



DESIGN AND OPTIMIZATION OF LATTICE STRUCTURES FOR AEROSPACE APPLICATIONS

Enrico Stragiotti

François-Xavier Irisarri¹, Cédric Julien¹ and Joseph Morlier²

1: ONERA - The French Aerospace Lab
DMAS - Département matériaux et structures
92320 Châtillon, France
{francois-xavier.irisarri, cedric.julien}@onera.fr

2: ICA - Institut Clément Ader
ISAE - SUPAERO
31400 Toulouse, France
joseph.morlier@isae-supero.fr
December 6, 2023

PhD manuscript

ONERA – ISAE Supaero

Colophon

This document was typeset with the help of KOMA-Script and L^AT_EX using the kaobook class.

ONERA – ISAE Supaero

CONTENTS

Contents	iii
List of Figures	v
List of Tables	v
1. Optimizing the layout of the modules in space	1
1.1. Optimize the modules' layout using a modified DMO algorithm	1
1.1.1. Variables penalization schemes	1
1.1.2. Modified DMO algorithm	1
1.1.3. Optimization formulation and resolution algorithm	3
1.1.4. Optimization initialization: a clustering algorithm to identify similarly behav- ing subdomains	3
1.2. Numerical application	4
1.2.1. Layout optimization of fixed modules	4
1.2.2. Modules and layout optimization	4
1.2.3. A benchmark case study: a simply supported modular bridge	6
1.2.4. On the importance of the local buckling	6
1.2.5. Simply supported 3D beam	6
1.3. Conclusion	10
Appendix	11
A. Sensitivity analysis of the modular structure optimization algorithm	13

LIST OF FIGURES

1.1.	1
1.2.	2
1.3.	4
1.4.	4
1.5. Boundary conditions of the 2D cantilever beam divided in 24x12 subdomains. In the upper part of the image the ground structure of the module composed of $\bar{n} = 6$ elements.	4
1.6.	5
1.7.	5
1.8.	5
1.9.	6
1.10.	7
1.11.	8
1.12.	9

LIST OF TABLES

1.1. Material data used for the 2D cantilever beam 2D.	6
1.2. Material data used for the simply supported 3D beam optimization.	10

OPTIMIZING THE LAYOUT OF THE MODULES IN SPACE

1

tables always small Introduction

1.1. OPTIMIZE THE MODULES' LAYOUT USING A MODIFIED DMO ALGORITHM

1.1 OPTIMIZE THE MODULES' LAYOUT USING A MODIFIED DMO ALGORITHM	1
1.2 NUMERICAL APPLICATION	4
1.3 CONCLUSION	10

difference with tugilimana, we take into account the buckling when solving the first subproblem of module layout, we can have an empty subdomain and we use a gradient descent algo

1.1.1. VARIABLES PENALIZATION SCHEMES

describe RAMP with paper of Lund. we use it because the derivative it is not infinite on $\alpha=0$

multi-phase versions of the well-known RAMP scheme (Hvejsel and Lund, 2011)

multiple penalizations

continuation scheme only on p (we use an interior point algo, we want to stay in the feasible region)

1.1.2. MODIFIED DMO ALGORITHM

we use a dmo like approach PRO: Optimize a discrete problem using continuous variables Gradient-based optimization

CONS: Convergence of the weight to 0000100 solution FOR EVERY ELEMENT Many optimization variables

difference with the original DMO; we are not only changing the weights but also the modules topology. This is more difficult

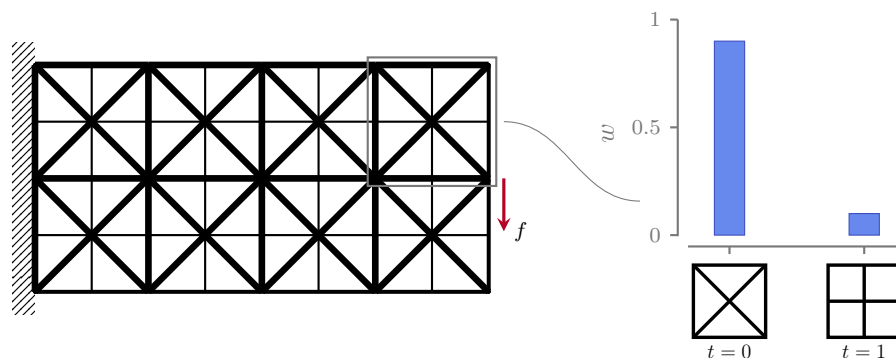


Figure 1.1.

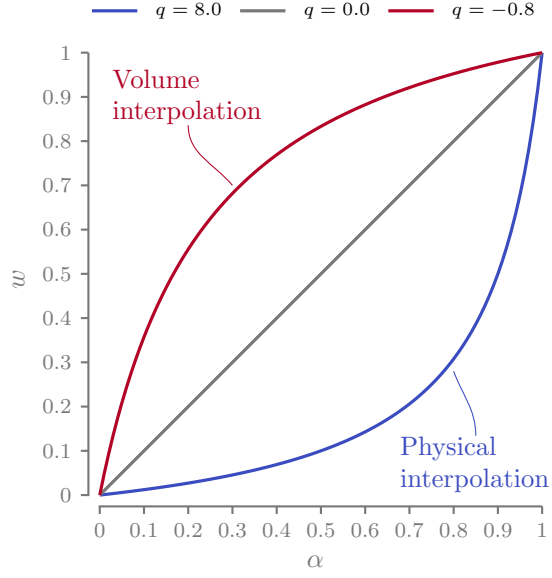


Figure 1.2.

PENALIZED VOLUME

$$V = \sum_{j=1}^{N_{\text{sub}}} \bar{\boldsymbol{\ell}}^T \tilde{\mathbf{a}}^j \quad (1.1)$$

$$\tilde{\mathbf{a}}^j = \sum_{t=1}^{N_T} \tilde{w}_t^j \bar{\mathbf{a}}_t \quad (1.2)$$

and where

$$\tilde{w}_t^j = \frac{\alpha_t^j}{1 + q(1 - \alpha_t^j)} \quad (1.3)$$

$$\mathbf{a}^j = \sum_{t=1}^{N_T} w_t^j \bar{\mathbf{a}}_t \quad (1.4)$$

and where

$$w_t^j = \frac{\alpha_t^j}{1 + p(1 - \alpha_t^j)} \quad (1.5)$$

$$\sum_{t=1}^{N_T} w_t^j = 1 \quad (1.6)$$

$$V = \sum_{j=1}^{N_{\text{sub}}} \bar{\boldsymbol{\ell}}^T \sum_{t=1}^{N_T} \frac{\alpha_t^j}{1 + q(1 - \alpha_t^j)} \bar{\mathbf{a}}_t \quad (1.7)$$

1.1.3. OPTIMIZATION FORMULATION AND RESOLUTION ALGORITHM

$$\begin{aligned}
\min_{\bar{a}, \alpha, q, U} \quad & V = \sum_{j=1}^{N_{\text{sub}}} \bar{\ell}^T \bar{a}^j \quad (\text{Volume minimization}) \\
\text{s.t.} \quad & Bq = f \quad (\text{Force equilibrium}) \\
& q = \frac{aE}{\ell} b^T U \quad (\text{Compatibility constraints}) \\
& q \geq -\frac{sa^2}{\ell^2} \quad (\text{Euler buckling constraints}) \quad (1.8) \\
& -\sigma_C a \leq q \leq \sigma_T a \quad (\text{Stress constraints}) \\
& 0 \leq \bar{a} \leq \frac{4\pi\bar{\ell}^2}{\lambda_{\max}} \quad (\text{Slenderness limit}) \\
& \sum_{t=1}^{N_T} \alpha_t^j \leq 1, \forall j \quad (\text{One selected module max.})
\end{aligned}$$

Solved using the two step algorithm, so before relaxed problem where we solve without compatibility constraints. this time, as the problem is nonlinear due to the alpha design variables, we solve it without linearizing the buckling constraints. here is the formulation of the first subproblem:

Then the compatibility constraints are added again we solve it fixing the submodules topology and using the VL formulation already used in ...

here is the schema of the solving algo:

1.1.4. OPTIMIZATION INITIALIZATION: A CLUSTERING ALGORITHM TO IDENTIFY SIMILARLY BEHAVING SUBDOMAINS

we are not only changing the weights but also the modules topology. This is more difficult. the layout is dependent on the module topology and vice versa. so we give a slightly influenced departure point x_0 . In this work we decided to influence the weight distribution as follows:

$$\alpha_{t, it=0}^j = \begin{cases} \frac{1}{N_T} \cdot 1.1 & \text{if the } j\text{-th subdomain has the } t\text{-th module selected,} \\ \frac{N_T - 1.1}{N_T(N_T - 1)} & \text{otherwise.} \end{cases} \quad (1.9)$$

the initial layout of modules is assessed using a k means clustering technique with n_t clusters. Given a set of observations (x_1, x_2, \dots, x_n) , where each observation is a d -dimensional real vector, k -means clustering aims to partition the n observations into n sets. we define the observation as the vector containing the stress of the bars of unoptimized initial ground structure plus the stress state S For the j -th submodule we define the

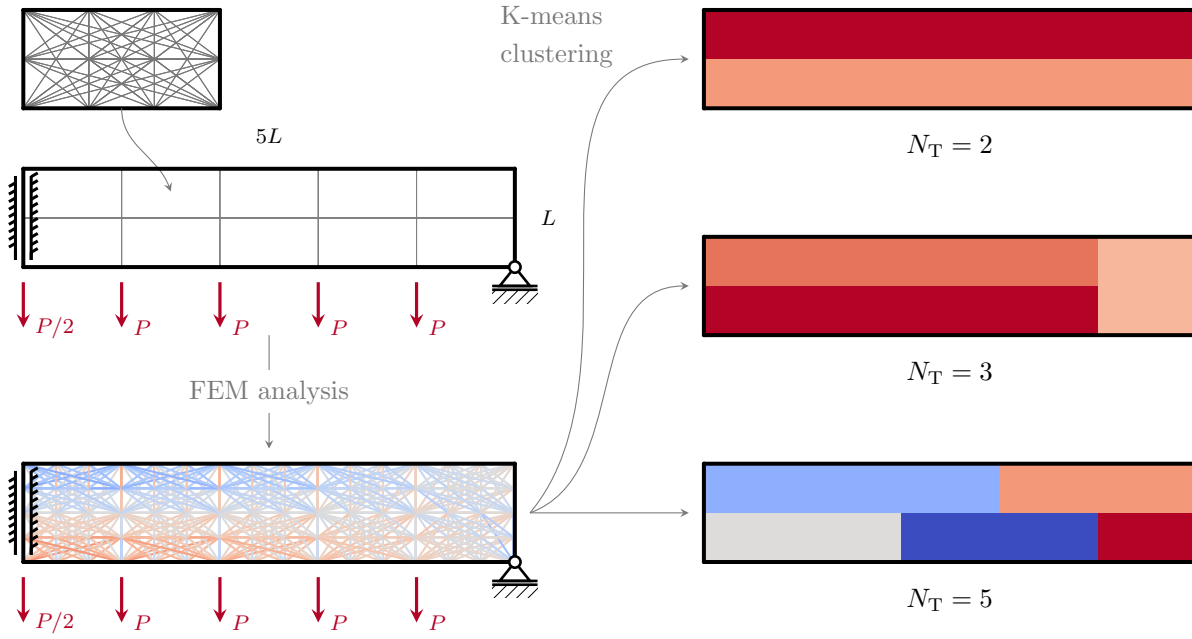


Figure 1.3.

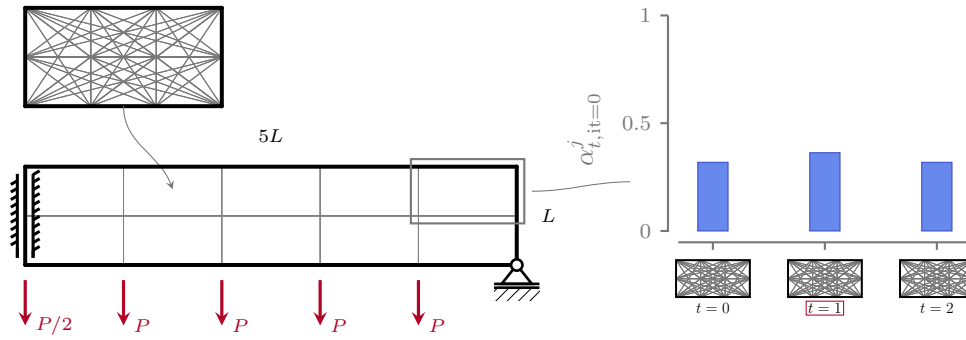


Figure 1.4.

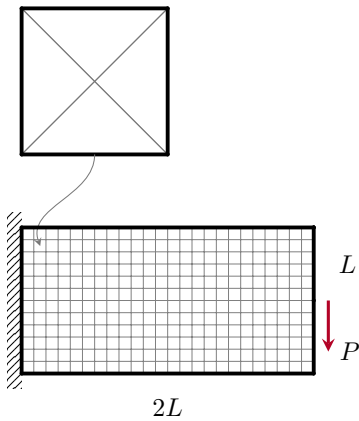


Figure 1.5.: Boundary conditions of the 2D cantilever beam divided in 24x12 subdomains. In the upper part of the image the ground structure of the module composed of $\bar{n} = 6$ elements.

$$S^j = \sum_{i=0}^{\bar{n}} |\sigma_i^j| \quad (1.10)$$

This add permits to promote the clustering of not only submodules loaded in similar ways, but also on similar magnitude (and have so more voluminous and less voluminous modules).

1.2. NUMERICAL APPLICATION

IPOPT for the two steps

1.2.1. LAYOUT OPTIMIZATION OF FIXED MODULES

1.2.2. MODULES AND LAYOUT OPTIMIZATION

tables with volume and phi and psi for different NT

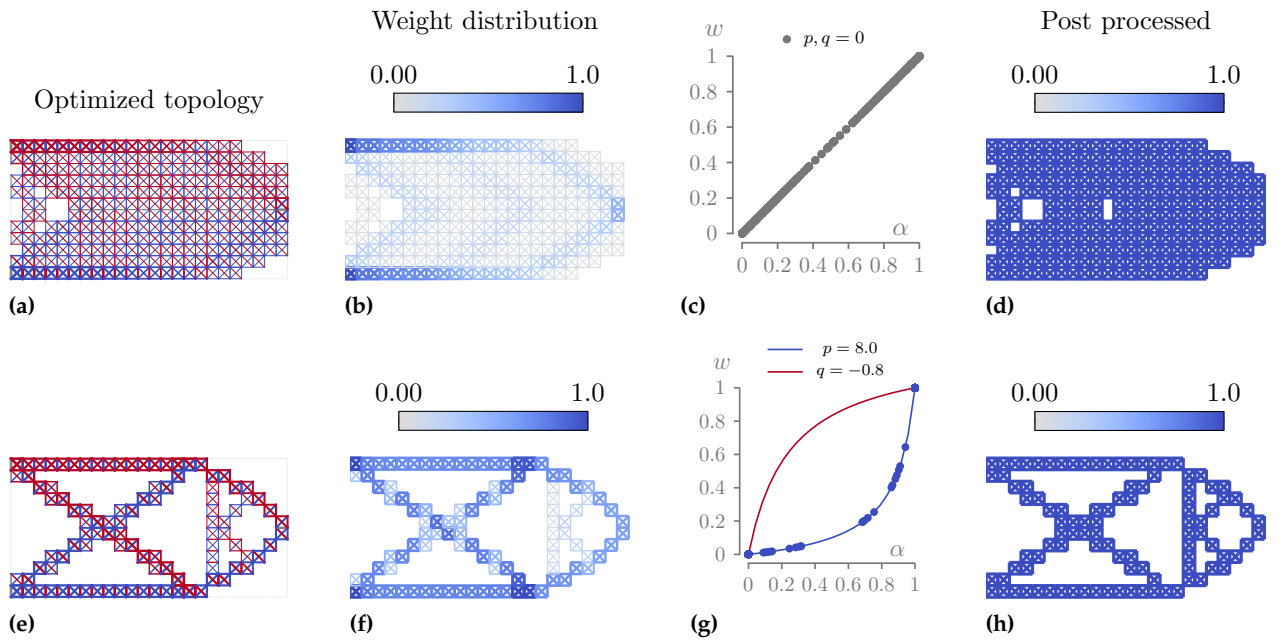


Figure 1.6.

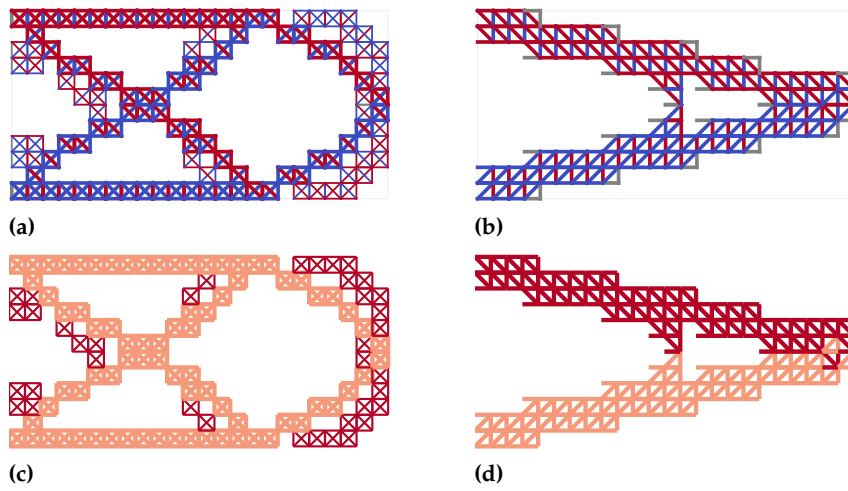


Figure 1.7.

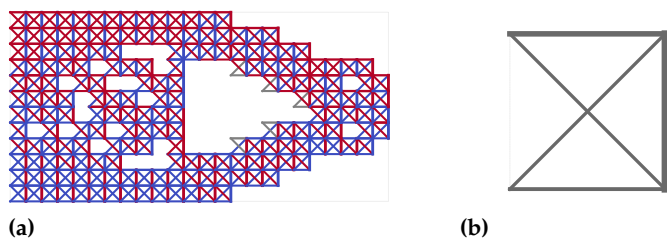


Figure 1.8.

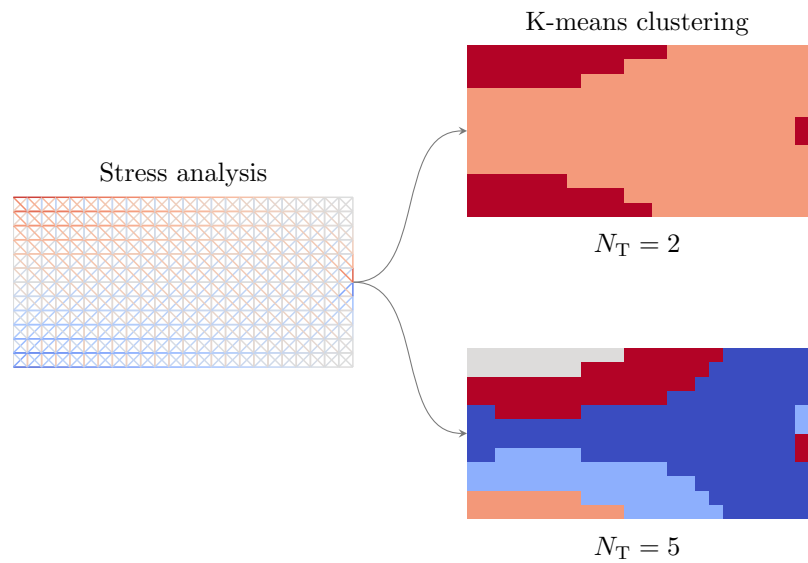


Figure 1.9.

Parameter	Value
L	100
σ_c, σ_t	± 1
P	1
a_{\max}	0.6

Table 1.1.: Material data used for the 2D cantilever beam 2D.

- 1.2.3. A BENCHMARK CASE STUDY: A SIMPLY SUPPORTED MODULAR BRIDGE
- 1.2.4. ON THE IMPORTANCE OF THE LOCAL BUCKLING
- 1.2.5. SIMPLY SUPPORTED 3D BEAM

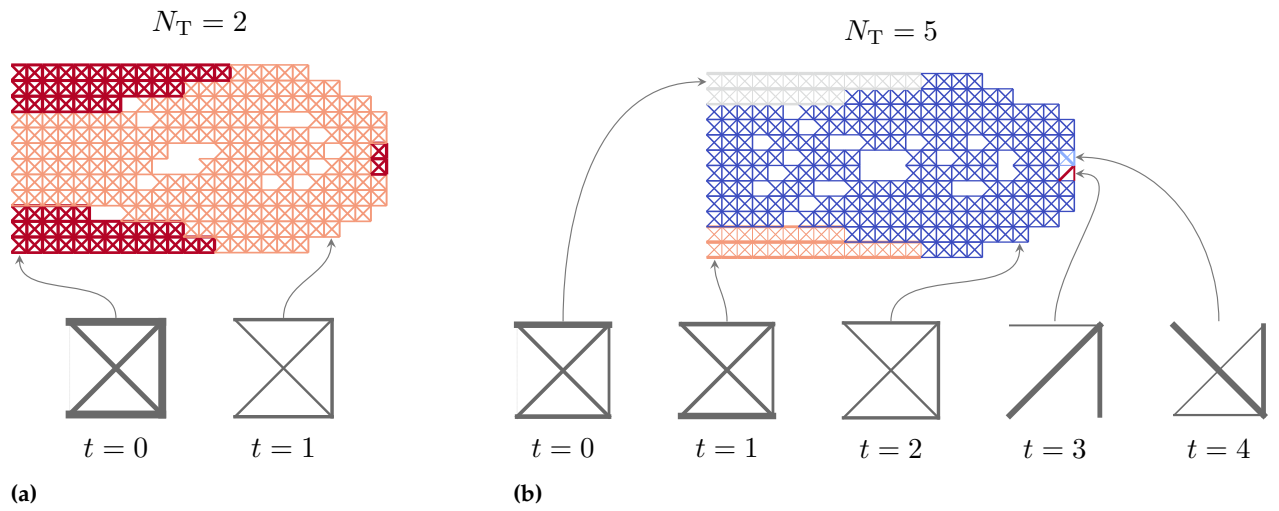


Figure 1.10.

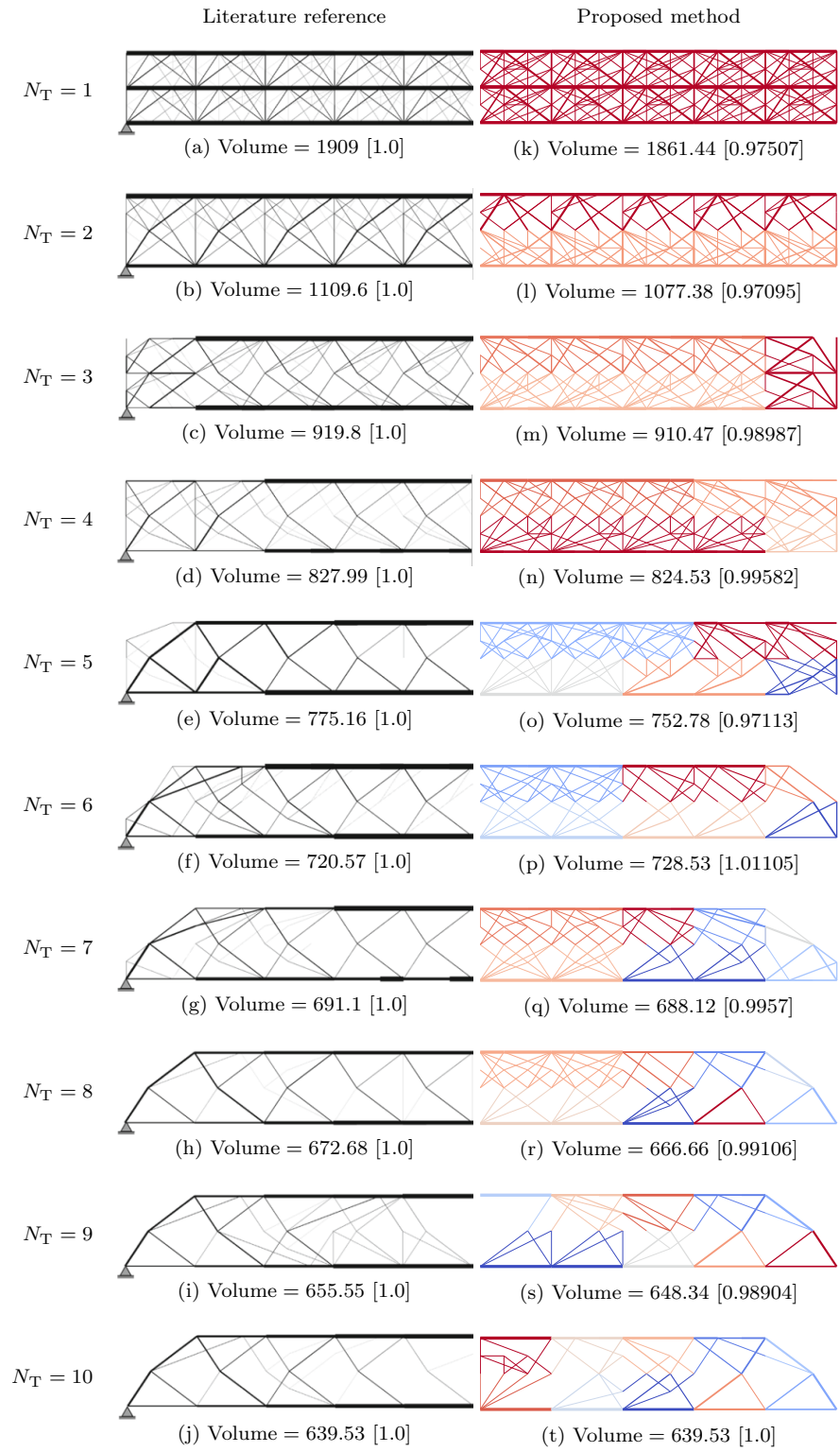


Figure 1.11.

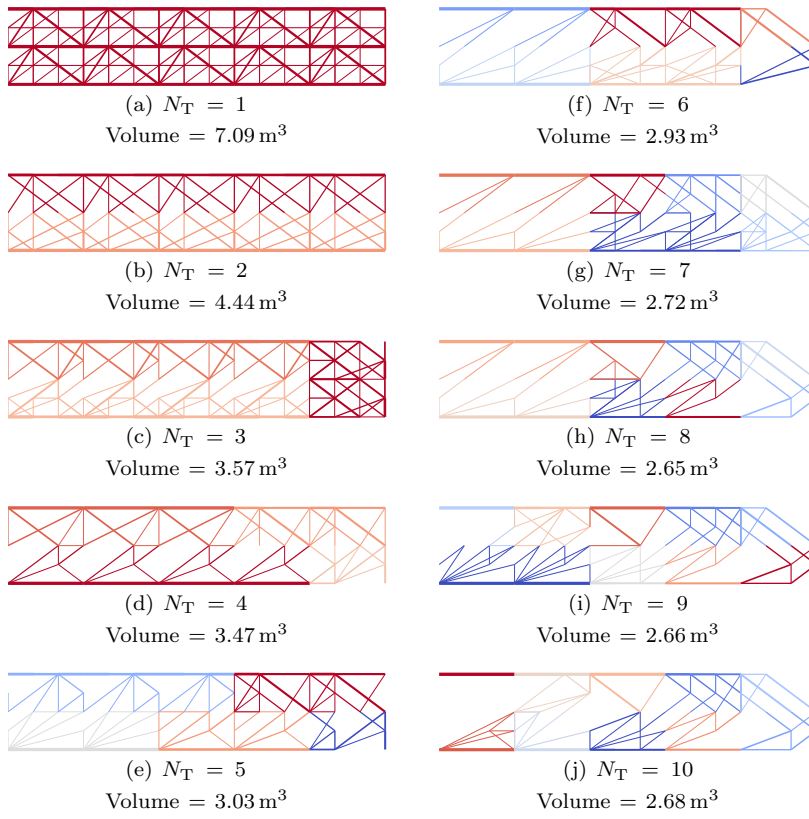


Figure 1.12.

Parameter	Value
E	2.7 GPa
ν	0.3
σ_c, σ_t	± 55 MPa
ρ	1.14 g cm^{-3}
P	100 N

Table 1.2.: Material data used for the simply supported 3D beam optimization.

1.3. CONCLUSION

APPENDIX

SENSITIVITY ANALYSIS OF THE MODULAR STRUCTURE OPTIMIZATION ALGORITHM

A

SENSITIVITY ANALYSIS

COMMON DERIVATIVES

$$\frac{\partial \mathbf{a}^j}{\partial \bar{\mathbf{a}}_t} = \mathbf{w}_t^j \quad (\text{A.1})$$

$$\frac{\partial \mathbf{a}^j}{\partial \alpha_t^j} = \frac{\partial \mathbf{a}^j}{\partial \mathbf{w}_t^j} \frac{\partial \mathbf{w}_t^j}{\partial \alpha_t^j} \quad (\text{A.2})$$

$$\frac{\partial \mathbf{a}^j}{\partial \mathbf{w}_t^j} = \bar{\mathbf{a}}_t \quad (\text{A.3})$$

$$\frac{\partial \mathbf{w}_t^j}{\partial \alpha_t^j} = \frac{1 + (\cdot)}{\left(1 + (\cdot)(1 - \alpha_t^j)\right)^2} \quad (\text{A.4})$$

where (\cdot) is either equal to p or q .

$$\frac{\partial^2 \mathbf{w}_t^j}{\partial (\alpha_t^j)^2} = \frac{2(\cdot)(1 + (\cdot))}{\left(1 + (\cdot)(1 - \alpha_t^j)\right)^3} \quad (\text{A.5})$$

VOLUME JACOBIAN

$$\frac{\partial V}{\partial \bar{\mathbf{a}}_t} = \bar{\boldsymbol{\ell}}^T \sum_{j=1}^{N_{\text{sub}}} \tilde{\mathbf{w}}_t^j, \text{ with } t \in [1, \dots, N_T] \quad (\text{A.6})$$

$$\frac{\partial V}{\partial \alpha_t^j} = \frac{\partial V}{\partial \mathbf{w}_t^j} \frac{\partial \mathbf{w}_t^j}{\partial \alpha_t^j} \quad (\text{A.7})$$

$$\frac{\partial V}{\partial \mathbf{w}_t^j} = \bar{\boldsymbol{\ell}}^T \bar{\mathbf{a}}_t \quad (\text{A.8})$$

$$\frac{\partial V}{\partial \mathbf{q}} = 0 \quad (\text{A.9})$$

$$\frac{\partial V}{\partial \mathbf{u}} = 0 \quad (\text{A.10})$$

VOLUME HESSIAN

$$\frac{\partial^2 V}{\partial \bar{a}_t \partial \alpha_t^j} = \bar{\ell}^T \frac{\partial \tilde{w}_t^j}{\partial \alpha_t^j} \quad (\text{A.11})$$

$$\frac{\partial^2 V}{\partial (\alpha_t^j)^2} = \bar{\ell}^T \bar{a}_t \frac{\partial^2 w_t^j}{\partial (\alpha_t^j)^2} \quad (\text{A.12})$$

$$\frac{\partial^2 V}{\partial \bar{a}_t^2} = 0 \quad (\text{A.13})$$

EQUILIBRIUM JACOBIAN

$$\mathbf{g}_{\text{eq}} := \mathbf{B}\mathbf{q} = \mathbf{f} \quad (\text{A.14})$$

Not impacted by the clustering of the variables.

$$\frac{\partial \mathbf{g}_{\text{eq}}}{\partial \boldsymbol{\alpha}} = 0 \quad (\text{A.15})$$

STRESS CONSTRAINTS TENSION JACOBIAN

$$\mathbf{g}_t := \mathbf{q} - \sigma_t \mathbf{a} \leq 0 \quad (\text{A.16})$$

$$\frac{\partial \mathbf{g}_t^j}{\partial \bar{a}_t} = \frac{\partial \mathbf{g}_t^j}{\partial \mathbf{a}^j} \frac{\partial \mathbf{a}^j}{\partial \bar{a}_t} \quad (\text{A.17})$$

$$\frac{\partial \mathbf{g}_t^j}{\partial \mathbf{a}^j} = -\sigma_t \quad (\text{A.18})$$

$$\frac{\partial \mathbf{g}_t^j}{\partial \bar{a}_t} = -\sigma_t w_t^j \quad (\text{A.19})$$

$$\frac{\partial \mathbf{g}_t^j}{\partial \alpha^j} = \frac{\partial \mathbf{g}_t^j}{\partial \mathbf{a}^j} \frac{\partial \mathbf{a}^j}{\partial \alpha^j} \quad (\text{A.20})$$

STRESS CONSTRAINTS TENSION HESSIAN

$$\frac{\partial^2 \mathbf{g}_t^j}{\partial \bar{a}_t \partial \alpha_t^j} = -\sigma_t \frac{\partial w_t^j}{\partial \alpha_t^j} \quad (\text{A.21})$$

$$\frac{\partial^2 \mathbf{g}_t^j}{\partial (\alpha_t^j)^2} = -\sigma_t \bar{a}_t \frac{\partial^2 w_t^j}{\partial (\alpha_t^j)^2} \quad (\text{A.22})$$

BUCKLING JACOBIAN

$$g_b := q \frac{s a^2}{\ell^2} \geq 0 \quad (\text{A.23})$$

$$\frac{\partial g_b^j}{\partial a^j} = 2 \frac{s a^j}{\ell^2} \quad (\text{A.24})$$

$$\frac{\partial g_b^j}{\partial \bar{a}_t} = \frac{\partial g_b^j}{\partial a^j} \frac{\partial a^j}{\partial \bar{a}_t} \quad (\text{A.25})$$

$$\frac{\partial g_b^j}{\partial \bar{a}_t} = 2 \frac{s a^j}{\ell^2} w_t^j \quad (\text{A.26})$$

$$\frac{\partial g_b^j}{\partial \alpha^j} = \frac{\partial g_b^j}{\partial a^j} \frac{\partial a^j}{\partial \alpha^j} \quad (\text{A.27})$$

$$\frac{\partial g_b^j}{\partial \alpha_t^j} = 2 \frac{s a^j}{\ell^2} \bar{a}_t \frac{\partial w_t^j}{\partial \alpha_t^j} \quad (\text{A.28})$$

$$\frac{\partial g_b^j}{\partial \alpha_t^j} = 2 \frac{s a^j}{\ell^2} \bar{a}_t \frac{1 + (\cdot)}{\left(1 + (\cdot)(1 - \alpha_t^j)\right)^2} \quad (\text{A.29})$$

BUCKLING HESSIAN

$$\frac{\partial^2 g_b^j}{\partial \bar{a}_l \partial \alpha_m^j} = 2 \frac{s}{\ell^2} w_l^j \frac{\partial a^j}{\partial \alpha_m^j} + 2 \frac{s a^j}{\ell^2} \frac{\partial w_l^j}{\partial \alpha_m^j} \quad (\text{A.30})$$

$$\frac{\partial^2 g_b^j}{\partial \bar{a}_l \partial \alpha_m^j} = 2 \frac{s}{\ell^2} w_l^j \frac{\partial w_m^j}{\partial \alpha_m^j} \bar{a}_m + 2 \frac{s a^j}{\ell^2} \frac{\partial w_l^j}{\partial \alpha_m^j} \quad (\text{A.31})$$

$$\frac{\partial^2 g_b^j}{\partial \bar{a}_l \partial \alpha_m^j} = \begin{cases} 2 \frac{s}{\ell^2} \frac{\partial w_t^j}{\partial \alpha_t^j} \left(w_t^j \bar{a}_t + a^j \right) & \text{if } l = m = t \\ 2 \frac{s}{\ell^2} w_l^j \frac{\partial w_m^j}{\partial \alpha_m^j} \bar{a}_m & \text{otherwise.} \end{cases} \quad (\text{A.32})$$

$$\frac{\partial^2 g_b^j}{\partial \bar{a}_l \partial \bar{a}_m} = 2 \frac{s}{\ell^2} w_l^j w_m^j \quad (\text{A.33})$$

$$\frac{\partial^2 g_b^j}{\partial \alpha_l^j \partial \alpha_m^j} = 2 \frac{s}{\ell^2} \bar{a}_l \frac{\partial a^j}{\partial \alpha_m^j} \frac{\partial w_l^j}{\partial \alpha_l^j} + 2 \frac{s a^j}{\ell^2} \bar{a}_l \frac{\partial^2 w_l^j}{\partial \alpha_l^j \partial \alpha_m^j} \quad (\text{A.34})$$

$$\frac{\partial^2 \mathbf{g}_b^j}{\partial \alpha_l^j \partial \alpha_m^j} = \begin{cases} 2 \frac{s}{\ell^2} \bar{a}_t^2 \left(\frac{\partial w_t^j}{\partial \alpha_t^j} \right)^2 + 2 \frac{s a^j}{\ell^2} \bar{a}_t \frac{\partial^2 w_t^j}{\partial (\alpha_t^j)^2} & \text{if } l = m = t \\ 2 \frac{s}{\ell^2} \bar{a}_l \bar{a}_m \left(\frac{\partial w_m^j}{\partial \alpha_m^j} \right) \left(\frac{\partial w_l^j}{\partial \alpha_l^j} \right) & \text{otherwise.} \end{cases} \quad (\text{A.35})$$