

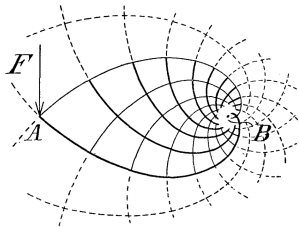


# Topology optimization I: Trusses

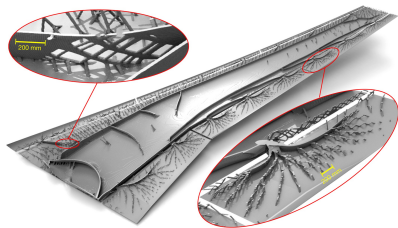
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- Truss structures possess high **stiffness-to-weight** ratio
- Truss-like or lattice structures are often achieved by continuum topology optimization
- There are **convex** (and easily solvable) formulations
- Quite mature theory (pioneered by Michell in 1904)

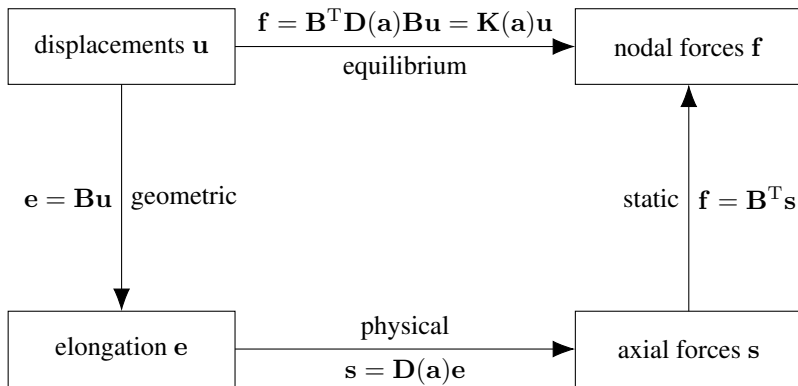


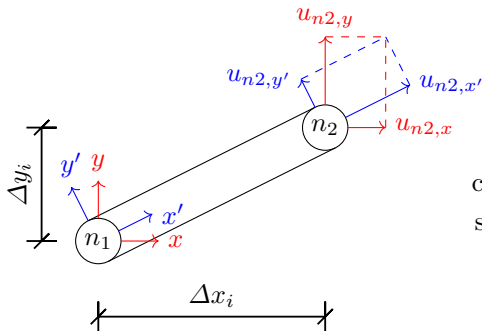
(a) Michell-type structure. Courtesy of A. G. M. Michell, The limits of economy of material in frame-structures, *Philosophical Magazine Series 6*, 8(47):589–597, 1904, doi: 10.1080/14786440409463229



(b) Lattice-like Wing structure. Courtesy of N. Aage, E. Andreassen, B. S. Lazarov, and O. Sigmund, Giga-voxel computational morphogenesis for structural design, *Nature*, 550(7674):84–86, 2017, doi: 10.1038/nature23911

# Finite elements overview





$$\ell_i = \|(\Delta x \quad \Delta y)\|_2$$

$$\cos(\alpha_i) = \Delta x_i / \ell_i$$

$$\sin(\alpha_i) = \Delta y_i / \ell_i$$

$$e_i = (u_{n2,x} - u_{n1,x}) \cos(\alpha_i) + (u_{n2,y} - u_{n1,y}) \sin(\alpha_i)$$

$$= \begin{pmatrix} -\cos(\alpha_i) & -\sin(\alpha_i) & \cos(\alpha_i) & \sin(\alpha_i) \end{pmatrix} \begin{pmatrix} u_{n1,x} & u_{n1,y} & u_{n2,x} & u_{n2,y} \end{pmatrix}^T$$

$$= \mathbf{b}_i \mathbf{u}$$

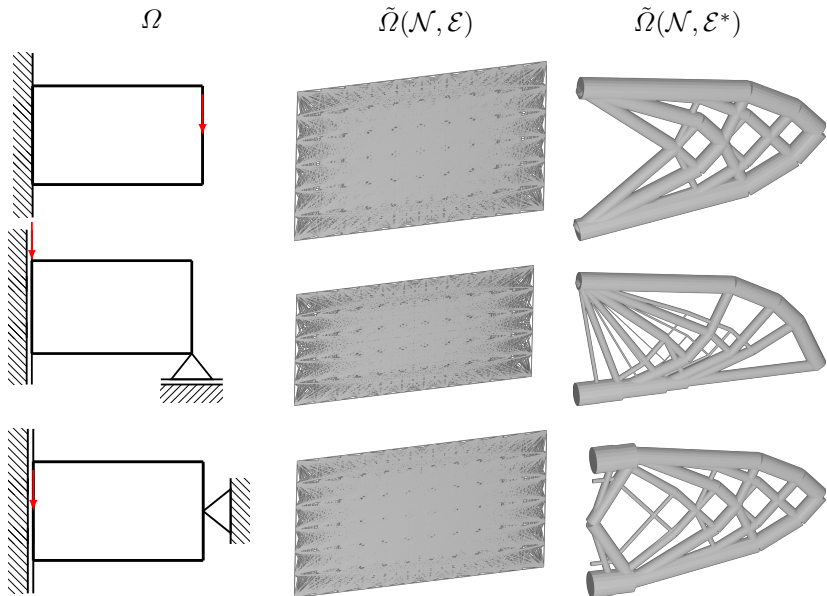
$$d_i = E_i a_i / \ell_i$$

$$\mathbf{K}_i(a_i) = \mathbf{b}_i^T d_i(a_i) \mathbf{b}_i \quad \longrightarrow \quad \mathbf{K}_i(a_i) \in \mathbb{S}_{\geq 0}^4 \text{ and has rank 1}$$

## Ground structure method

- Approximation of the continuum **design domain**  $\Omega$  by **discretization**  $\tilde{\Omega} := G(\mathcal{N}, \mathcal{E})$ , where  $\mathcal{N} = \{1, \dots, n_n\}$  is the **set of nodes** and  $\mathcal{E} = \{\{n_{1,1}, n_{2,1}\}, \dots, \{n_{1,n_e}, n_{2,n_e}\}\}$  with  $n_{\bullet,\bullet} \in \mathcal{N}$  standing for the **set of elements** (bars)
- Topology optimization (TO): which elements from  $\mathcal{E}$  appear in an optimal design to
  - reach target/optimize performance
  - reach target/minimize weight
  - satisfy/optimize other constraints/objectives (resonance frequency, buckling, manufacturing ...)
- Truss TO:
  - problem usually parametrized via **cross-section areas**  $\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}$
  - $a_i > 0 \iff$  element  $i$  is present in the design
  - $a_i = 0 \iff$  element  $i$  is not present in the design
  - we do not know a priori whether  $a_i > 0$  or  $a_i = 0$





# Compliance minimization: sizing

- **Compliance**: inverse measure of structural stiffness w.r.t.  $\mathbf{f} \in \mathbb{R}^{n_{\text{dof}}}$

$$c(\mathbf{a}) := \mathbf{f}^T \mathbf{u}, \text{ where } \mathbf{K}(\mathbf{a})\mathbf{u} = \mathbf{f} \quad (1)$$

- Basic elastic-design formulation:

$$\min_{\mathbf{a} \in \mathbb{R}^{n_e}, \mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} \mathbf{f}^T \mathbf{u} \quad (2a)$$

$$\text{subject to } \mathbf{K}(\mathbf{a})\mathbf{u} = \mathbf{f}, \quad (2b)$$

$$\ell^T \mathbf{a} \leq \bar{V}, \quad (2c)$$

$$\mathbf{a} \geq \mathbf{0} \quad (2d)$$

- Why do we need  $\ell^T \mathbf{a} \leq \bar{V}$ ?
- $\mathbf{a} \geq \mathbf{0} \implies \mathbf{K}(\mathbf{a}) \succeq 0$  ( $\succeq$  means positive semi-definiteness)
- We assume  $\forall \mathbf{a} > \mathbf{0} : \mathbf{K}(\mathbf{a}) \succ 0$  (positive definiteness)



- To avoid  $\text{Det}(\mathbf{K}(\mathbf{a})) = 0$ , we set  $\mathbf{a} \geq \varepsilon \mathbf{1} > \mathbf{0}$ , where  $\varepsilon \rightarrow 0$
- Then,  $\mathbf{u} = \mathbf{K}(\mathbf{a})^{-1} \mathbf{f}$  is unique and can be eliminated from the formulation:

$$\min_{\mathbf{a} \in \mathbb{R}^{n_e}} \mathbf{f}^T \mathbf{K}(\mathbf{a})^{-1} \mathbf{f} \quad (3a)$$

$$\text{subject to } \ell^T \mathbf{a} \leq \bar{V}, \quad (3b)$$

$$\mathbf{a} \geq \varepsilon \mathbf{1} \quad (3c)$$

- **HW:** Show that the problem (3) is convex. Hint: Hessian matrix
- $\varepsilon \rightarrow 0$  impairs the **conditioning** of  $\mathbf{K}(\mathbf{a})$ 
  - $\lambda_{\max}(\mathbf{K}(\mathbf{a}))$  driven by  $\bar{V}$
  - $\lambda_{\min}(\mathbf{K}(\mathbf{a}))$  driven by  $\varepsilon$

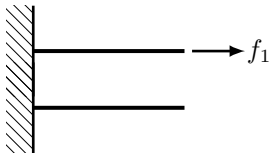
- To avoid  $\text{Det}(\mathbf{K}(\mathbf{a})) = 0$ , we set  $\mathbf{a} \geq \varepsilon \mathbf{1} > \mathbf{0}$ , where  $\varepsilon \rightarrow 0$
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$$\text{subject to } \ell^T \mathbf{a} \leq \bar{V}, \quad (3b)$$

$$\mathbf{a} \geq \varepsilon \mathbf{1} \quad (3c)$$

- **HW:** Show that the problem (3) is convex. Hint: Hessian matrix
- $\varepsilon \rightarrow 0$  impairs the **conditioning** of  $\mathbf{K}(\mathbf{a})$



$$\mathbf{K} = \frac{E}{\ell} \begin{pmatrix} \frac{\bar{V} - \varepsilon \ell}{\ell} & 0 \\ 0 & \varepsilon \end{pmatrix}$$

$$\frac{\varepsilon}{\bar{V}} \rightarrow 0 \quad \longrightarrow \quad \text{Cond}(\mathbf{K}) = \frac{\bar{V} - \varepsilon \ell}{\varepsilon \ell} \rightarrow \infty$$



## Compliance minimization: potential-energy-based SDP



- **Potential energy function** (convex, minimum  $-\mathbf{f}^T \mathbf{u}$ )

$$\Pi(\mathbf{a}, \mathbf{u}) := \mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u} - 2\mathbf{f}^T \mathbf{u} \quad (4)$$

- Optimum design solves

$$\begin{aligned} \min_{\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}, \ell^T \mathbf{a} \leq \bar{V}} \min_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} (\mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u} - 2\mathbf{f}^T \mathbf{u}) &\iff \\ \min_{\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}, \ell^T \mathbf{a} \leq \bar{V}} \max_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} (2\mathbf{f}^T \mathbf{u} - \mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u}) & \end{aligned}$$

- The inner max is equivalent to infinite number of inequalities

$$\begin{aligned} \min_{\mathbf{a} \in \mathbb{R}^{n_e}, c \in \mathbb{R}} c \\ \text{s.t. } c &\geq (2\mathbf{f}^T \mathbf{u} - \mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u}), \forall \mathbf{u} \in \mathbb{R}^{n_{\text{dof}}} \\ \ell^T \mathbf{a} &\leq \bar{V} \\ \mathbf{a} &\geq \mathbf{0} \end{aligned}$$

- **Potential energy function** (convex, minimum  $-\mathbf{f}^T \mathbf{u}$ )

$$H(\mathbf{a}, \mathbf{u}) := \mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u} - 2\mathbf{f}^T \mathbf{u} \quad (4)$$

- Optimum design solves

$$\begin{aligned} \min_{\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}, \ell^T \mathbf{a} \leq \bar{V}} \min_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} (\mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u} - 2\mathbf{f}^T \mathbf{u}) &\iff \\ \min_{\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}, \ell^T \mathbf{a} \leq \bar{V}} \max_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} (2\mathbf{f}^T \mathbf{u} - \mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u}) \end{aligned}$$

- The inner max is equivalent to infinite number of inequalities

$$\begin{aligned} \min_{\mathbf{a} \in \mathbb{R}^{n_e}, c \in \mathbb{R}} \quad &c \\ \text{s.t.} \quad &c \geq \left( \frac{1}{\alpha} 2\mathbf{f}^T \mathbf{v} - \frac{1}{\alpha^2} \mathbf{v}^T \mathbf{K}(\mathbf{a}) \mathbf{v} \right), \forall \mathbf{v} \in \mathbb{R}^{n_{\text{dof}}}, \forall \alpha \in \mathbb{R} \setminus \{0\} \\ &\ell^T \mathbf{a} \leq \bar{V} \\ &\mathbf{a} \geq \mathbf{0} \end{aligned}$$



- Next, we rearrange the terms and multiply by  $\alpha^2$

$$\begin{aligned}
 & \min_{\mathbf{a} \in \mathbb{R}^{n_e}, c \in \mathbb{R}} c \\
 & \text{s.t. } \alpha^2 c - 2\alpha \mathbf{f}^T \mathbf{v} + \mathbf{v}^T \mathbf{K}(\mathbf{a}) \mathbf{v} \geq 0, \forall \mathbf{v} \in \mathbb{R}^{n_{\text{dof}}}, \forall \alpha \in \mathbb{R} \setminus \{0\} \\
 & \quad \ell^T \mathbf{a} \leq \bar{V} \\
 & \quad \mathbf{a} \geq \mathbf{0}
 \end{aligned}$$

- We observe that the **first inequality** is actually

$$\underbrace{(\alpha \quad \mathbf{v}^T) \begin{pmatrix} c & -\mathbf{f}^T \\ -\mathbf{f} & \mathbf{K}(\mathbf{a}) \end{pmatrix} \begin{pmatrix} \alpha \\ \mathbf{v} \end{pmatrix} \geq 0, \forall \mathbf{v} \in \mathbb{R}^{n_{\text{dof}}}, \forall \alpha \in \mathbb{R} \setminus \{0\}}_{\begin{pmatrix} \alpha \\ \mathbf{v} \end{pmatrix} \notin \text{Ker} \begin{pmatrix} c & -\mathbf{f}^T \\ -\mathbf{f} & \mathbf{K}(\mathbf{a}) \end{pmatrix}}$$

- The inequality holds  $\forall \mathbf{v} \in \mathbb{R}^{n_{\text{dof}}}, \forall \alpha \in \mathbb{R} \implies$  we can write SDP formulation

- Linear SDP formulation:

$$\min_{\mathbf{a} \in \mathbb{R}^{n_e}, c \in \mathbb{R}} c \quad (5a)$$

$$\text{subject to } \begin{pmatrix} c & -\mathbf{f}^T \\ -\mathbf{f} & \mathbf{K}(\mathbf{a}) \end{pmatrix} \succeq 0, \quad (5b)$$

$$\boldsymbol{\ell}^T \mathbf{a} \leq \bar{V}, \quad (5c)$$

$$\mathbf{a} \geq \mathbf{0} \quad (5d)$$

- Convex problem

- Let  $\mathbf{X}, \mathbf{Y} \succeq 0$  and  $\alpha \in [0, 1]$ . Then,  $\alpha \mathbf{X} + (1 - \alpha) \mathbf{Y} \succeq 0$ :

$$\forall \mathbf{v}, \alpha : \quad \alpha \mathbf{v}^T \mathbf{X} \mathbf{v} + (1 - \alpha) \mathbf{v}^T \mathbf{Y} \mathbf{v} \geq 0$$

- No specific assumptions on  $\mathbf{K}(\mathbf{a})$  except for the linearity in  $\mathbf{a}$
- Linear SDP solvers (MOSEK, SeDuMi, SDPA, ...)



## Compliance minimization: potential-energy-based QP

- **Potential energy function** (convex, minimum  $-\mathbf{f}^T \mathbf{u}$ )

$$H(\mathbf{a}, \mathbf{u}) := \mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u} - 2\mathbf{f}^T \mathbf{u} \quad (6)$$

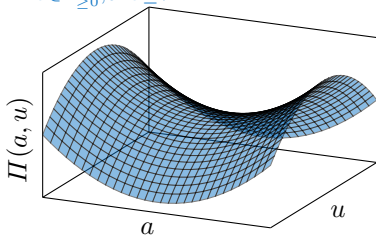
- Optimum design solves

$$\min_{\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}, \ell^T \mathbf{a} \leq \bar{V}} \min_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} (\mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u} - 2\mathbf{f}^T \mathbf{u}) \iff$$

$$\min_{\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}, \ell^T \mathbf{a} \leq \bar{V}} \max_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} (2\mathbf{f}^T \mathbf{u} - \mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u})$$

- By saddle point theorem, order min and max can be switched

$$\max_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} \min_{\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}, \ell^T \mathbf{a} \leq \bar{V}} (2\mathbf{f}^T \mathbf{u} - \mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u})$$



- $\min_{\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}, \ell^T \mathbf{a} \leq \bar{V}} (2\mathbf{f}^T \mathbf{u} - \sum_{i=1}^{n_e} [\mathbf{u}^T \mathbf{K}_i(a_i) \mathbf{u}])$  is a **linear program**
- Optimal solution: assign all  $\bar{V}$  to elements with **maximum specific strain energy**  $\mathbf{u}^T \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \mathbf{u}$  (remark:  $\mathbf{K}_i(a_i)$  not required to be rank 1)

$$\max_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} \left( 2\mathbf{f}^T \mathbf{u} - \bar{V} \max_i \left\{ \mathbf{u}^T \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \mathbf{u} \right\} \right)$$

- We introduce a slack variable  $\beta \in \mathbb{R}$  to avoid the **non-differentiable** max operator

$$\max_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}, \beta \in \mathbb{R}} (2\mathbf{f}^T \mathbf{u} - \bar{V}\beta) \quad (7a)$$

$$\text{subject to } \mathbf{u}^T \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \mathbf{u} \leq \beta, \quad \forall i \in \{1, \dots, n_e\} \quad (7b)$$

## ■ Lagrangian function

$$\mathcal{L}(\mathbf{u}, \beta, \boldsymbol{\lambda}) = -2\mathbf{f}^T \mathbf{u} + \bar{V} \beta + \sum_{i=1}^{n_e} \left[ \lambda_i \left( \mathbf{u}^T \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \mathbf{u} - \beta \right) \right]$$

## ■ Karush-Kuhn-Tucker conditions (Slater's condition satisfied)

$$\text{stationarity: } \frac{\partial \mathcal{L}}{\partial \mathbf{u}} = -2\mathbf{f} + 2 \left( \sum_{i=1}^{n_e} \lambda_i^* \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \right) \mathbf{u}^* = \mathbf{0}$$

$$\frac{\partial \mathcal{L}}{\partial \beta} = \bar{V} - \sum_{i=1}^{n_e} \lambda_i^* = 0$$

$$\text{primal feasibility: } 0 \geq (\mathbf{u}^*)^T \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \mathbf{u}^* - \beta^*$$

$$\text{dual feasibility: } \mathbf{0} \leq \boldsymbol{\lambda}^*$$

$$\text{complementary slackness: } \mathbf{0} = \sum_{i=1}^{n_e} \lambda_i^* \left( (\mathbf{u}^*)^T \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \mathbf{u}^* - \beta^* \right)$$

## ■ What is the physical interpretation of $\lambda_i^*$ ?

- Lagrangian function

$$\mathcal{L}(\mathbf{u}, \beta, \boldsymbol{\lambda}) = -2\mathbf{f}^T \mathbf{u} + \bar{V} \beta + \sum_{i=1}^{n_e} \left[ \lambda_i \left( \mathbf{u}^T \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \mathbf{u} - \beta \right) \right]$$

- Karush-Kuhn-Tucker conditions (Slater's condition satisfied)

$$\text{stationarity: } \frac{\partial \mathcal{L}}{\partial \mathbf{u}} = -2\mathbf{f} + 2 \left( \sum_{i=1}^{n_e} \lambda_i^* \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \right) \mathbf{u}^* = \mathbf{0}$$

$$\frac{\partial \mathcal{L}}{\partial \beta} = \bar{V} - \sum_{i=1}^{n_e} \lambda_i^* = 0$$

$$\text{primal feasibility: } 0 \geq (\mathbf{u}^*)^T \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \mathbf{u}^* - \beta^*$$

$$\text{dual feasibility: } \mathbf{0} \leq \boldsymbol{\lambda}^*$$

$$\text{complementary slackness: } \mathbf{0} = \sum_{i=1}^{n_e} \lambda_i^* \left( (\mathbf{u}^*)^T \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \mathbf{u}^* - \beta^* \right)$$

- At the optimum, we have  $\lambda_i^* = \ell_i a_i^*$

## Compliance minimization: potential-energy-based LP



- Exploiting that for single load case and no additional constraints on  $\mathbf{a}$  (lower bounds/upper bounds/mapping),  $\mathbf{K}_i(a_i)$  is of **rank 1**
- Put  $\gamma^2 = \beta$  to (7)<sup>1</sup>

$$\max_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}, \gamma \in \mathbb{R}} (2\mathbf{f}^T \mathbf{u} - \bar{V} \gamma^2) \quad (8a)$$

$$\text{subject to } \mathbf{u}^T \mathbf{b}_i^T \frac{E_i}{\ell_i^2} \mathbf{b}_i \mathbf{u} \leq \gamma^2, \quad \forall i \in \{1, \dots, n_e\} \quad (8b)$$

- Constraint (8b) can be rewritten as

$$\left( \frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i \mathbf{u} \right)^2 \leq \gamma^2, \quad \forall i \in \{1, \dots, n_e\} \iff$$
$$-\gamma \leq \frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i \mathbf{u} \leq \gamma, \quad \forall i \in \{1, \dots, n_e\}$$

- Fix  $\gamma = 1 \rightarrow$  we expect the dual multipliers to be ratios of bar volumes

<sup>1</sup>Then,  $\lambda_i^* = 2\gamma^* \ell_i a_i^*$

- We arrive at a linear program

$$\max_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} \mathbf{f}^T \mathbf{u} \quad (9a)$$

$$\text{subject to } \frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i \mathbf{u} \leq 1, \quad \forall i \in \{1, \dots, n_e\} \quad (9b)$$

$$\frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i \mathbf{u} \geq -1, \quad \forall i \in \{1, \dots, n_e\} \quad (9c)$$

- Lagrangian function

$$\begin{aligned} \mathcal{L}(\mathbf{u}, \boldsymbol{\lambda}_+, \boldsymbol{\lambda}_-) = & -\mathbf{f}^T \mathbf{u} + \sum_{i=1}^{n_e} \lambda_{+,i} \left( \frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i \mathbf{u} - 1 \right) \\ & + \sum_{i=1}^{n_e} \lambda_{-,i} \left( -\frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i \mathbf{u} - 1 \right) \end{aligned}$$

■ KKT conditions:

$$\text{stationarity: } \frac{\partial \mathcal{L}}{\partial \mathbf{u}} = -\mathbf{f} + \sum_{i=1}^{n_e} (\lambda_{+,i}^* - \lambda_{-,i}^*) \frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i^T = \mathbf{0}$$

$$\text{primal feas.: } -1 \leq \frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i^T \hat{\mathbf{u}}^* \leq 1, \quad \forall i \in \{1, \dots, n_e\}$$

$$\text{dual feas.: } \boldsymbol{\lambda}_+^* \geq \mathbf{0}$$

$$\boldsymbol{\lambda}_-^* \geq \mathbf{0}$$

$$\text{compl. slack.: } 0 = \sum_{i=1}^{n_e} \left[ \lambda_{+,i}^* \left( \frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i^T \hat{\mathbf{u}}^* - 1 \right) - \lambda_{-,i}^* \left( \frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i^T \hat{\mathbf{u}}^* + 1 \right) \right]$$

■ Stationarity implies static equilibrium  $\mathbf{B}^T (\mathbf{s}_+^T \quad -\mathbf{s}_-^T)^T = \mathbf{f}$ , where

$$s_{+,i} = \frac{\sqrt{E_i} \lambda_{+,i}^*}{\ell_i} \text{ and } s_{-,i} = \frac{\sqrt{E_i} \lambda_{-,i}^*}{\ell_i}$$

■  $\sqrt{E_i}$  can be interpreted as a (dimensionless) yield stress  $\sigma_{0,i}$  and  $(\lambda_{i,+} + \lambda_{i,-})$  as (scaled) bar volume

■ Unscaling:  $a_i^* = \frac{\lambda_{+,i}^* + \lambda_{-,i}^*}{\ell_i} \frac{\bar{V}}{\mathbf{1}^T \boldsymbol{\lambda}_+^* + \mathbf{1}^T \boldsymbol{\lambda}_-^*}$ ,  $\mathbf{u}^* = \hat{\mathbf{u}}^* \frac{\mathbf{1}^T \boldsymbol{\lambda}_+^* + \mathbf{1}^T \boldsymbol{\lambda}_-^*}{\bar{V}}$

# Compliance minimization: complementary-strain-energy-based LP

- Lagrangian function

$$\begin{aligned}\mathcal{L}(\mathbf{u}, \boldsymbol{\lambda}_+, \boldsymbol{\lambda}_-) &= -\mathbf{f}^T \mathbf{u} + \sum_{i=1}^{n_e} \lambda_{+,i} \left( \frac{\sqrt{E_i}}{l_i} \mathbf{b}_i \mathbf{u} - 1 \right) \\ &\quad + \sum_{i=1}^{n_e} \lambda_{-,i} \left( -\frac{\sqrt{E_i}}{l_i} \mathbf{b}_i \mathbf{u} - 1 \right)\end{aligned}$$

- Lagrange dual function

$$\begin{aligned}d(\boldsymbol{\lambda}_+, \boldsymbol{\lambda}_-) &= \inf_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} \left[ \left( -\mathbf{f}^T + \sum_{i=1}^{n_e} \lambda_{+,i} \frac{\sqrt{E_i}}{l_i} \mathbf{b}_i - \sum_{i=1}^{n_e} \lambda_{-,i} \frac{\sqrt{E_i}}{l_i} \mathbf{b}_i \right) \mathbf{u} \right. \\ &\quad \left. - \sum_{i=1}^{n_e} \lambda_{+,i} - \sum_{i=1}^{n_e} \lambda_{-,i} \right]\end{aligned}$$

## ■ Lagrangian function

$$\begin{aligned} \mathcal{L}(\mathbf{u}, \boldsymbol{\lambda}_+, \boldsymbol{\lambda}_-) = & -\mathbf{f}^T \mathbf{u} + \sum_{i=1}^{n_e} \lambda_{+,i} \left( \frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i \mathbf{u} - 1 \right) \\ & + \sum_{i=1}^{n_e} \lambda_{-,i} \left( -\frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i \mathbf{u} - 1 \right) \end{aligned}$$

## ■ Lagrange dual function after substituting $s_{+,i} = \frac{\sqrt{E_i} \lambda_{+,i}^*}{\ell_i}$ and

$$s_{-,i} = \frac{\sqrt{E_i} \lambda_{-,i}^*}{\ell_i}$$

$$d(\mathbf{s}_+, \mathbf{s}_-) =$$

$$\inf_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} \left[ \left( -\mathbf{f}^T + \sum_{i=1}^{n_e} [s_{+,i} - s_{-,i}] \mathbf{b}_i \right) \mathbf{u} - \sum_{i=1}^{n_e} \frac{\ell_i (\mathbf{s}_+ + \mathbf{s}_-)}{\sqrt{E_i}} \right]$$

■ Lagrangian function

$$\begin{aligned}\mathcal{L}(\mathbf{u}, \boldsymbol{\lambda}_+, \boldsymbol{\lambda}_-) &= -\mathbf{f}^T \mathbf{u} + \sum_{i=1}^{n_e} \lambda_{+,i} \left( \frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i \mathbf{u} - 1 \right) \\ &\quad + \sum_{i=1}^{n_e} \lambda_{-,i} \left( -\frac{\sqrt{E_i}}{\ell_i} \mathbf{b}_i \mathbf{u} - 1 \right)\end{aligned}$$

- Lagrange dual function after substituting  $s_{+,i} = \frac{\sqrt{E_i} \lambda_{+,i}^*}{\ell_i}$  and  $s_{-,i} = \frac{\sqrt{E_i} \lambda_{-,i}^*}{\ell_i}$  and  $\sqrt{E_i} = \sigma_{0,i}$

$$\begin{aligned}d(\mathbf{s}_+, \mathbf{s}_-) &= \\ \inf_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} &\left[ \left( -\mathbf{f}^T + \sum_{i=1}^{n_e} [s_{+,i} - s_{-,i}] \mathbf{b}_i \right) \mathbf{u} - \sum_{i=1}^{n_e} \frac{\ell_i (s_{+,i} + s_{-,i})}{\sigma_{0,i}} \right]\end{aligned}$$

- Lagrangian dual formulation: we search for

$$\sup_{\mathbf{s}_+ \in \mathbb{R}^{n_e}, \mathbf{s}_- \in \mathbb{R}^{n_e}} d(\mathbf{s}_+, \mathbf{s}_-)$$

$$\min_{\mathbf{s}_+ \in \mathbb{R}^{n_e}, \mathbf{s}_- \in \mathbb{R}^{n_e}} \sum_{i=1}^{n_e} \frac{s_{+,i} + s_{-,i}}{\sigma_{0,i}} \ell_i \quad (10a)$$

$$\text{subject to } \mathbf{B}^T (\mathbf{s}_+^T \quad -\mathbf{s}_-^T)^T = \mathbf{f} \quad (10b)$$

$$\mathbf{s}_+ \geq \mathbf{0} \quad (10c)$$

$$\mathbf{s}_- \geq \mathbf{0} \quad (10d)$$

- Objective function equivalent to  $\ell^T \mathbf{a}$  (substitution possible)
- Optimum design is **fully stressed** (by assumptions) and **statically determinate** (unique solution to static equation, compatibility satisfied automatically)



# Compliance minimization: complementary-strain-energy-based SOCP

- **Complementary strain energy** function (1/2 removed to stay consistent)

$$\Pi_2(\mathbf{a}, \mathbf{s}) = \sum_{i=1}^{n_e} \int_{v_e} E_i \varepsilon_i(a_i, s_i)^2 dv = \sum_{i=1}^{n_e} \frac{\ell_i s_i^2}{E_i a_i} \quad \text{such that } \mathbf{B}^T \mathbf{s} = \mathbf{f}$$

- Optimum design solves

$$\inf_{\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}, \ell^T \mathbf{a} \leq \bar{V}} \min_{\mathbf{s} \in \mathbb{R}^{n_e}} \sum_{i=1}^{n_e} \frac{\ell_i s_i^2}{E_i a_i} \quad (11a)$$

$$\text{subject to} \quad \mathbf{B}^T \mathbf{s} = \mathbf{f} \quad (11b)$$

- We need inf because of  $a_i = 0$
- Define  $w_i \in \mathbb{R}$  to be the energy of the  $i$ -th bar

$$\inf_{\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}, \ell^T \mathbf{a} \leq \bar{V}} \min_{\mathbf{s} \in \mathbb{R}^{n_e}, \mathbf{w} \in \mathbb{R}^{n_e}} \sum_{i=1}^{n_e} w_i$$

$$\text{subject to} \quad \mathbf{B}^T \mathbf{s} = \mathbf{f}$$

$$w_i \geq \frac{\ell_i s_i^2}{E_i a_i}, \quad \forall i \in \{1, \dots, n_e\}$$

- To eliminate inf, we must take care of  $a_i = 0$

$$4w_i a_i \geq 4 \frac{\ell_i s_i^2}{E_i}$$

- Add  $w_i^2 - 2w_i a_i + a_i^2$  to both sides of the inequality

$$(w_i + a_i)^2 \geq 4 \frac{\ell_i s_i^2}{E_i} + (w_i - a_i)^2$$

- This is equivalent to  $w_i = w_i^- + w_i^+$  and  $a_i = a_i^- + a_i^+$

$$\begin{aligned} w_i^+ + a_i^+ &\geq \left\| \begin{pmatrix} 2\sqrt{\frac{\ell_i}{E_i}} s_i & w_i^+ - a_i^+ \end{pmatrix} \right\|_2 \\ -w_i^- - a_i^- &\geq \left\| \begin{pmatrix} 2\sqrt{\frac{\ell_i}{E_i}} s_i & w_i^- - a_i^- \end{pmatrix} \right\|_2, \end{aligned}$$

- The second constraint is redundant because  $\mathbf{a} \geq \mathbf{0}$  and  $\mathbf{w} \geq \mathbf{0}$  by definition

- Final SOCP formulation:

$$\min_{\mathbf{a} \in \mathbb{R}^{n_e}, \mathbf{s} \in \mathbb{R}^{n_e}, \mathbf{w} \in \mathbb{R}^{n_e}} \mathbf{1}^T \mathbf{w} \quad (12a)$$

$$\text{subject to } \mathbf{B}^T \mathbf{s} = \mathbf{f} \quad (12b)$$

$$w_i + a_i \geq \left\| \begin{pmatrix} 2\sqrt{\frac{\ell_i}{E_i}} s_i & w_i - a_i \end{pmatrix} \right\|_2, \quad \forall i \in \{1, \dots, n_e\} \quad (12c)$$

$$\boldsymbol{\ell}^T \mathbf{a} \leq \bar{V} \quad (12d)$$

$$\mathbf{a} \geq \mathbf{0} \quad (12e)$$

- What is the relation to the minimum-volume LP?
- What is the relation to the SDP formulation?
- Convex: Let  $t, u \geq 0$ ,  $\|\mathbf{x}\|_2 \leq t$ ,  $\|\mathbf{y}\|_2 \leq u$

$$\alpha \|\mathbf{x}\|_2 + (1 - \alpha) \|\mathbf{y}\|_2 \leq \alpha t + (1 - \alpha) u$$

$$\|\alpha \mathbf{x}\|_2 + \|(1 - \alpha) \mathbf{y}\|_2 \leq \alpha t + (1 - \alpha) u$$

by Cauchy-Schwarz ineq.:  $\|\alpha \mathbf{x} + (1 - \alpha) \mathbf{y}\|_2 \leq \alpha t + (1 - \alpha) u$



# Extensions

- Free-vibrations ( $\lambda = 4\pi^2 f^2$ ):

$$\mathbf{K}(\mathbf{a})\mathbf{u} - \lambda\mathbf{M}(\mathbf{a})\mathbf{u} = \mathbf{0}$$

- Rayleigh principle

$$\lambda_{\min} = \inf_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}} \setminus \text{Ker}(\mathbf{M}(\mathbf{a}))} \frac{\mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u}}{\mathbf{u}^T \mathbf{M}(\mathbf{a}) \mathbf{u}}$$

$$\lambda_{\min} \leq \frac{\mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u}}{\mathbf{u}^T \mathbf{M}(\mathbf{a}) \mathbf{u}}, \quad \forall \mathbf{u} \in \mathbb{R}^{n_{\text{dof}}} \setminus \text{Ker}(\mathbf{M}(\mathbf{a}))$$

$$0 \leq \mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u} - \lambda_{\min} \mathbf{u}^T \mathbf{M}(\mathbf{a}) \mathbf{u}, \quad \forall \mathbf{u} \in \mathbb{R}^{n_{\text{dof}}} \setminus \text{Ker}(\mathbf{M}(\mathbf{a}))$$

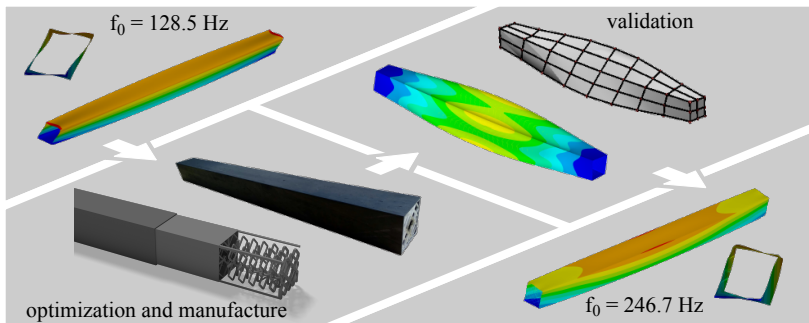
- Set  $\mathbf{u} \in \text{Ker}(\mathbf{M}(\mathbf{a}))$ : the inequality remains valid

$$\mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u} - \lambda_{\min} \mathbf{u}^T \mathbf{M}(\mathbf{a}) \mathbf{u} \geq 0, \quad \forall \mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}$$

$$\mathbf{K}(\mathbf{a}) - \lambda_{\min} \mathbf{M}(\mathbf{a}) \succeq \mathbf{0}$$

- Eigenvalue maximization: quasi-convex problem solvable by bisection

- Industrial application: decreasing elastic wall instabilities of thin-walled carbon fiber beams by designing minimum-weight truss stiffeners



- Instead of optimizing over fixed  $\mathbf{f} \in \mathbb{R}^{n_{\text{dof}}}$ , consider optimizing over the worst-case load from the ellipsoid  $\mathbf{f} = \mathbf{Q}\mathbf{e}$  with  $\mathbf{e}^T\mathbf{e} \leq 1$  and  $\mathbf{Q} \in \mathbb{R}^{n_{\text{dof}} \times q}$  and  $\mathbf{e} \in \mathbb{R}^q$
- Potential energy function

$$\min_{\mathbf{a} \in \mathbb{R}_{\geq 0}^{n_e}, \ell^T \mathbf{a} \leq \bar{V}} \max_{\mathbf{e}^T \mathbf{e} \leq 1} \max_{\mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}} 2(\mathbf{Q}\mathbf{e})^T \mathbf{u} - \mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u}$$

- The inner max operators are equivalent to infinite number of matrix inequalities

$$\min_{\mathbf{a} \in \mathbb{R}^{n_e}, c \in \mathbb{R}} c$$

$$\text{s.t. } c \geq \left( 2(\mathbf{Q}\mathbf{e})^T \mathbf{u} - \mathbf{u}^T \mathbf{K}(\mathbf{a}) \mathbf{u} \right), \forall \mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}, \forall \mathbf{e} \in \mathbb{R}^q : \mathbf{e}^T \mathbf{e} \leq 1$$

$$\ell^T \mathbf{a} \leq \bar{V}$$

$$\mathbf{a} \geq \mathbf{0}$$



- Thus, we also have for  $\gamma > 0$

$$\gamma^2 c - 2(\mathbf{Q}\gamma\mathbf{e})^T \gamma\mathbf{u} + \gamma\mathbf{u}^T \mathbf{K}(\mathbf{a})\gamma\mathbf{u} \geq 0, \forall \mathbf{u} \in \mathbb{R}^{n_{\text{dof}}}, \forall \mathbf{e} \in \mathbb{R}^q : \mathbf{e}^T \mathbf{e} \leq 1$$

- Set  $\gamma\mathbf{e} = \mathbf{t}$  and  $\gamma\mathbf{u} = \mathbf{w}$

$$\gamma^2 c - 2(\mathbf{Q}\mathbf{t})^T \mathbf{w} + \mathbf{w}^T \mathbf{K}(\mathbf{a})\mathbf{w} \geq 0, \forall \mathbf{w} \in \mathbb{R}^{n_{\text{dof}}}, \forall \mathbf{t} \in \mathbb{R}^q : \mathbf{t}^T \mathbf{t} \leq \gamma^2$$

- Finally, we obtain

$$\mathbf{t}^T \mathbf{t} c - 2(\mathbf{Q}\mathbf{t})^T \mathbf{w} + \mathbf{w}^T \mathbf{K}(\mathbf{a})\mathbf{w} \geq 0 \iff \begin{pmatrix} c\mathbf{I} & -\mathbf{Q}^T \\ -\mathbf{Q} & \mathbf{K}(\mathbf{a}) \end{pmatrix} \succeq 0$$

and thus the linear SDP

$$\begin{aligned} & \min_{\mathbf{a} \in \mathbb{R}^{n_e}, c \in \mathbb{R}} c \\ & \text{s.t.} \quad \begin{pmatrix} c\mathbf{I} & -\mathbf{Q}^T \\ -\mathbf{Q} & \mathbf{K}(\mathbf{a}) \end{pmatrix} \succeq 0 \\ & \quad \ell^T \mathbf{a} \leq \bar{V} \\ & \quad \mathbf{a} \geq \mathbf{0} \end{aligned}$$



- Other extensions:
  - Multiple loading conditions
    - Can be incorporated in QP, SOCP, SDP formulations
    - Not in LP!
  - Power of in-phase harmonic vibrations (linear SDP)
  - Linear buckling (nonlinear SDP)
  - Robust optimization (linear SDP)
  - Displacement constraints (nonconvex)
  - Stress constraints (nonconvex)
  - Manufacturability constraints



## Summary



- +
- High stiffness/weight ratio
- Many convex formulations
- Fast solution
- Straightforward implementation
- 
- Not everything behaves as trusses
- Some constraints ruin the problem structure
- Collinear members
- Singularity in straight bars with refined discretization



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