

# Multiple state optimal design problems with explicit solution

Marko Vrdoljak

Department of Mathematics  
Faculty of Science  
University of Zagreb, Croatia



Krešimir Burazin

Department of Mathematics  
University of Osijek, Croatia



**88th GAMM Annual Meeting, Weimar, March 2017**



WeConMApp

# Multiple state problem optimizing energy

Fill  $\Omega \subseteq \mathbf{R}^d$  with two isotropic materials with conductivity  $0 < \alpha < \beta$ , quantity  $q_\alpha$  of the first material is given:

$$\mathbf{A} = \chi\alpha\mathbf{I} + (1 - \chi)\beta\mathbf{I}, \quad \chi \in L^\infty(\Omega; \{0, 1\})$$

$$\int_\Omega \chi \, d\mathbf{x} = q_\alpha$$

State equations

$$\begin{cases} -\operatorname{div}(\mathbf{A}\nabla u_i) = f_i \\ u_i \in H_0^1(\Omega) \end{cases} \quad i = 1, \dots, m,$$

Goal functional is a conic sum of energies ( $\mu_i > 0$ )

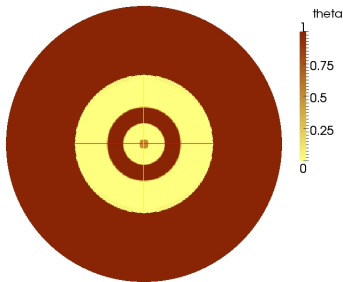
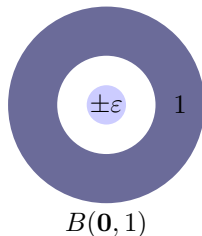
$$I(\chi) = \sum_{i=1}^m \mu_i \int_\Omega f_i(\mathbf{x}) u_i(\mathbf{x}) \, d\mathbf{x} \longrightarrow \min / \max$$

Relaxation via homogenization theory:

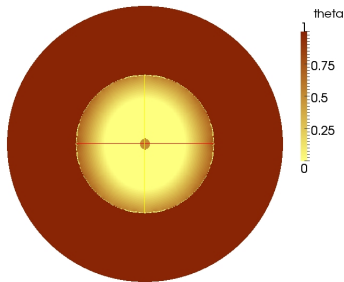
<b>classical design</b>		<b>relaxed design</b>
$\chi \in L^\infty(\Omega; \{0, 1\})$	$\dots$	$\theta \in L^\infty(\Omega; [0, 1])$
		$\mathbf{A} \in \mathcal{K}(\theta) \quad \text{a.e. on } \Omega$
$I(\chi)$		$J(\theta, \mathbf{A}) - \text{given by the same formula}$

# Example – maximization

$$\Omega := B(\mathbf{0}, 1) \subseteq \mathbf{R}^2, \quad q_\alpha := 0.8|\Omega|$$
$$I(\chi) = \sum_{i=1}^2 \int_{\Omega} f_i(\mathbf{x}) u_i(\mathbf{x}) d\mathbf{x} \longrightarrow \max$$
$$f_1 = \chi_A + \varepsilon \chi_B, \quad \text{where}$$
$$f_2 = \chi_A - \varepsilon \chi_B$$
$$A := B(\mathbf{0}, \frac{1}{2})^c, \quad B := B(\mathbf{0}, \frac{1}{5})$$



Numerical solution,  $\varepsilon = 0.01$



Numerical solution,  $\varepsilon = 0$

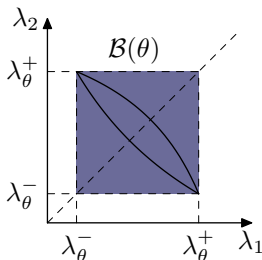
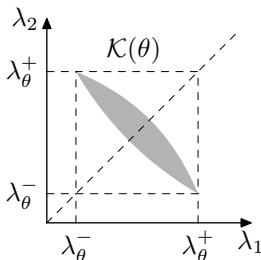
# Representation by a concave maximization problem

The space of admissible local fractions

$$\mathcal{T} := \left\{ \theta \in L^\infty(\Omega; [0, 1]) : \int_{\Omega} \theta \, d\mathbf{x} = q_\alpha \right\}$$

Admissible (relaxed) designs

$$\mathcal{A} = \{(\theta, \mathbf{A}) \in \mathcal{T} \times L^\infty(\Omega; \text{Sym}) : \mathbf{A} \in \mathcal{K}(\theta) \text{ (a.e. on } \Omega)\}$$



$$\begin{aligned} \lambda_\theta^+ &= \theta\alpha + (1-\theta)\beta \\ \frac{1}{\lambda_\theta^-} &= \frac{\theta}{\alpha} + \frac{1-\theta}{\beta} \end{aligned}$$

$$\mathcal{B} = \{(\theta, \mathbf{A}) \in \mathcal{T} \times L^\infty(\Omega; \text{Sym}) : \mathbf{A} \in \mathcal{B}(\theta) \text{ (a.e. on } \Omega)\}$$

# Maximization over $\mathcal{B}$

Murat and Tartar (1985), Casado-Díaz (2015) – one state equation.

## Lemma

There exists a unique  $\boldsymbol{\sigma}^* \in \mathcal{S} = \{\boldsymbol{\sigma} \in L^2(\Omega; \mathbf{R}^d)^m : -\operatorname{div} \boldsymbol{\sigma}_i = f_i, i = 1..m\}$  such that

$$\max_{(\theta, \mathbf{A}) \in \mathcal{B}} J(\theta, \mathbf{A}) = \max_{(\theta, \mathbf{A}) \in \mathcal{B}} \sum_{i=1}^m \mu_i \int_{\Omega} \mathbf{A}^{-1} \boldsymbol{\sigma}_i^* \cdot \boldsymbol{\sigma}_i^* dx. \quad (1)$$

Moreover, if  $(\theta^*, \mathbf{A}^*)$  is an optimal design for problem  $\max_{\mathcal{B}} J$  and  $u^*$  the corresponding state function, then  $\mathbf{A}^* \nabla u_i^* = \boldsymbol{\sigma}_i^*$ ,  $i = 1, \dots, m$ .

Above maximization problems is easily solved:

Design  $(\theta^*, \mathbf{A}^*)$  is optimal if and only if (almost everywhere in  $\Omega$ )

$$\mathbf{A}^* \boldsymbol{\sigma}_i^* = \lambda_{\theta^*}^- \boldsymbol{\sigma}_i^*, \quad i = 1..m.$$

If  $u^*$  is the corresponding state function, we have

$$\boldsymbol{\sigma}_i^* = \lambda_{\theta^*}^- \nabla u_i^* \text{ or equivalently } \mathbf{A}^* \nabla u_i^* = \lambda_{\theta^*}^- \nabla u_i^*, \quad i = 1..m.$$

## Theorem

Let  $(\theta^*, \mathbf{A}^*)$  be an optimal design for the problem  $\max_{\mathcal{B}} J$ . Then  $\theta^*$  solves

$$I(\theta) = \sum_{i=1}^m \mu_i \int_{\Omega} f_i u_i \, d\mathbf{x} \longrightarrow \max$$

$\theta \in \mathcal{T}$  and  $u$  determined uniquely by

$$\begin{cases} -\operatorname{div}(\lambda_{\theta}^{-} \nabla u_i) = f_i \\ u_i \in H_0^1(\Omega) \end{cases} \quad i = 1, \dots, m, \quad (2)$$

Conversely, if  $\tilde{\theta}$  is a solution of optimal design problem (2), and  $\tilde{u}$  is the corresponding state function, then for any measurable  $\tilde{\mathbf{A}} \in \mathcal{B}(\tilde{\theta})$  such that  $\tilde{\mathbf{A}} \nabla \tilde{u}_i = \lambda_{-}(\tilde{\theta}) \nabla \tilde{u}_i$ , e.g. for  $\tilde{\mathbf{A}} = \lambda_{-}(\tilde{\theta}) \mathbf{I}$ ,  $(\tilde{\theta}, \tilde{\mathbf{A}})$  is an optimal design for the problem  $\max_{\mathcal{B}} J$ .

# Necessary and sufficient optimality conditions

Similar to Lemma above, one can rephrase the simpler relaxation problem (2): there exists a unique  $\sigma^* \in \mathcal{S} = \{\sigma \in L^2(\Omega; \mathbf{R}^d)^m : -\operatorname{div} \sigma_i = f_i, i = 1..m\}$  such that

$$\max_{\mathcal{T}} I = \max_{\theta \in \mathcal{T}} \sum_{i=1}^m \mu_i \int_{\Omega} \frac{\beta - \alpha}{\alpha\beta} \theta |\sigma_i^*|^2 dx.$$

Moreover,  $\sigma^*$  is the same as for  $\max_{\mathcal{B}} J$ .

## Lemma

*The necessary and sufficient condition of optimality for solution  $\theta^* \in \mathcal{T}$  of optimal design problem (2) simplifies to the existence of a Lagrange multiplier  $c \geq 0$  such that*

$$\begin{aligned} \sum_{i=1}^m \mu_i |\sigma_i^*|^2 > c &\Rightarrow \theta^* = 1, \\ \sum_{i=1}^m \mu_i |\sigma_i^*|^2 < c &\Rightarrow \theta^* = 0. \end{aligned}$$

# Spherically symmetric case

Let  $\Omega \subseteq \mathbf{R}^d$  be spherically symmetric (ball or annulus), and let the right-hand sides be radial functions:  $f_i = f_i(r)$ .

Since  $\boldsymbol{\sigma}^*$  is unique, it must be radial:  $\boldsymbol{\sigma}_i^* = \sigma_i^*(r)\mathbf{e}_r$ .

## Theorem

For any maximizer  $\theta^*$  for  $\max_{\mathcal{T}} I$ , the radial function

$$\tilde{\theta}(r) = \int_{\partial B(\mathbf{0}, r)} \theta^* dS$$

is also a maximizer.

- If  $\tilde{\theta}$  is a maximizer of  $I$  over  $\mathcal{T}$ , then for a simple laminate  $\tilde{\mathbf{A}} \in \mathcal{K}(\tilde{\theta})$  with layers orthogonal to  $\mathbf{e}_r$ ,  $(\tilde{\theta}, \tilde{\mathbf{A}})$  is a maximizer of  $J$  over  $\mathcal{A}$ .
- For any maximizer  $(\theta^*, \mathbf{A}^*)$  of  $J$  over  $\mathcal{A}$ ,  $\theta^*$  is a maximizer of  $I$  over  $\mathcal{T}$ .

For problems on a ball,  $\boldsymbol{\sigma}^*$  is a unique (radial) solution of  $-\operatorname{div} \boldsymbol{\sigma}_i = f_i, i = 1..m$ , and so conditions of optimality easily determine optimal  $\theta^*$ .



## A. Single state equation:

[Murat & Tartar, 1985]

$$I(\theta) = \int_{\Omega} f u \, d\mathbf{x} \longrightarrow \min$$

$\theta \in \mathcal{T}$ , and  $u$  determined uniquely by

$$\begin{cases} -\operatorname{div}(\lambda_{\theta}^{+} \nabla u) = f \\ u \in H_0^1(\Omega) \end{cases}$$

## B. Multiple state equations:

$$I(\theta) = \sum_{i=1}^m \mu_i \int_{\Omega} f_i u_i \, d\mathbf{x} \longrightarrow \min$$

$\theta \in \mathcal{T}$ , and  $u_i$  determined uniquely by

$$\begin{cases} -\operatorname{div}(\lambda_{\theta}^{+} \nabla u_i) = f_i & i = 1, \dots, m \\ u_i \in H_0^1(\Omega) \end{cases}$$

$$\min_{\mathcal{A}} J \iff \min_{\mathcal{T}} I$$

A: Holds always!

B: Holds in spherically symmetric case or when  $m < d$ .

## Theorem

If  $m < d$  then  $\min_{\mathcal{A}} J = \min_{\mathcal{T}} I$  and:

- There is unique  $u^* \in H_0^1(\Omega; \mathbf{R}^m)$  which is the state for every solution of  $\min_{\mathcal{A}} J$  and  $\min_{\mathcal{T}} I$ .
- If  $(\theta^*, \mathbf{A}^*)$  is an optimal design for the problem  $\min_{\mathcal{A}} J$ , then  $\theta^*$  is optimal design for  $\min_{\mathcal{T}} I$ .
- Conversely, if  $\theta^*$  is a solution of optimal design problem  $\min_{\mathcal{T}} I$ , then any  $(\theta^*, \mathbf{A}^*) \in \mathcal{A}$  satisfying  $\mathbf{A}^* \nabla u_i^* = \lambda_{\theta^*}^+ \nabla u_i^*$ ,  $i = 1, \dots, m$  (e.g. simple laminates) is an optimal design for the problem  $\min_{\mathcal{A}} J$ .

$\Omega \subseteq \mathbf{R}^d$  is spherically symmetric and right-hand sides  $f_i = f_i(r)$ ,  $i = 1, \dots, m$  are radial functions.

## Theorem

*There is a unique radial  $u^*$  which is the state for any solution of  $\min_{\mathcal{A}} J$  and  $\min_{\mathcal{T}} I$ . Moreover,*

- *If  $(\theta^*, \mathbf{A}^*) \in \mathcal{A}$  is a solution of the relaxed problem  $\min_{\mathcal{A}} J$  then  $\theta^*$  is optimal for  $\min_{\mathcal{T}} I$ , and  $\mathbf{A}^* \nabla u_i^* = \lambda_{\theta^*}^+ \nabla u_i^*$ ,  $i = 1, \dots, m$ .*
- *There exists a radial minimizer  $\theta^*$  of  $I$  over  $\mathcal{T}$  and for any radial minimizer  $\theta^*$  of  $I$  over  $\mathcal{T}$  there exists a simple laminate  $\mathbf{A}^* \in \mathcal{K}(\theta^*)$  such that  $(\theta^*, \mathbf{A}^*)$  is an optimal design for  $\min_{\mathcal{A}} J$ .*

# Optimality conditions for $\min_{\mathcal{T}} I$

$$\min_{\theta \in \mathcal{T}} I(\theta) = - \max_{\theta \in \mathcal{T}} \min_{v \in H_0^1(\Omega; \mathbf{R}^m)} \sum_{i=1}^m \mu_i \int_{\Omega} \lambda_{\theta}^+ |\nabla v_i|^2 - 2f_i v_i dx$$

Saddle points exist . . . share the same  $v$  (aka  $u^*$ ).

$$\min_{\theta \in \mathcal{T}} I(\theta) = - \max_{\theta \in \mathcal{T}} \sum_{i=1}^m \mu_i \int_{\Omega} \lambda_{\theta}^+ |\nabla u_i^*|^2 - 2f_i u_i^* dx$$

## Lemma

$\theta^* \in \mathcal{T}$  is a solution  $\min_{\mathcal{T}} I$  if and only if there exists a Lagrange multiplier  $c \geq 0$  such that

$$\sum_{i=1}^m \mu_i |\nabla u_i^*|^2 > c \Rightarrow \theta^* = 0,$$
$$\sum_{i=1}^m \mu_i |\nabla u_i^*|^2 < c \Rightarrow \theta^* = 1.$$

# Example – energy minimization

- $\Omega = B(\mathbf{0}, 2)$ ,  $f_1 = \chi_{B(\mathbf{0}, 1)}$ ,  $f_2 \equiv 1$ ,
- $$\begin{cases} -\operatorname{div}(\lambda_\theta^+ \nabla u_i) = f_i \\ u_i \in H_0^1(\Omega) \end{cases} \quad i = 1, 2$$
- $\mu \int_{\Omega} f_1 u_1 \, d\mathbf{x} + \int_{\Omega} f_2 u_2 \, d\mathbf{x} \rightarrow \min$

Solving state equation in polar coordinates

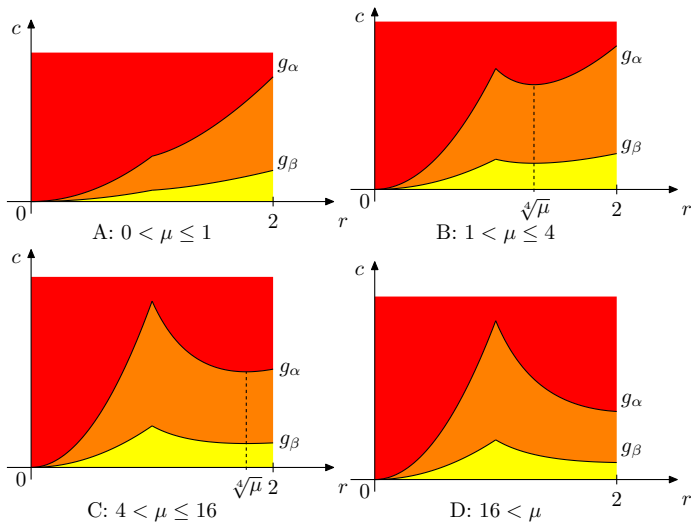
$$u_i'(r) = \frac{\sigma_i(r)}{\theta(r)\alpha + (1 - \theta(r))\beta}, \quad i = 1, 2,$$

with

$$\sigma_1(r) = \begin{cases} -\frac{r}{2}, & 0 \leq r < 1, \\ -\frac{1}{2r}, & 1 \leq r \leq 2, \end{cases} \quad \text{and} \quad \sigma_2(r) = -\frac{r}{2}.$$

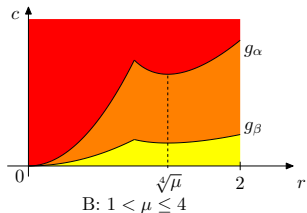
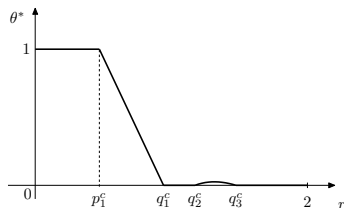
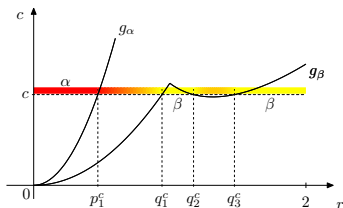
Define  $\psi := \mu\sigma_1^2 + \sigma_2^2$ ,  $\mathbf{g}_\alpha := \frac{\psi}{\alpha^2}$ ,  $\mathbf{g}_\beta := \frac{\psi}{\beta^2}$ .

# Geometric interpretation of optimality conditions



# Optimal $\theta^*$ for case B

Optimal state  $u^*$  is unknown but  $\sum_{i=1}^m \mu_i |\nabla u_i^*|^2 = \mu |u_1^*|^2 + |u_2^*|^2 \in [g_\beta, g_\alpha]$ .  
 By necessary conditions of optimality, on a set where  $c > g_\alpha$  we have  $\theta^* = 1$ , on a set where  $c < g_\beta$  we have  $\theta^* = 0$ , and if  $g_\beta < c < g_\alpha$  we have  $\theta^* \in (0, 1)$ , and  $\theta^*$  is uniquely determined from  $\frac{\psi}{\lambda_+(\theta^*)^2} = c$ .



All possible optimal configurations (for various  $q_\alpha$ ):

- $\alpha$
- $\alpha - mix$
- $\alpha - mix - \alpha - mix$
- $\alpha - mix - \beta$
- $\alpha - mix - \beta - mix - \beta$