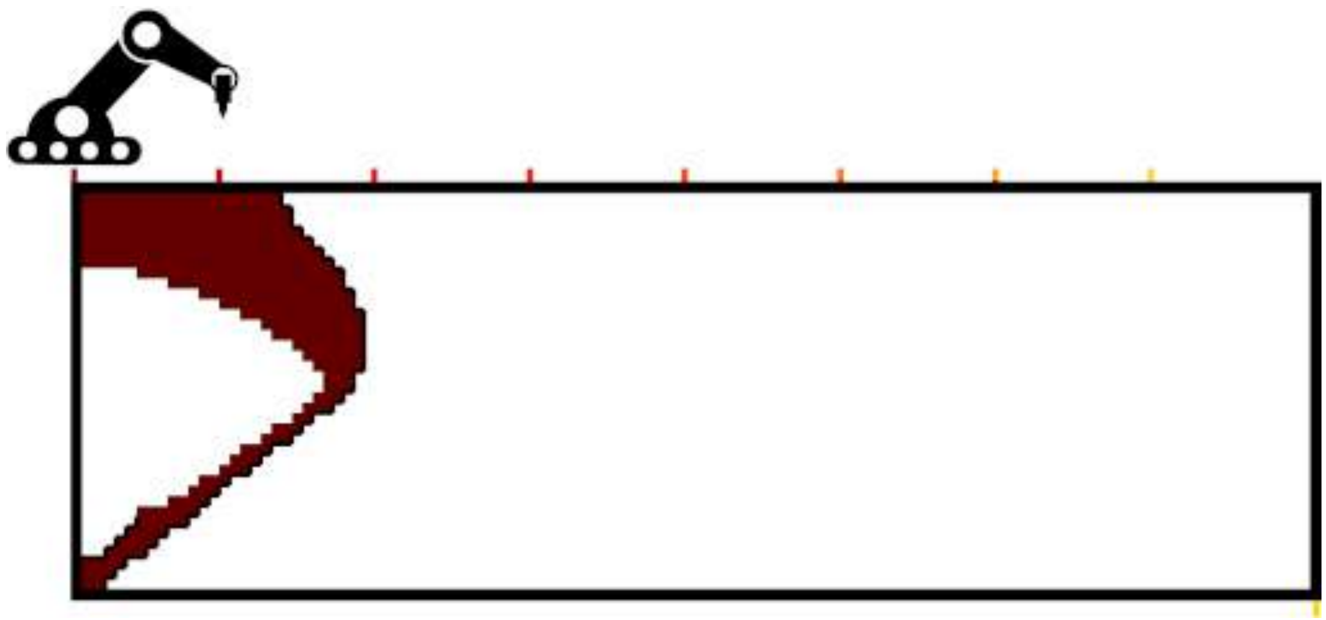
```
89.75,0.25,1
89.75,0.25,0
89.235,0.25,1
89.25,0.36605,1
89.302,0.75,1
89.412,1.25,1
89.578,1.75,1
89.75,2.1778,0
88.775,0.25,1
88.851,0.75,1
88.962,1.25,1
89.117,1.75,1
89.25,2.1088,1
89.306,2.25,1
89.523,2.75,1
89.748,3.25,1
89.75,3.2537,0
88.329,0.25,1
88.408,0.75,1
88.521,1.25,1
88.674,1.75,1
88.75,1.961,1
88.857,2.25,1
89.058,2.75,1
89.25,3.2061,1
```

Optimum
vs
Manufacturable



Computational fabrication @Tudelft (Jun Wu)

http://homepage.tudelft.nl/z0s1z/projects/2021-multiscale-review.html



BTW Prof….and lattice structures?

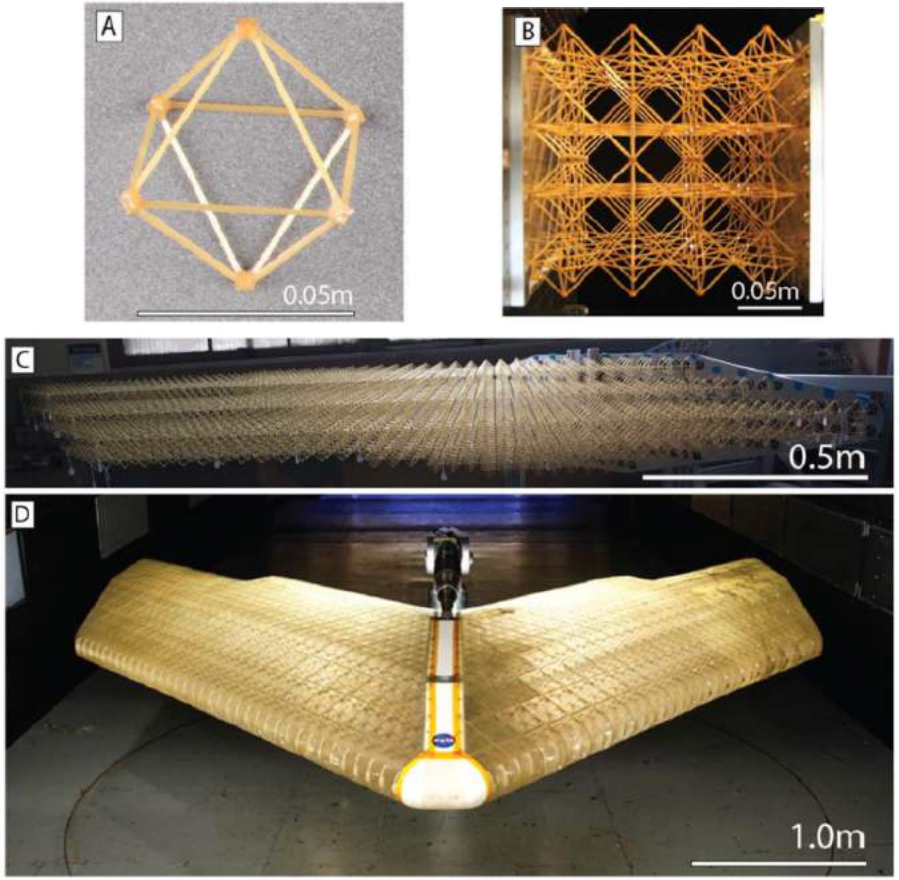
Lattice (or cellular architected) structures are:

- Cellular
- Reticulated

Lattice structures have interesting properties:

- Ultralight
- Fast assembly
- Easier to manufacture compared to traditional structures.

Interesting application in the aerospace field → NASA MADCAT project → Extremely light structures, good aeroelastic properties.

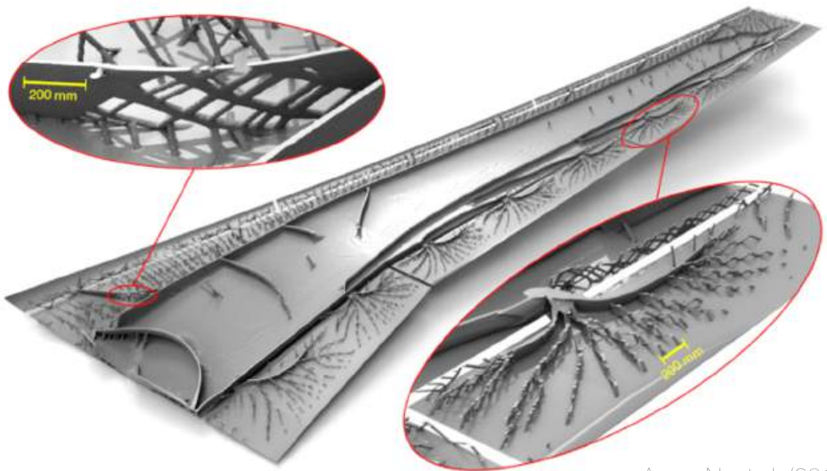


Cramer, N. B. et al. (2019)

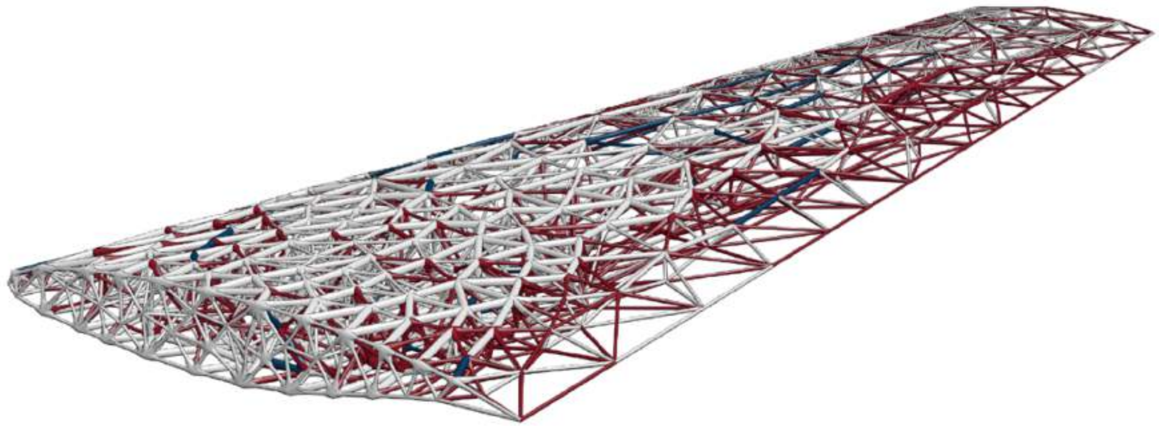
Topology vs layout optimization

Topology optimization

Layout optimization



Aage, N. et al. (2017)

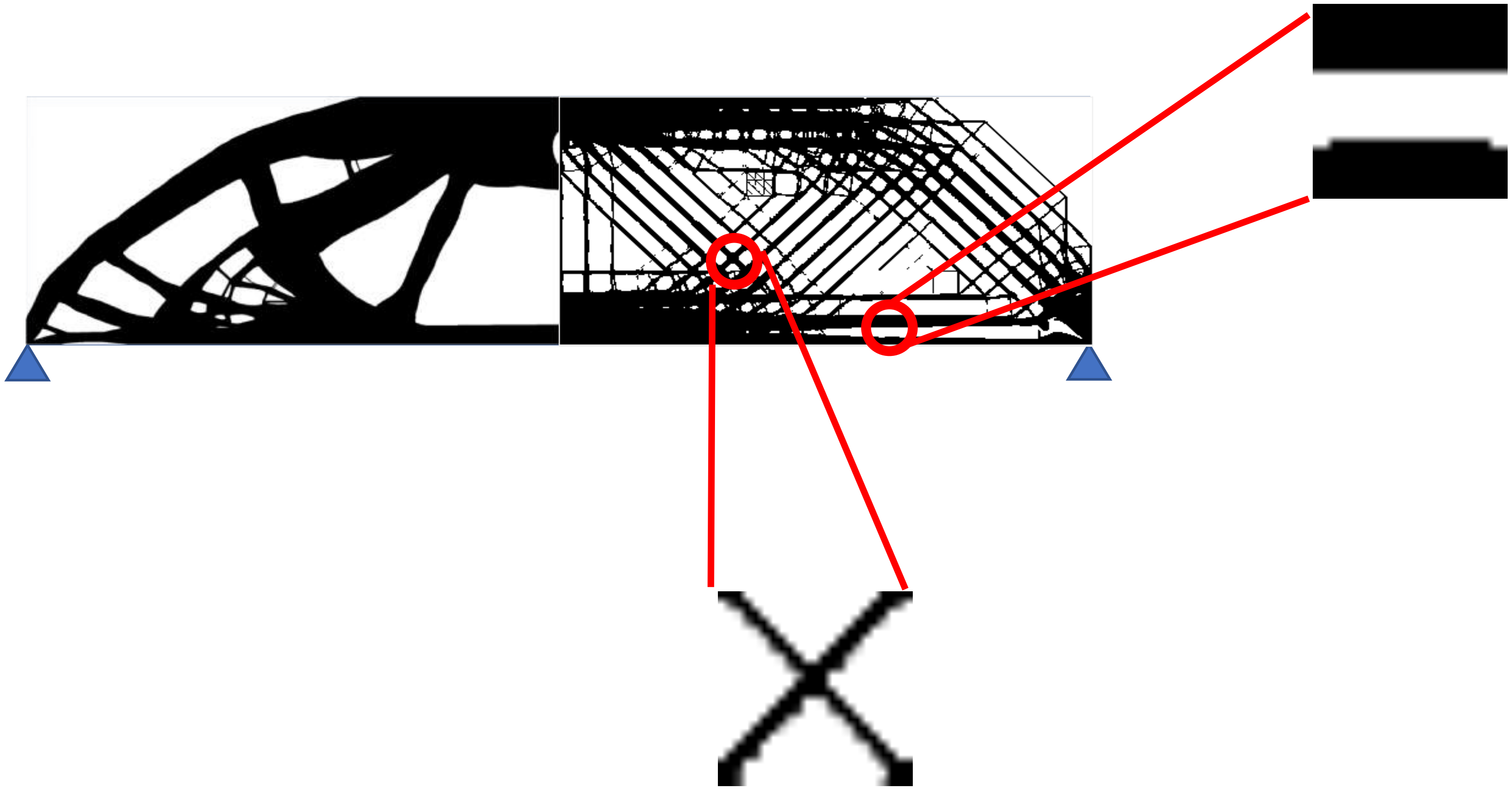


Opgenoord, M. M. and Willcox, K. E. (2018)

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

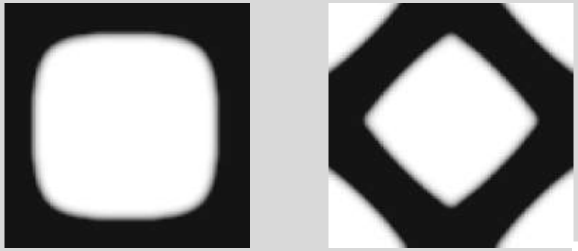
Prof. Joseph Morlier, Edouard Duriez, Miguel Charlotte, Catherine Azzaro-Pantel

https://github.com/mid2SUPAERO/EMTO



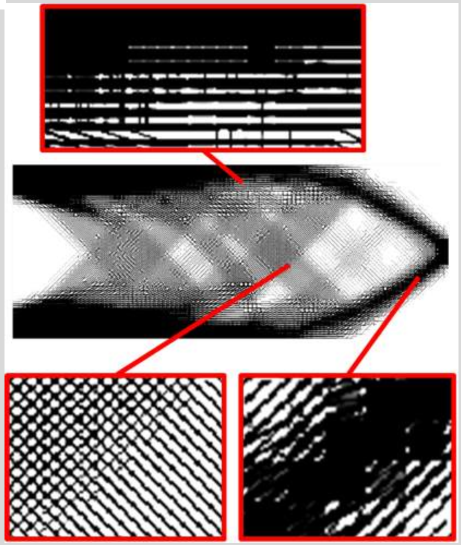
Multi-scale TO

Topology optimization
for material design



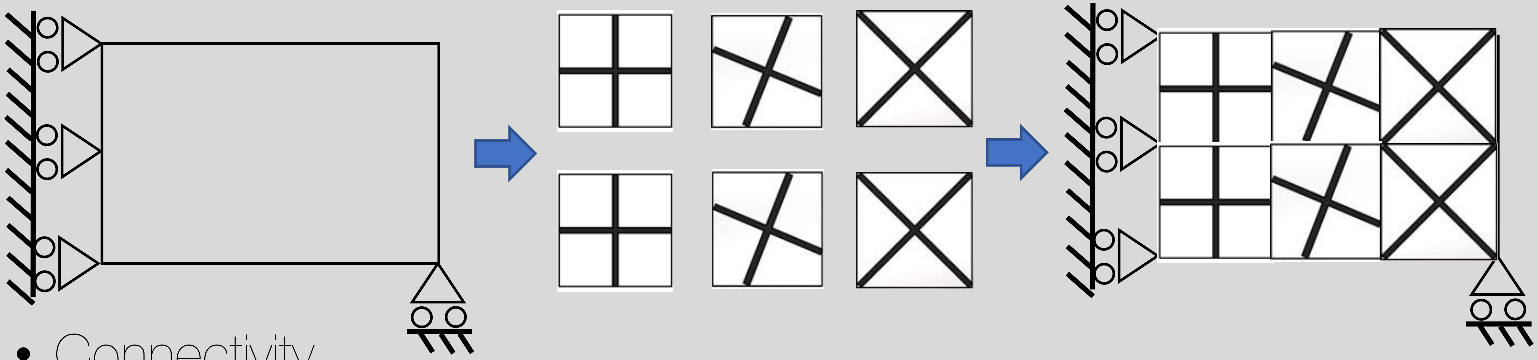
Macro-scale
topology optimization

Multi-scale
topology
optimization

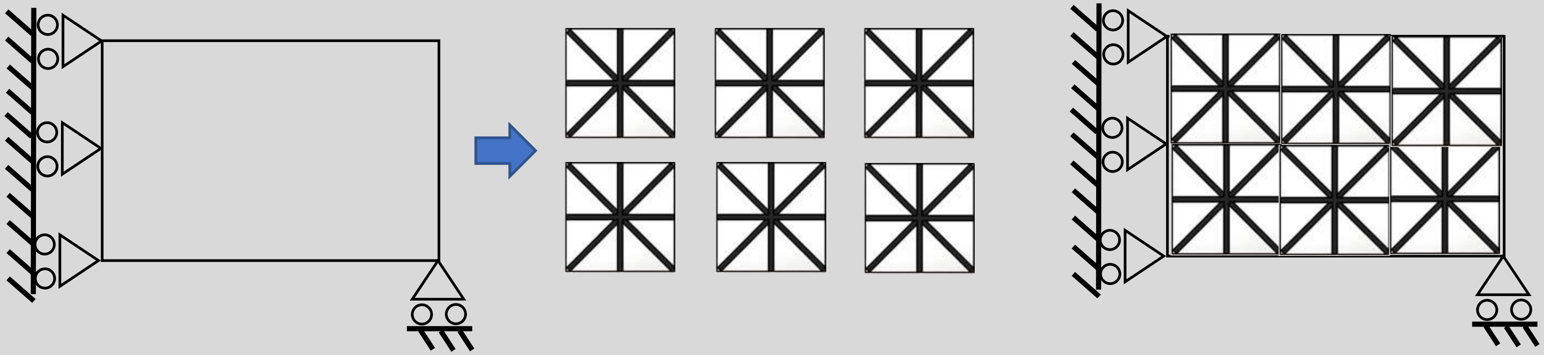


Xia L, Breitkopf P (2015) Design of materials using topology optimization and energy-based homogenization approach in Matlab. Struct Multidisc Optim 52(6):1229–1241. https://doi.org/10.1007/s00158-015-1294-0

MTO challenges



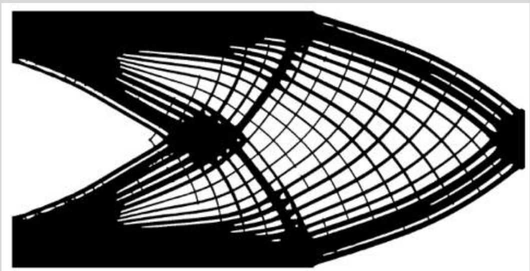
- Connectivity



- Adaptation to local stress
- Speed

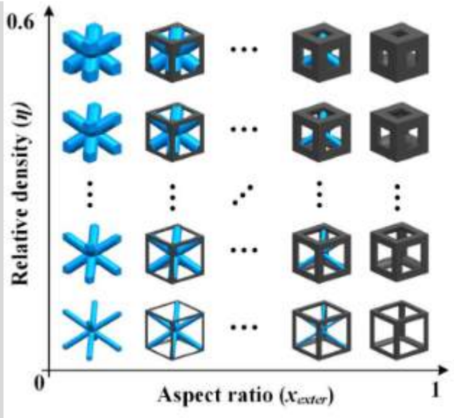
Main MTO methods

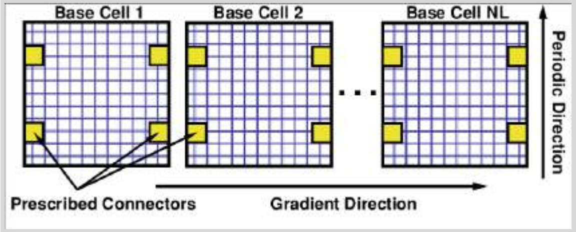
Approach	Examples	Connectivity	Locally **adapted**	Speed	Manufacturability
De-**homogenization**	[1],[2]				
Parametrized **lattice**	[3]				
Connectors	[4]				



[2]

[3]





[4]

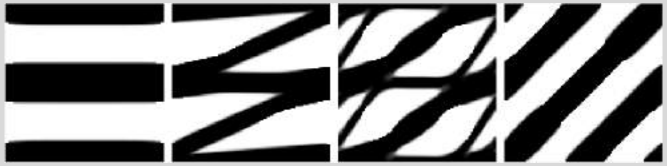
- More : review [5], topwebinar : https://topwebinar.weblog.tudelft.nl/

[1] Pantz, Olivier, and K. Trabelsi. "A Post-Treatment of the Homogenization Method for Shape Optimization." SIAM J. Control and Optimization
[2] Groen, Jeroen P., and Ole Sigmund. "Homogenization-Based Topology Optimization for High-Resolution Manufacturable Microstructures: 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

Scale-bridging variables

- Density

- Orientation



- Cubicity

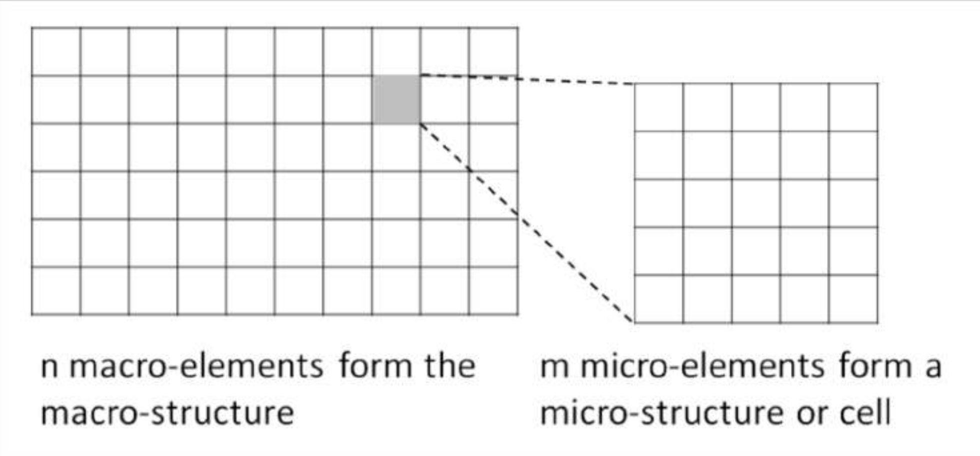
- Micro-optimization objective function:

Rotated homogenized stiffness tensor

$$\boldsymbol{E}^{\alpha} = \boldsymbol{M}_{\alpha}^{T} * \mathbf{E} * \boldsymbol{M}_{\alpha}$$
$$= (E_{klmn}^{\alpha})_{k,l,m,n\in\{1,2\}}$$

Objective function

$$c = \left(1 - \frac{x_{cub}}{2}\right) E_{1111}^{\alpha} + \frac{x_{cub}}{2} E_{2222}^{\alpha}$$

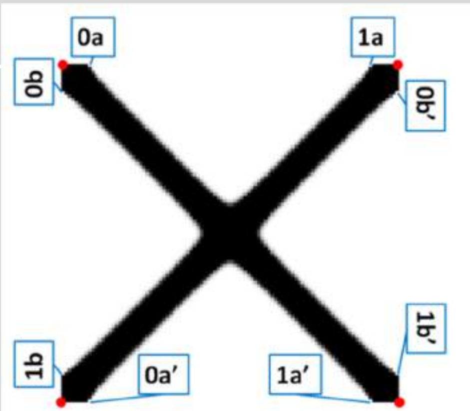


$$\underset{x^i_{dens},x^i_a,x^i_b,\ldots}{minimize} \quad u^T K u \tag{2a}$$

$$subject\ to \quad Ku = f \tag{2b}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{m} \rho_{i,j} \leq n * m * vf \tag{2c}$$

$$\epsilon < \rho_{i,j} < 1 \tag{2d}$$



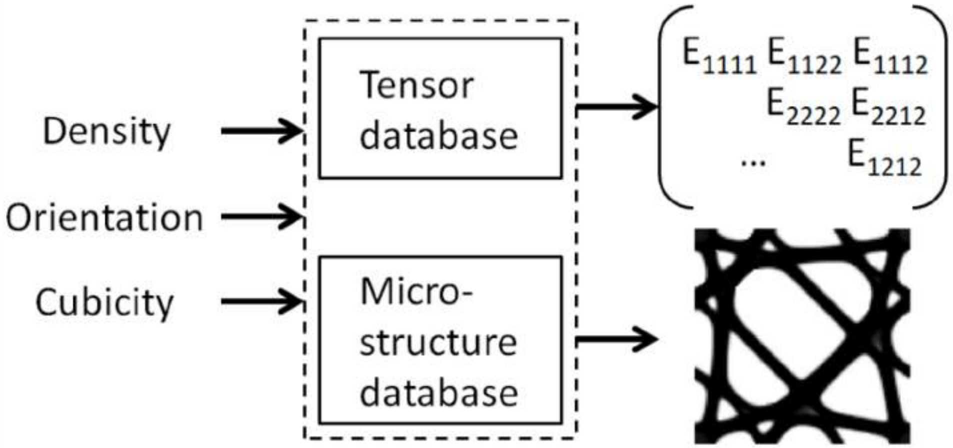


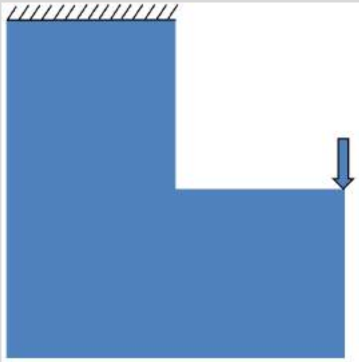
Fig. 8: Scheme of the two databases illustrating the inputs and outputs.

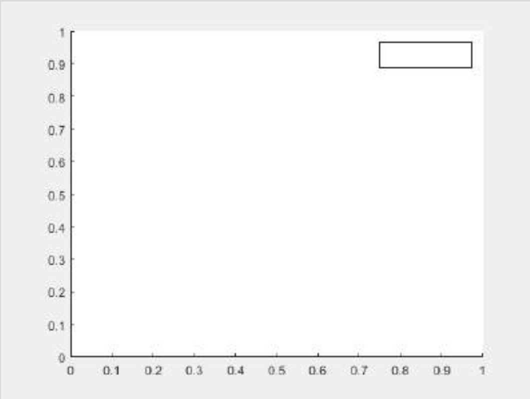
Surrogate modeling with GPs

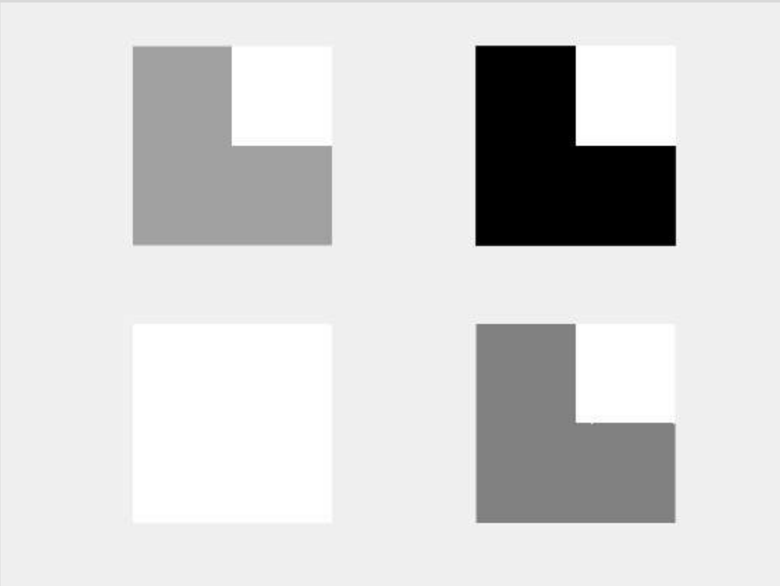
Validation on classical test cases

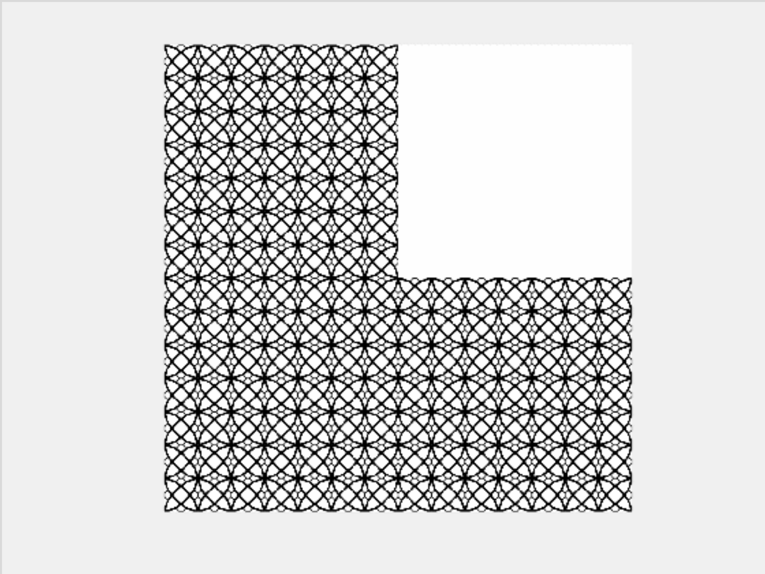
- Validation on small grid

⇒ Evaluate full-scale design





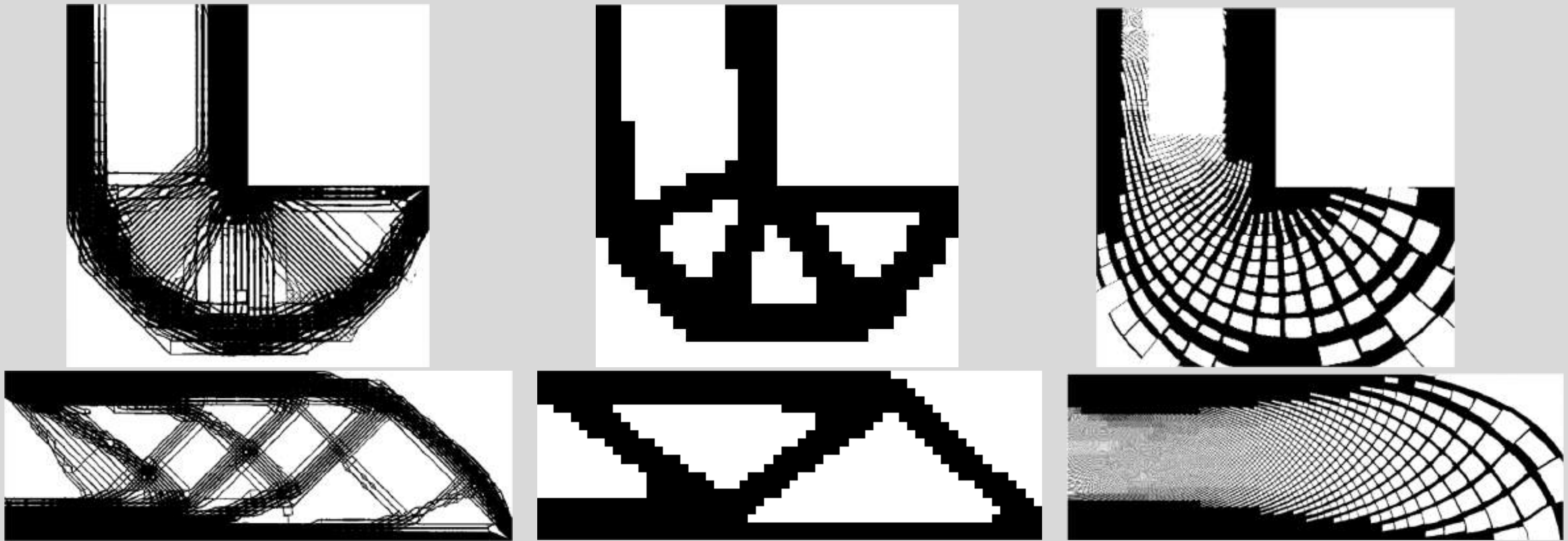




Validation on classical test cases

- Comparison to top88 (0/1) and oriented-grid method on same grid
- Final compliances:

Case	EMTO	Top88 (0/1)	EMTO	Oriented **grid***
L-**shaped**	90.7 (28*28)	93.6 (28*28)	94.3(14*14)	108.1 (14*14)
MBB	202.3 (60*20)	211.7 (60*20)	203.8(30*10)	316.9 (75*25)

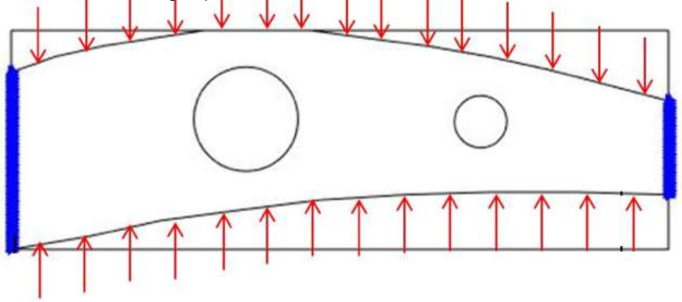


*Kumar T, Suresh K (2020) A density-and-strain-based K-clustering approach to microstructuraltopology optimization. Structural and Multidisci-plinary Optimization 61(4):1399–1415, DOI 10.1007/s00158-019-02422-4
Andreassen E, Clausen A, Schevenels M, Lazarov BS,Sigmund O (2011) Efficient topology optimization inMATLAB using 88 lines of code. Structural and Mul-tidisciplinary Optimization 43(1):1–16, DOI 10.1007/s00158-010-0594-7

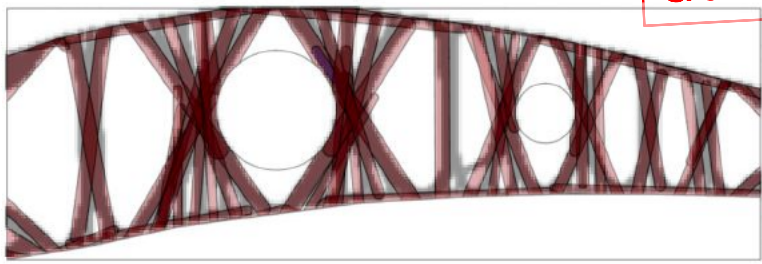
Aircraft rib design

GGP ;= EASY EXPLORATION of POTENTIAL DESIGN OF STRUCTURES
GGP-AGP: C=0.165

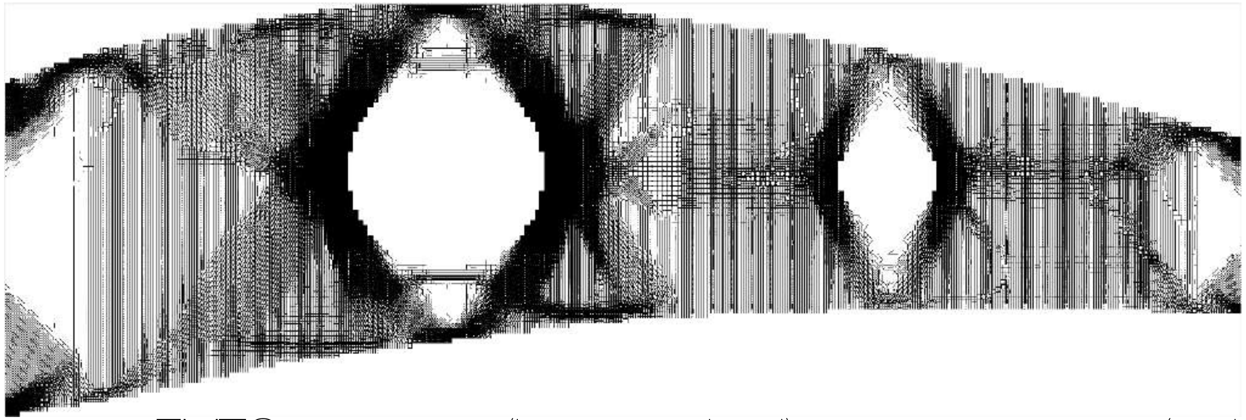
- Only pressure loads



RIB problem

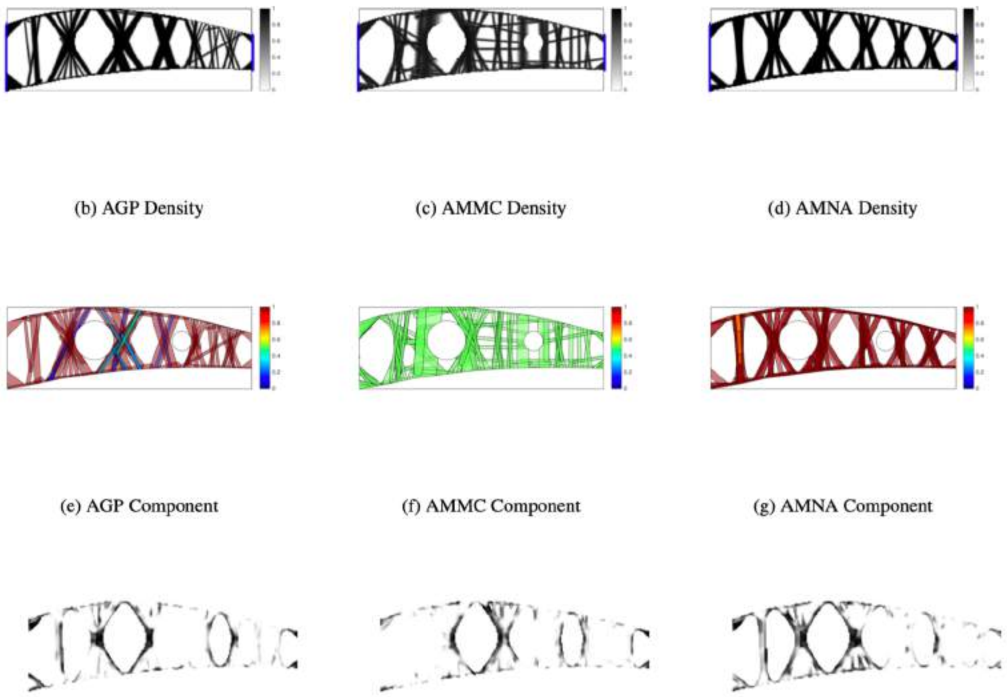


SIMP : c=0.198



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

GGP results



(b) AGP Density (c) AMMC Density (d) AMNA Density

(e) AGP Component (f) AMMC Component (g) AMNA Component

(h) AGP Similarity Map (i) AMMC Similarity Map (j) AMNA Similarity Map

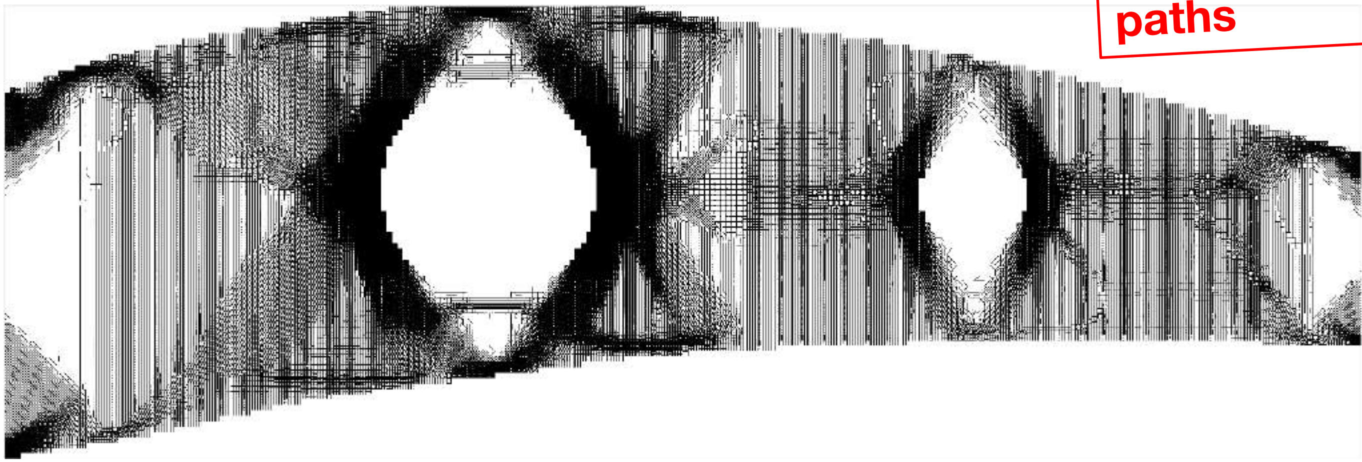
FIGURE 24: Rib problem solutions for Volume Fraction 0.5

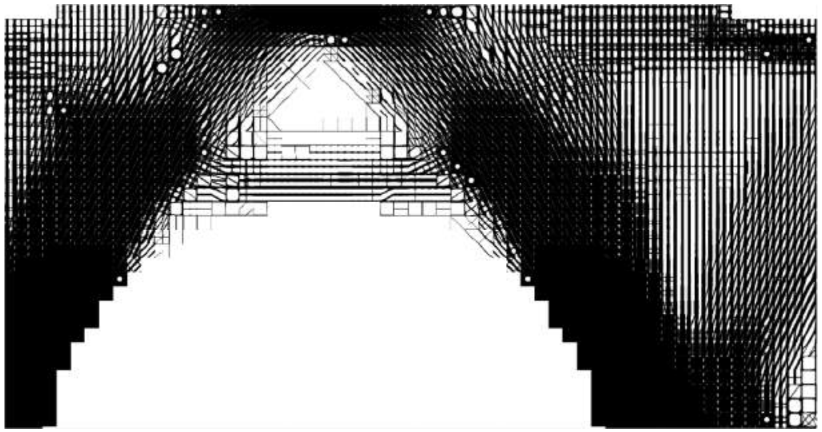
Method	Parameters	Volume Fraction			
		0.3	0.4	0.5	0.6
SIMP	Objective	0.4332	0.2719	0.1975	0.1549
	grayness	0.167	0.149	0.134	0.121
AGP	Objective	0.296	0.206	0.165	0.137
	Deviation	31.6%	24.31%	16.3%	11.5%
	Grayness	0.169	0.163	0.142	0.084
AMNA	Objective	0.756	0.293	0.194	0.15
	Deviation	74.5%	7.94%	1.67%	3.49%
	Grayness	0.049	0.071	0.075	0.042
AMMC	Objective	0.565	0.345	0.257	0.181
	Deviation	30.4%	26.88%	30.07%	16.98%
	Grayness	0.19	0.22	0.253	0.24

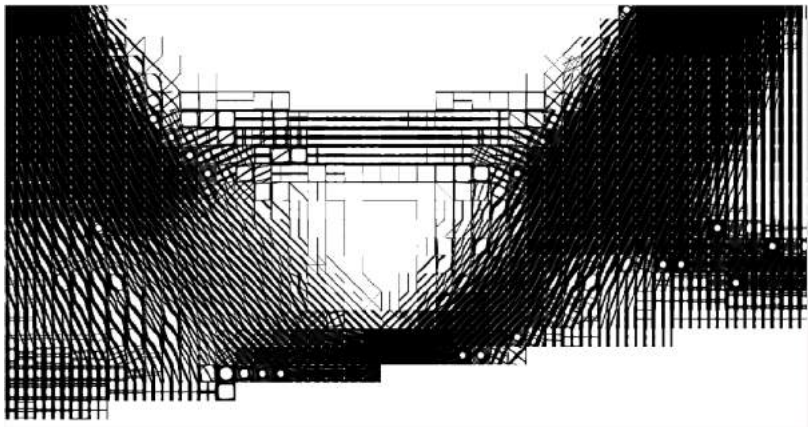
TABLE 6: Compliance values for a Wing Rib with uniformly distributed force

EMTO vs GGP

Multiscale approach is a complete REDESIGN: Multiply of internal force paths







ML and TOPOPT

« Data sciences view » of design

not compatible

with engineer approach

Neural reparameterization improves structural optimization

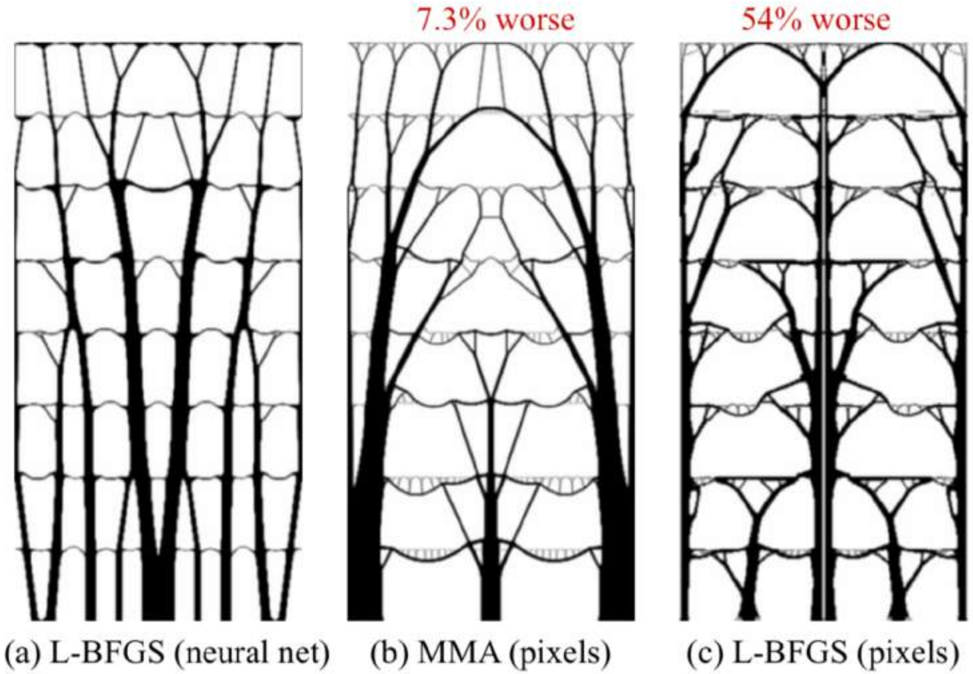
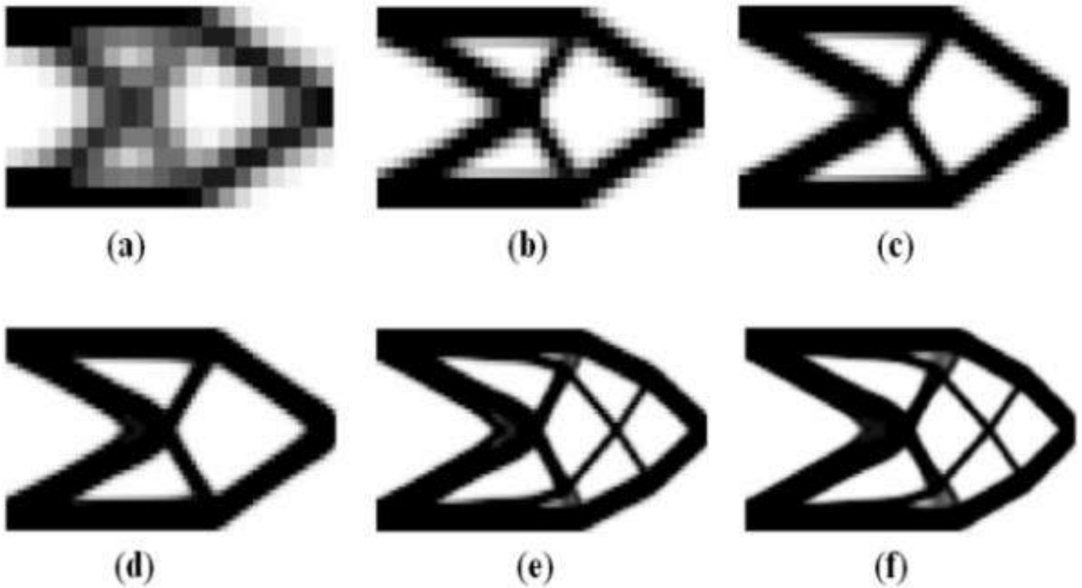


Figure 1: A multi-story building task. Figure (a) is a structure optimized in CNN weight space. Figures (b) and (c) are structures optimized in pixel space.

Remember

Even more complex for multimaterial

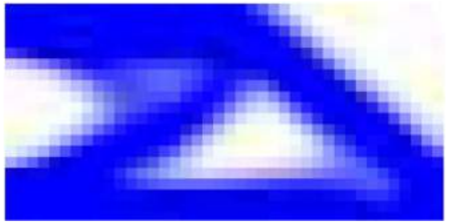
Optimal topology is defined for a certain mesh



(a) 20x10 elements with C=88.8544
(b) 40x20 elements C=69.0953
(c) 60x30 elements C=66.6591
(d) 80x40 elements C=65.0711
(e) 100x50 elements C=65.1185
(f) 120x60 elements C=64.9388

Can we predict f using info from lower resolution , a/b…or e for example?

Can we Predict HR Multimaterial Topopt from LR results?



DL

80% of Total Data To train

20% to test

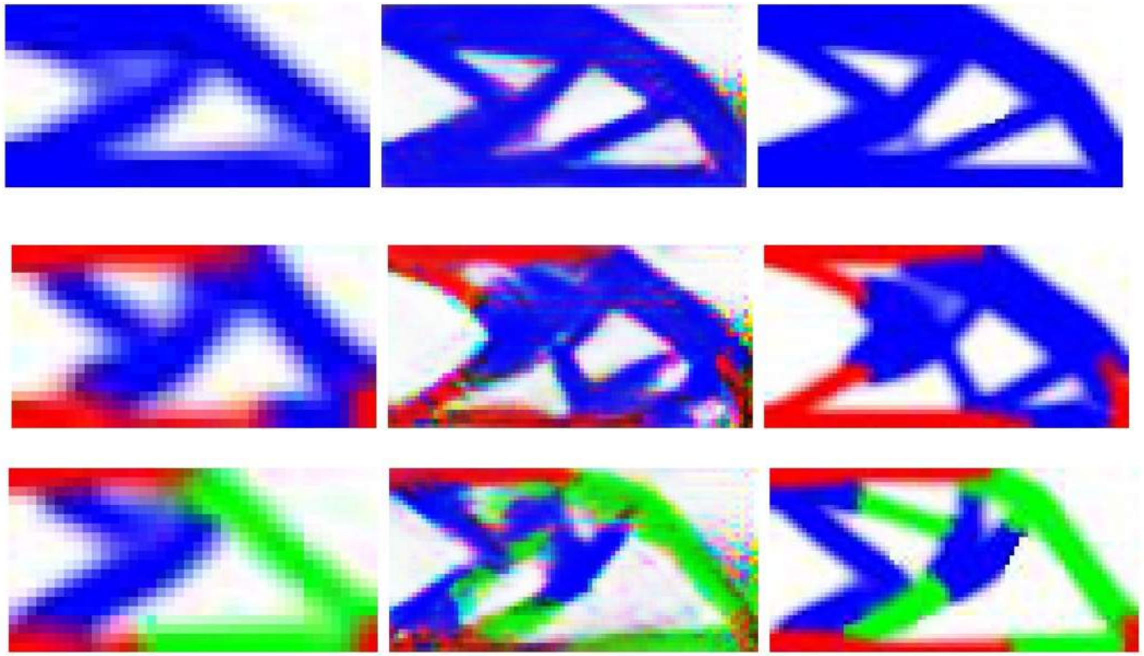
Convolutional Neural Networks (CNNs)

SRGAN –

Super Resolution Generative Adversarial Network

Quasi a Yes… https://github.com/mid2SUPAERO/Multi-Material-Topology-Optimisation

- Experiment 1 – Cantilever BC Input Img 40x20 Output Image 80x40 5000 Epochs

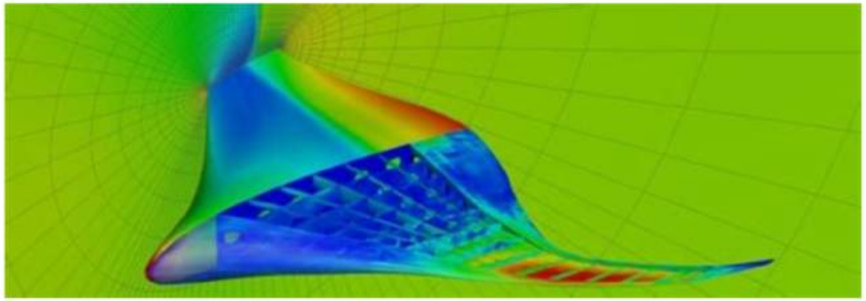


LR **CNN-Prediction-HR** **Ground Truth-HR**

Popularization

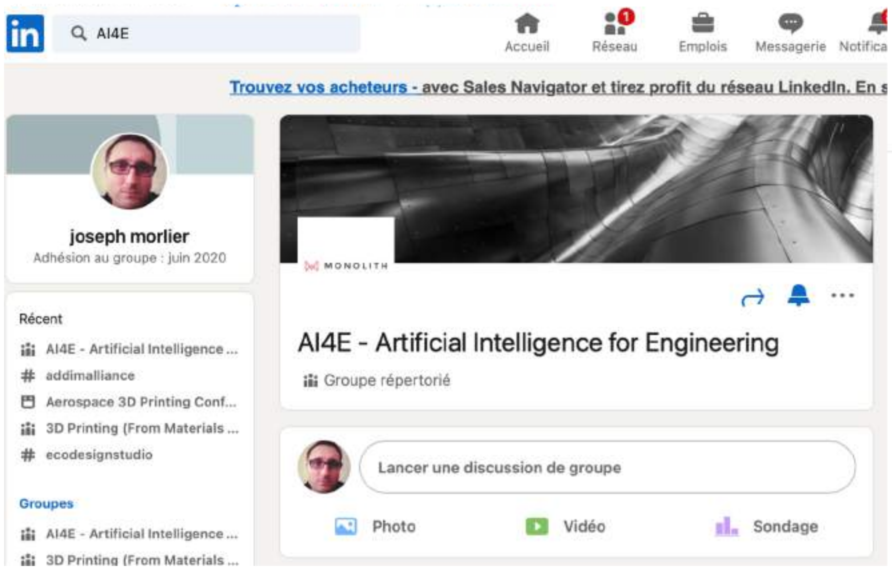
https://www.linkedin.com/pulse/optimization-mdo-connecting-people-joseph-morlier/

Join us on #AI4E on linkedin

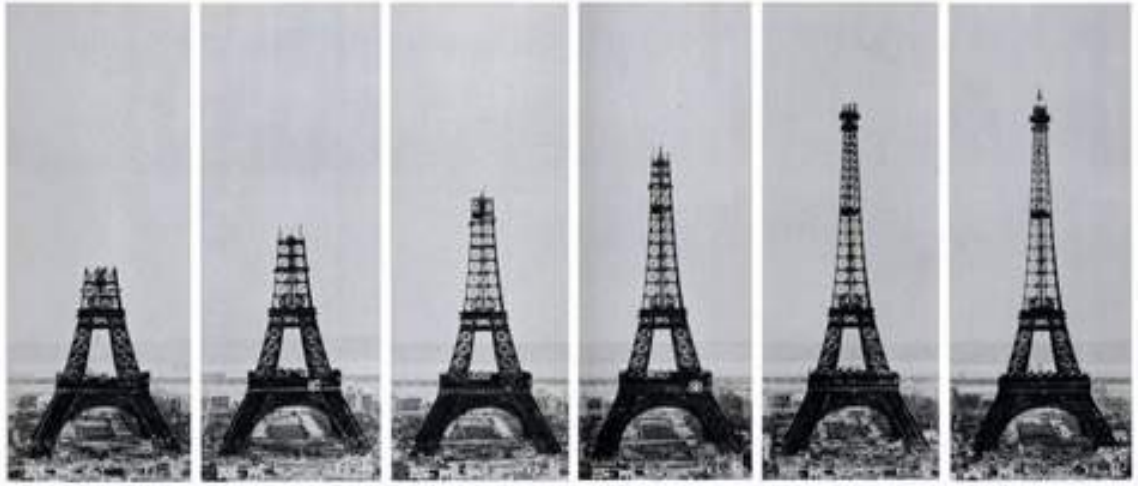


http://mdolab.engin.umich.edu

Optimization [MDO] for connecting people?



Conclusions



- "The art of structure is where to put the holes. ~Robert Le Ricolais (1894-1977)
- NextGen Aerostructures : Structural mass optimization: CO2 optimization & Manufacturable solution using ALM & AFP
- Revolution is. **Material discovery** through **ML&TopOpt**

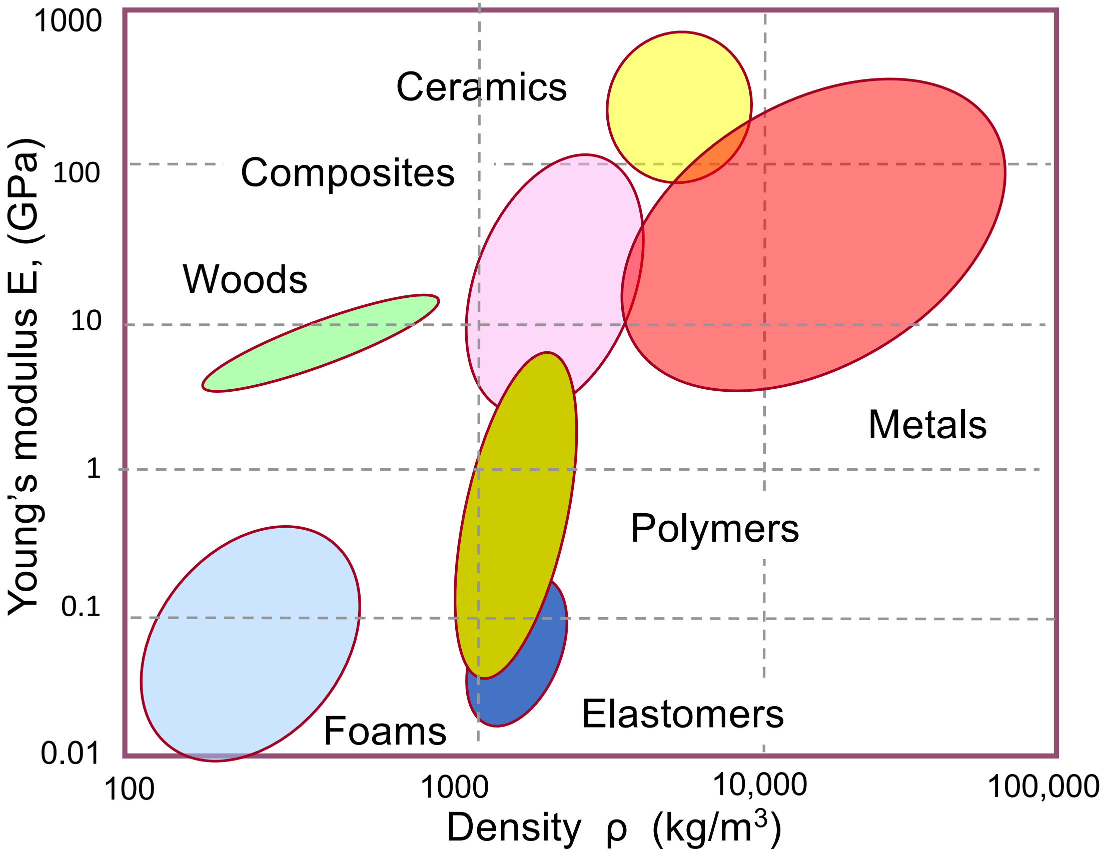
TOPOPT vs Generative Design

- https://www.autodesk.com/products/fusion-360/blog/topology-optimization-is-not-generative-design/

- **Is the outcome returned CAD ready, or does it have to be rebuilt?**
  - *A mesh model that must be rebuilt as valid geometry in a CAD system. (This is topology optimization)*
    OR
  - *CAD ready for any CAD System Geometry (This is generative design in Fusion 360)*

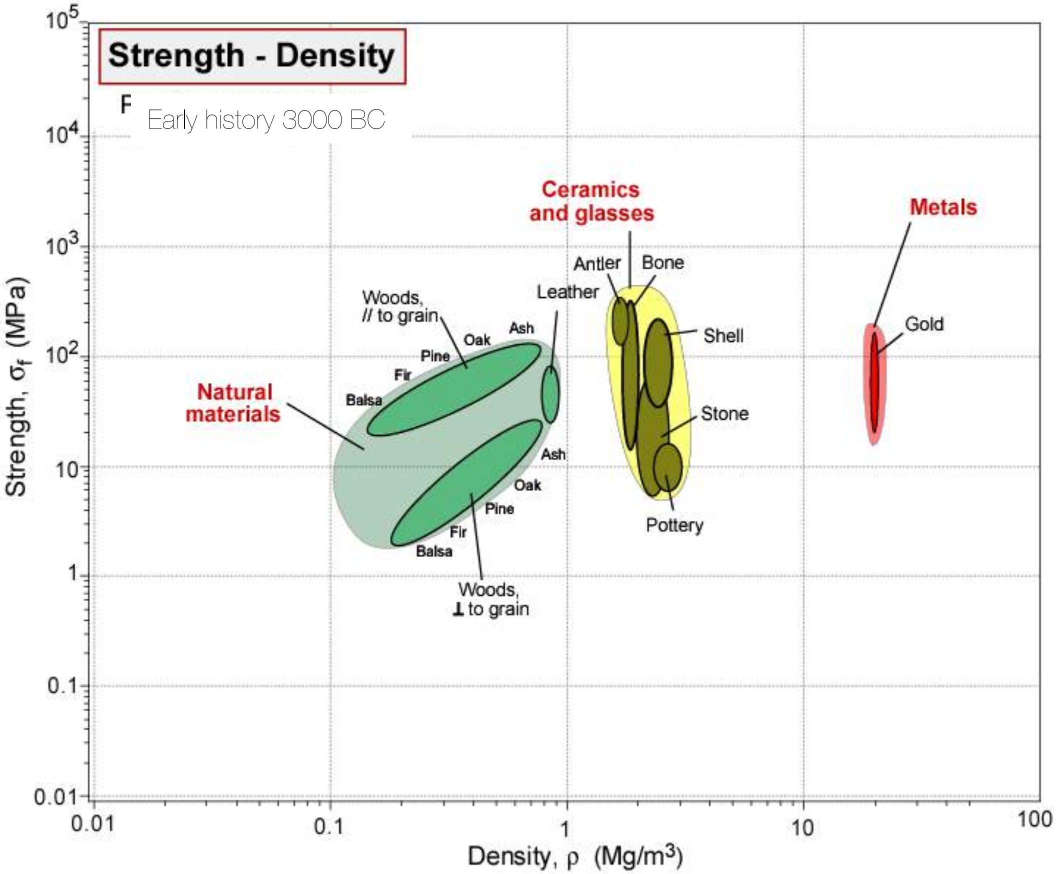
Epilogue

I started the course using Ashby's Diagram



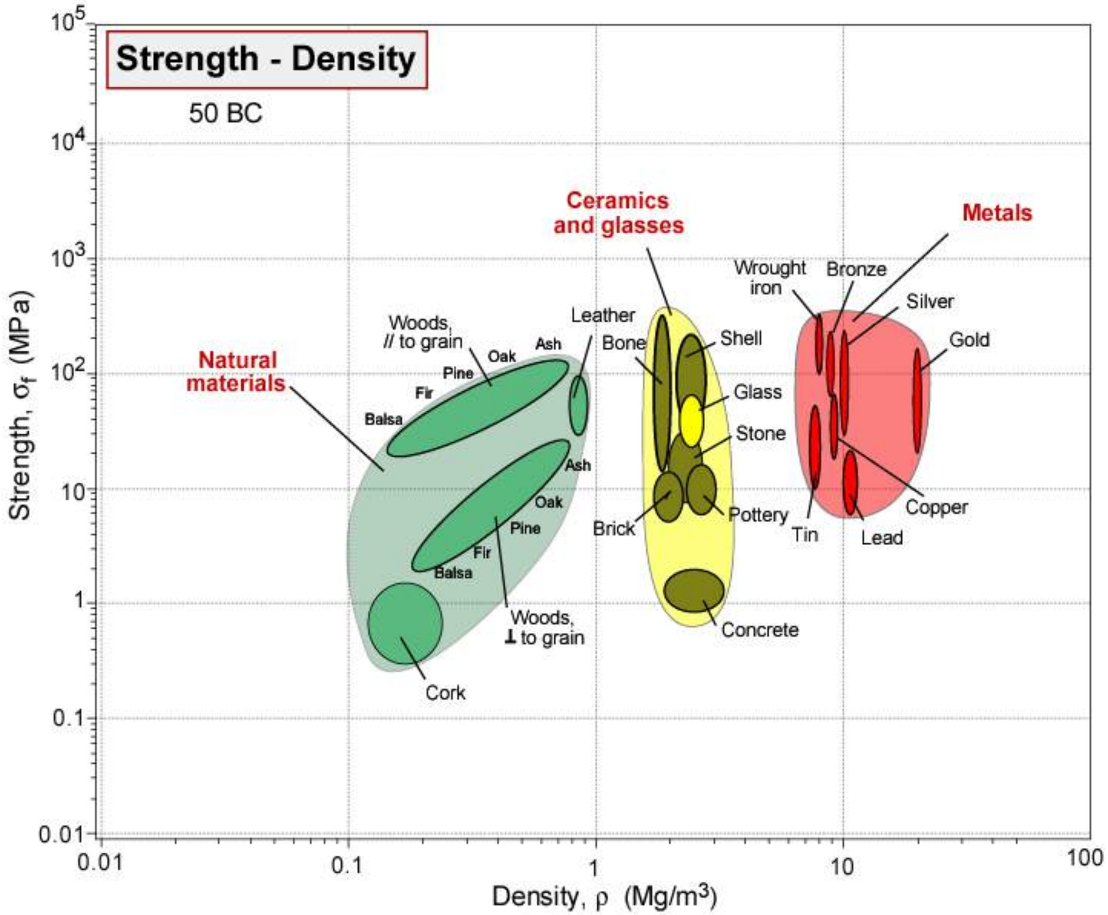
The evolution of structural materials

from Mike Ashby, 2018



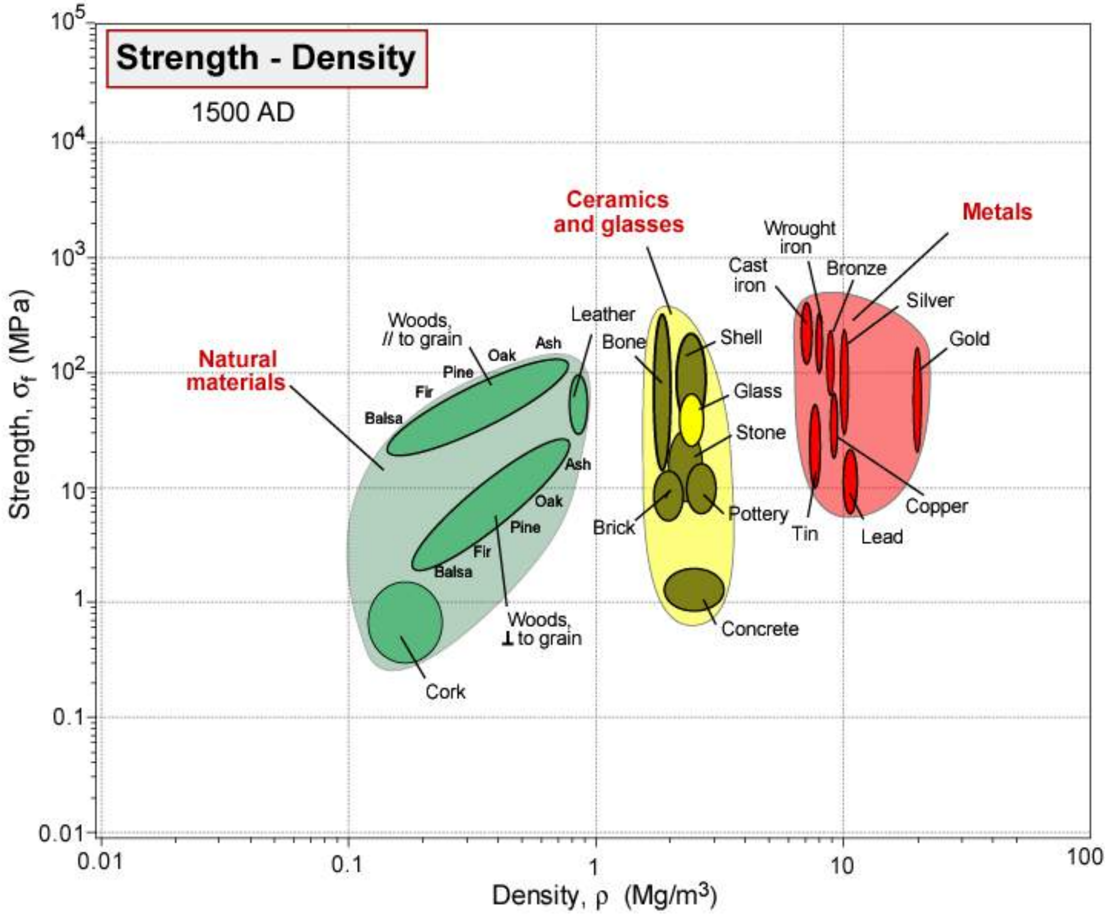
Egyptian Pyramids

50BC

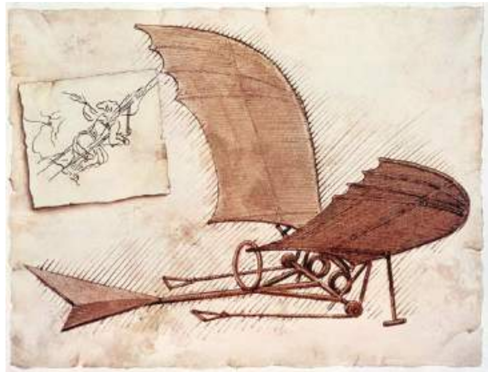


Roman Temples

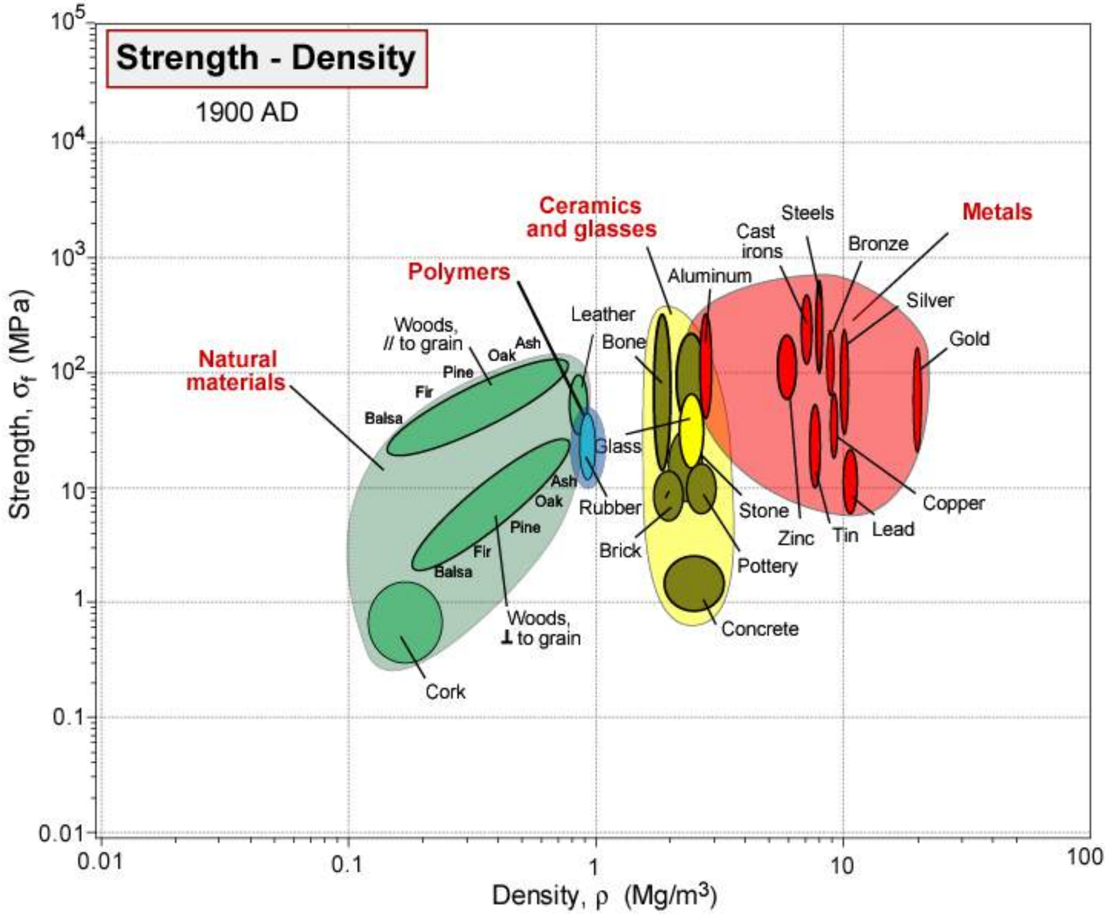
1500 AD



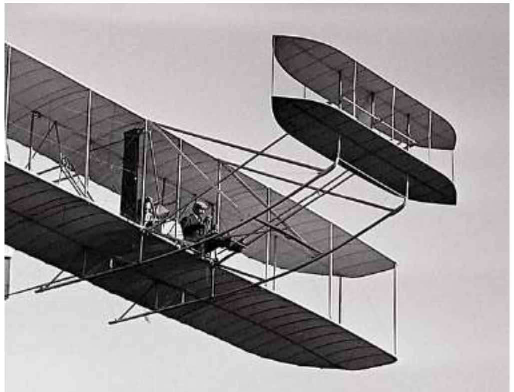
Medieval Castles



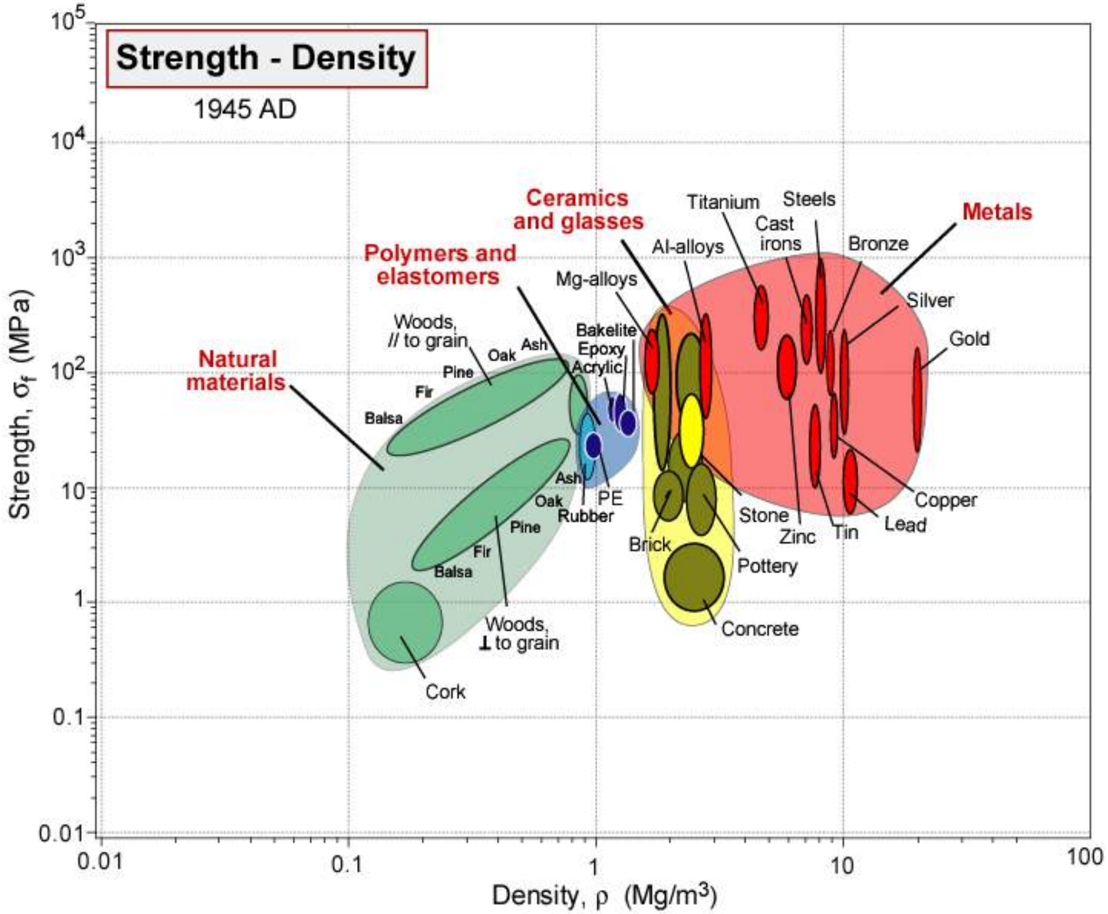
1900 AD



Art Nouveaux

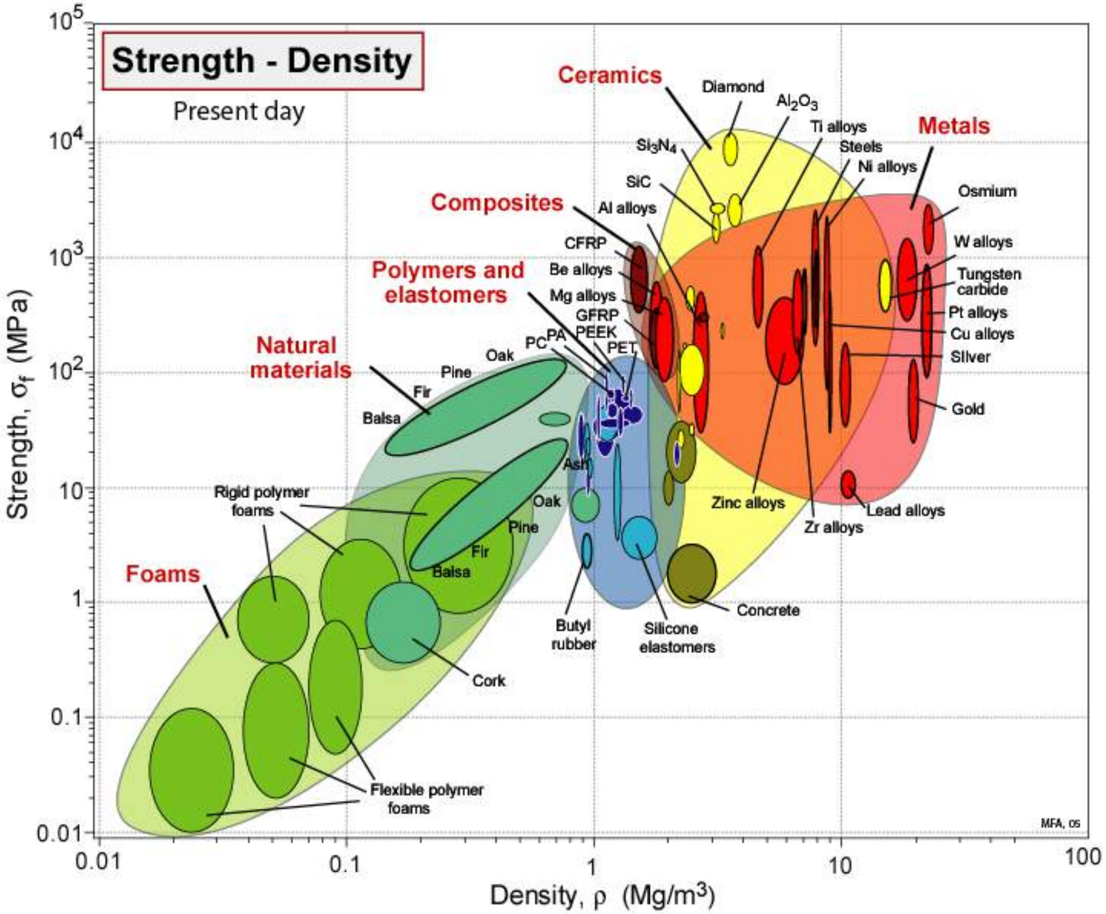


1945 AD



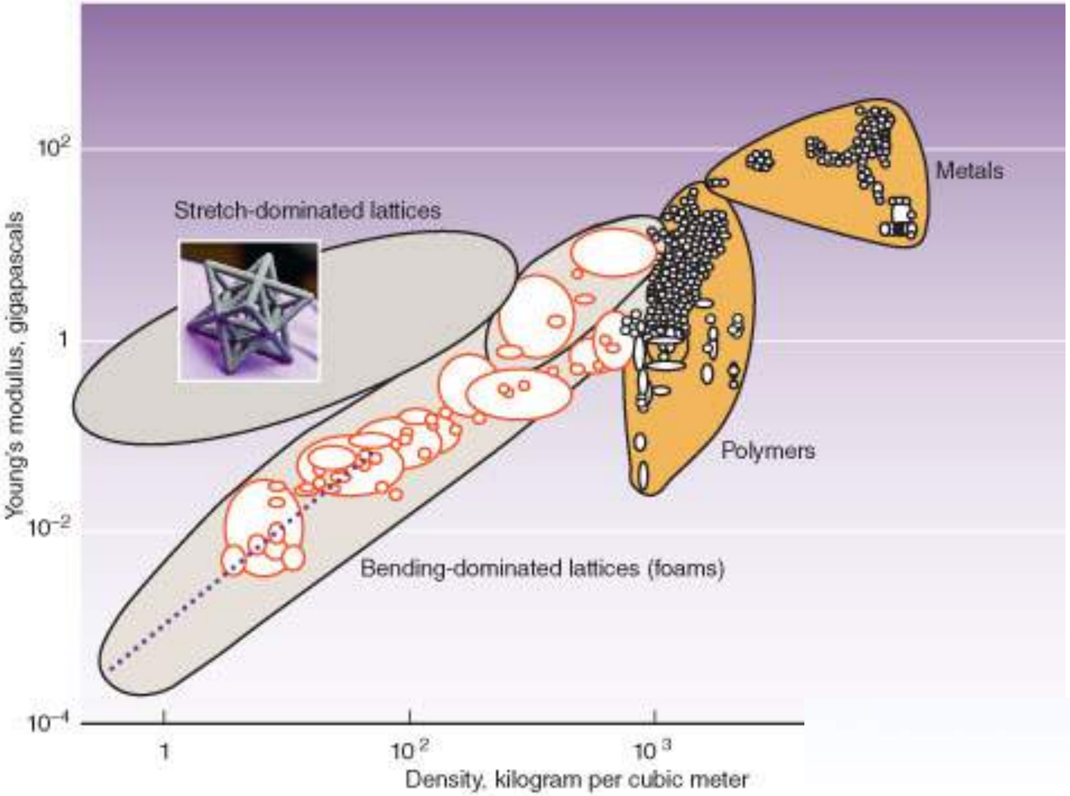
Skyscrapers

PRESENT DAY



21st Century

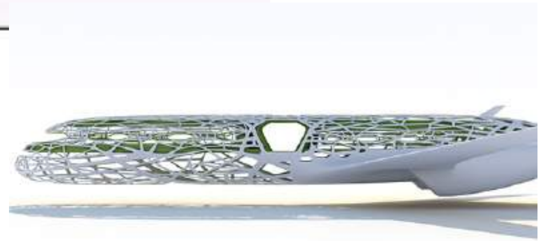
AND TOMORROW?

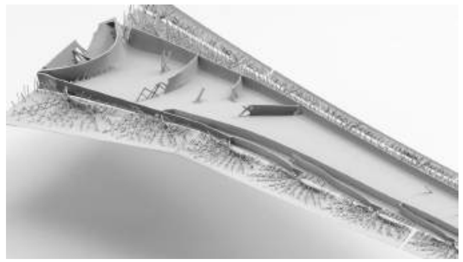


(a)

(b)

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





Multidisciplinary Optimization and Machine Learning for Engineering Design

19 July 2021 – 5 August 2021

https://mdoml2021.ftmd.itb.ac.id/

Jointly organized by

香港科技大學
THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

Thanks To All My Co-authors (Students, Researchers, Professors All Over The World)

*And Thanks To **Pram** For The Invitation !*

2021-07-21	08:00 - 10:00	Optimization problem formulation	Rommel Regis, Ph.D. (Saint Joseph University, USA)
2021-08-04	19:00 - 21:00	Real World Optimization	Joaquim Martins, Ph.D. (University of Michigan, USA)
2021-07-28	13:00 - 15:00	Multidisciplinary Design Optimization	Nathalie Bartoli, Ph.D. (ONERA, France)
2021-07-29	14:00 - 16:00	Real-world application II	Joel Henry, Ph.D. (Monolith AI, UK)
2021-08-03	08:00 - 10:00	Surrogate modelling and machine learning: modern approximation tools	Pramudita Satria Palar, Ph.D. (Institut Teknologi Bandung, Indonesia)
2021-07-22	14:00 - 16:00	Advanced modelling and simulations in engineering design	Lavi Rizki Zuhal, Ph.D. (Institut Teknologi Bandung, Indonesia) and Eky Valentian Febrianto, Ph.D. (University of Cambridge, UK)

Multidisciplinary Optimization and Machine Learning for Engineering Design

19 July 2021 – 5 August 2021

https://mdoml2021.ftmd.itb.ac.id/

Jointly organized by

More Questions ? Email me →

joseph.morlier@isae-supaero.fr