

Classical Optimal Design in Two-phase Conductivity Problems



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International Workshop on PDEs: Analysis and Modelling

Celebrating 80th Anniversary of Professor **Nedžad Limić**

Zagreb, June 2016

Compliance maximization

State equation ($\Omega \subseteq \mathbf{R}^d$ open and bounded)

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

Two phases: $0 < \alpha < \beta$

$\mathbf{A} = \chi\alpha\mathbf{I} + (1 - \chi)\beta\mathbf{I}$, $\chi \in L^\infty(\Omega; \{0, 1\})$, $\int_\Omega \chi \, d\mathbf{x} = q_\alpha$, for given $0 < q_\alpha < |\Omega|$

Cost functional:

$$J(\chi) = \int_\Omega u(\mathbf{x}) \, d\mathbf{x} \longrightarrow \max$$

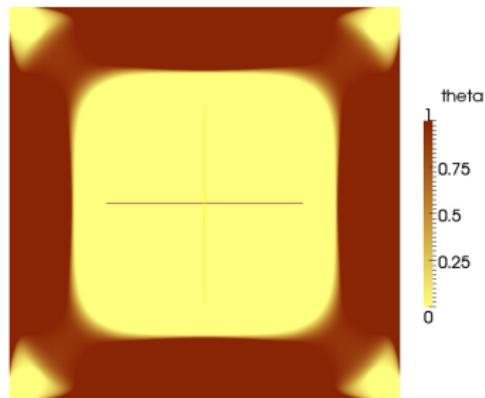
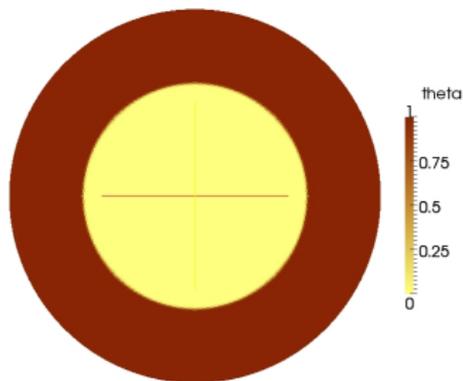
Interpretations:

- Maximize the amount of heat kept inside body
- Maximize the torsional rigidity of a rod made of two materials
- Maximize the flow rate of two viscous immiscible fluids through pipe

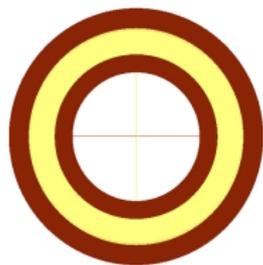
In general, compliance functional

$$J(\chi) = \int_\Omega f(\mathbf{x})u(\mathbf{x}) \, d\mathbf{x} \longrightarrow \max$$

Classical vs. relaxed optimal design



Intuition for annulus?



In general, there might exist no classical optimal design. The relaxation is needed, introducing composite materials

$$\begin{array}{ll} \chi \in L^\infty(\Omega; \{0, 1\}) & \dots \quad \theta \in L^\infty(\Omega; [0, 1]) \\ \text{classical design} & \mathbf{A} \in \mathcal{K}(\theta) \quad \text{a.e. on } \Omega \\ & \text{relaxed design} \end{array}$$

Effective conductivities – set $\mathcal{K}(\theta)$

2D:

$\mathcal{K}(\theta)$ is given in terms of eigenvalues:

$$\lambda_{\theta}^{-} \leq \lambda_j \leq \lambda_{\theta}^{+} \quad j = 1, \dots, d$$

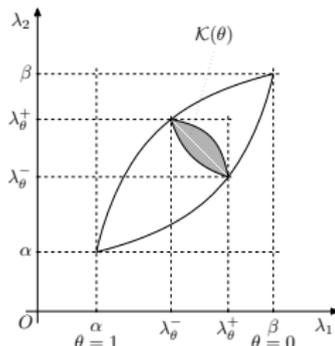
$$\sum_{j=1}^d \frac{1}{\lambda_j - \alpha} \leq \frac{1}{\lambda_{\theta}^{-} - \alpha} + \frac{d-1}{\lambda_{\theta}^{+} - \alpha}$$

$$\sum_{j=1}^d \frac{1}{\beta - \lambda_j} \leq \frac{1}{\beta - \lambda_{\theta}^{-}} + \frac{d-1}{\beta - \lambda_{\theta}^{+}},$$

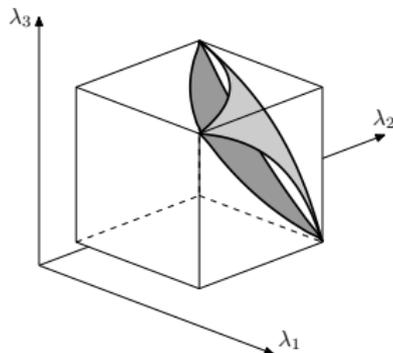
where

$$\lambda_{\theta}^{+} = \theta\alpha + (1-\theta)\beta$$

$$\frac{1}{\lambda_{\theta}^{-}} = \frac{\theta}{\alpha} + \frac{1-\theta}{\beta}$$



3D:



Multiple state optimal design problem

State equations

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

State function $\mathbf{u} = (u_1, \dots, u_m)$

$$\begin{cases} J(\chi) = \sum_{i=1}^m \mu_i \int_{\Omega} f_i u_i \, d\mathbf{x} \rightarrow \max \\ \mathbf{u} = (u_1, \dots, u_m) \text{ state function for } \mathbf{A} = \chi\alpha\mathbf{I} + (1 - \chi)\beta\mathbf{I} \\ \chi \in L^\infty(\Omega; \{0, 1\}), \int_{\Omega} \chi \, d\mathbf{x} = q_\alpha, \end{cases}$$

for some given weights $\mu_i > 0$. Relaxed designs:

$$\mathcal{A} := \left\{ (\theta, \mathbf{A}) \in L^\infty(\Omega; [0, 1] \times M_d(\mathbf{R})) : \int_{\Omega} \theta \, d\mathbf{x} = q_\alpha, \mathbf{A}(\mathbf{x}) \in \mathcal{K}(\theta(\mathbf{x})) \text{ a.e. on } \Omega \right\}$$

Relaxation ...
$$\begin{cases} J(\theta, \mathbf{A}) = \sum_{i=1}^m \mu_i \int_{\Omega} f_i u_i \, d\mathbf{x} \rightarrow \max \\ (\theta, \mathbf{A}) \in \mathcal{A} \end{cases}$$

Single vs. multiple state problems

A. Single state equation

[Murat & Tartar, 1985] There exists relaxed solution (θ^*, \mathbf{A}^*) among simple laminates ... conductivity λ_θ^- in one direction (∇u) , and λ_θ^+ in orthogonal directions. As a consequence, θ^* is also a solution of

$$I(\theta) = \int_{\Omega} f u \, d\mathbf{x} \rightarrow \max$$
$$\theta \in L^\infty(\Omega; [0, 1]), \quad \int_{\Omega} \theta \, d\mathbf{x} = q_\alpha,$$
$$\begin{cases} -\operatorname{div}(\lambda_\theta^- \nabla u) = f \\ u \in H_0^1(\Omega) \end{cases} \quad \text{can be rewritten as a convex minimization problem}$$

B. Multiple state equations

It is not enough to use only simple laminates, but composite materials that correspond to a non-affine boundary of $\mathcal{K}(\theta)$... higher order sequential laminates. The above simpler relaxation **fails**.

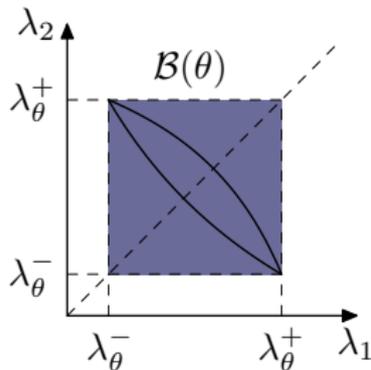
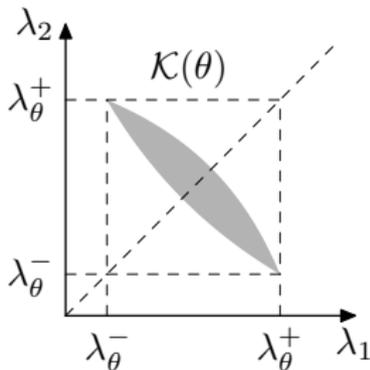
The aim of this talk

- in spherically symmetric case, simpler relaxation is correct
- present some problems with classical optimal design

Extended set of admissible designs

We shall enlarge the set \mathcal{A} of admissible designs

$$\mathcal{A} = \left\{ (\theta, \mathbf{A}) \in L^\infty(\Omega; [0, 1] \times \text{Sym}) : \int_{\Omega} \theta \, d\mathbf{x} = q_\alpha, \mathbf{A} \in \mathcal{K}(\theta) \text{ (a.e. on } \Omega) \right\}$$



$$\mathcal{B} = \left\{ (\theta, \mathbf{A}) \in L^\infty(\Omega; [0, 1] \times \text{Sym}) : \int_{\Omega} \theta \, d\mathbf{x} = q_\alpha, \mathbf{A} \in \mathcal{B}(\theta) \text{ (a.e. on } \Omega) \right\}$$

$$\mathcal{C} := \{ (\theta, \mathbf{B}) \in L^\infty(\Omega; [0, 1] \times \text{Sym}) : (\theta, \mathbf{B}^{-1}) \in \mathcal{B} \}.$$

Extended set of admissible designs

\mathcal{B} and \mathcal{C} are convex sets: e.g. \mathcal{B} can be rewritten as

$$\lambda_{\min}(\mathbf{A}) \geq \lambda_{\theta}^{-}, \quad \lambda_{\max}(\mathbf{A}) \leq \lambda_{\theta}^{+}, \quad \text{a.e. on } \Omega,$$

where λ_{\min} and λ_{θ}^{+} are concave, and λ_{\max} and λ_{θ}^{-} are convex functions.

$$\begin{aligned} -J(\theta, \mathbf{A}) &= -\sum_{i=1}^m \mu_i \int_{\Omega} f_i u_i \, d\mathbf{x} \\ &= -\sum_{i=1}^m \mu_i \int_{\Omega} \mathbf{A} \nabla u_i \cdot \nabla u_i - 2f_i u_i \, d\mathbf{x} \\ &= -\min_{v \in H_0^1(\Omega; \mathbf{R}^m)} \sum_{i=1}^m \mu_i \int_{\Omega} \mathbf{A} \nabla v_i \cdot \nabla v_i - 2f_i v_i \, d\mathbf{x} \\ &= -\max_{\sigma \in \mathcal{S}} \left(-\sum_{i=1}^m \mu_i \int_{\Omega} \mathbf{A}^{-1} \sigma_i \cdot \sigma_i \, d\mathbf{x} \right), \end{aligned}$$

where $\mathcal{S} = \{\sigma \in L^2(\Omega; \mathbf{R}^d)^m : -\operatorname{div} \sigma_i = f_i, i = 1, \dots, m\}$.

Representation by a convex optimization problem

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

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

Moreover, if (θ^*, \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 are easily solved:

Design (θ^*, \mathbf{A}^*) is optimal if and only if (almost everywhere in Ω)

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

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

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

Simpler relaxation problem

... in terms of only local fraction θ belonging to the set

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

Theorem

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

$$\begin{aligned} I(\theta) &= \sum_{i=1}^m \mu_i \int_{\Omega} f_i u_i \, d\mathbf{x} \longrightarrow \max \\ \theta &\in \mathcal{T} \text{ and } u \text{ determined uniquely by} \\ \begin{cases} -\operatorname{div}(\lambda_{\theta}^{-} \nabla u_i) = f_i \\ u_i \in H_0^1(\Omega) \end{cases} & \quad i = 1, \dots, m, \end{aligned} \tag{2}$$

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 $\tilde{\mathbf{A}} \nabla \tilde{u}_i = \lambda_{-}(\tilde{\theta}) \nabla \tilde{u}_i$ almost everywhere on Ω , 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, σ^* is the same as for the problem $\max_B J$.

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: in spherical coordinates given by $r \in \omega$ (an interval), and the right-hand side $f = f(r)$, $r \in \omega$ be a radial function.

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

Lemma

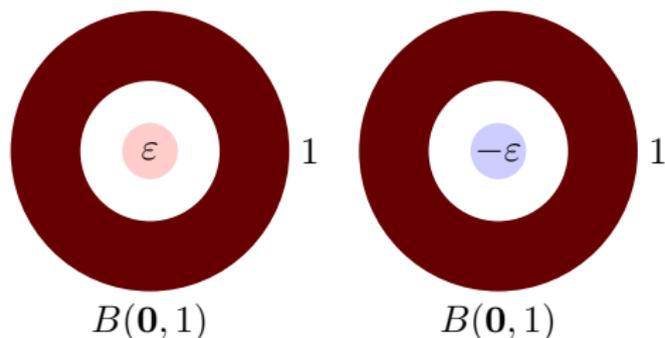
For any maximizer (θ^*, \mathbf{A}^*) for the problem $\max_{\mathcal{B}} J$, there exist a radial maximizer $(\tilde{\theta}, \tilde{\mathbf{A}}) \in \mathcal{B}$ where

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

Theorem

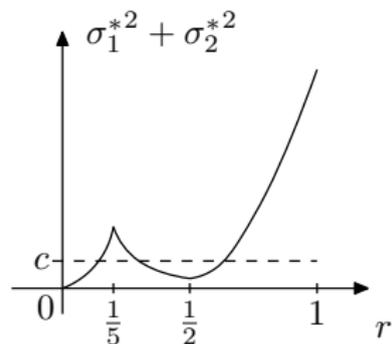
- If $\tilde{\theta}$ is a maximizer of I over \mathcal{T} , then for a simple laminate $\tilde{\mathbf{A}} \in \mathcal{K}(\tilde{\theta})$ with layers orthogonal to \mathbf{e}_r , $(\tilde{\theta}, \tilde{\mathbf{A}})$ is a maximizer of J over \mathcal{A} .
- For any maximizer (θ^*, \mathbf{A}^*) of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

Back to the example $\varepsilon > 0$



$$f_{1,2}(r) = \begin{cases} \pm\varepsilon, & 0 \leq r \leq \frac{1}{5} \\ 0, & \frac{1}{5} < r \leq \frac{1}{2} \\ 1, & \frac{1}{2} < r \leq 1. \end{cases}$$

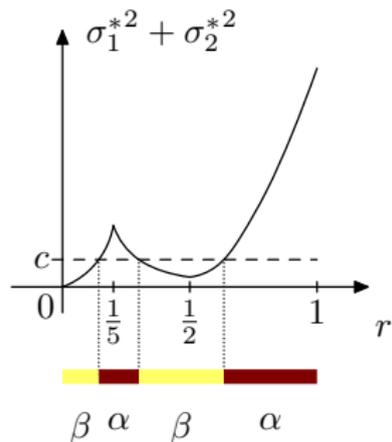
$-\operatorname{div} \sigma_i = f_i, i = 1, 2$ in polar coordinates: $-\frac{1}{r} (r\sigma_i)' = f_i$. Due to regularity at $r=0$, we can calculate unique solutions σ_1^* and σ_2^* :



$$\begin{aligned} \sigma_1^{*2} + \sigma_2^{*2} > c &\Rightarrow \theta^* = 1, \\ \sigma_1^{*2} + \sigma_2^{*2} < c &\Rightarrow \theta^* = 0. \end{aligned}$$

For any c , the solution θ^* is **unique and classical** (more precisely, the uniqueness of solution for $\max_B J$ follows).

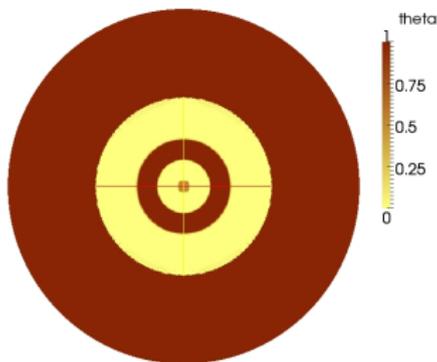
How to determine Lagrange multiplier c ?



$$\sigma_1^{*2} + \sigma_2^{*2} > c \Rightarrow \theta^* = 1,$$

$$\sigma_1^{*2} + \sigma_2^{*2} < c \Rightarrow \theta^* = 0.$$

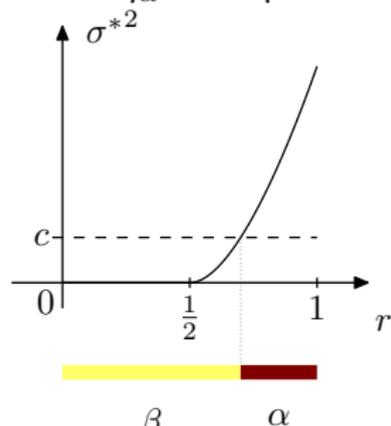
Amount q_α of the first phase uniquely determines c (as usual).



The case $\varepsilon = 0$

$$f_{1,2}(r) := f(r) = \begin{cases} 0, & 0 < r \leq \frac{1}{2} \\ 1, & \frac{1}{2} < r \leq 1. \end{cases}$$

Small q_α : unique classical solution



$$\begin{aligned} \sigma^{*2} > c &\Rightarrow \theta^* = 1, \\ \sigma^{*2} < c &\Rightarrow \theta^* = 0. \end{aligned}$$

If $q_\alpha > \frac{3}{4}\pi$ then c have to be zero. Now, solution is not unique – it is only important to put α in annulus $B(\mathbf{0}, \frac{1}{2})^c$.

Uniqueness

Conditions of optimality:

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

In case of spherical symmetry $\sigma_i^* = \sigma_i^*(r)\mathbf{e}_r$, we denote

$$\psi(r) := \sum_{i=1}^m \mu_i |\sigma_i^*|^2 = \sum_{i=1}^m \mu_i (\sigma_i^*)^2.$$

Corollary

For spherically symmetric case, if ψ is piecewise strictly monotone on ω then the problem $\max_{\mathcal{T}} I$ has a unique solution θ^ , which is a characteristic function. Consequently, the solutions of the problems $\max_B J$ and $\max_A J$ are unique and classical.*

Example

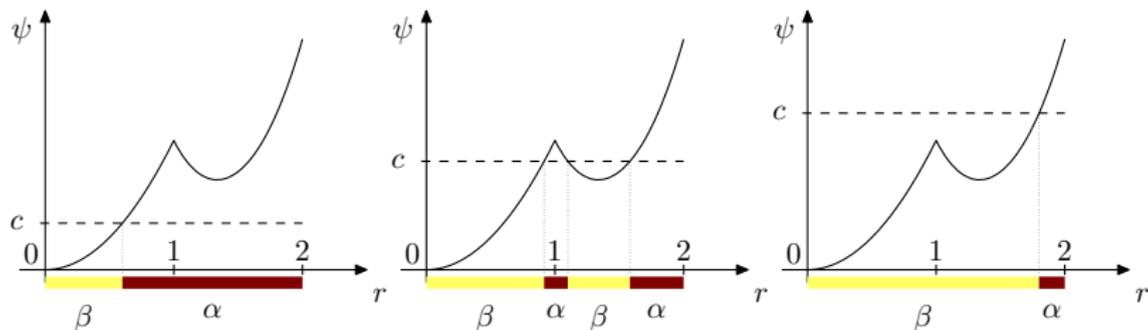
Two state equations on a ball $\Omega = B(\mathbf{0}, 2R) \subseteq \mathbf{R}^d$, $d = 2$ or 3 .

- $f_1 = \chi_{B(\mathbf{0}, R)}$, $f_2 = \chi_{B(\mathbf{0}, R)^c}$,
- $\begin{cases} -\operatorname{div}(\lambda_\theta^- \nabla u_i) = f_i \\ u_i \in H_0^1(\Omega) \end{cases} \quad i = 1, 2$
- $\mu_1 \int_{\Omega} f_1 u_1 \, d\mathbf{x} + \int_{\Omega} f_2 u_2 \, d\mathbf{x} \rightarrow \max$

For studying conditions of optimality, we introduce

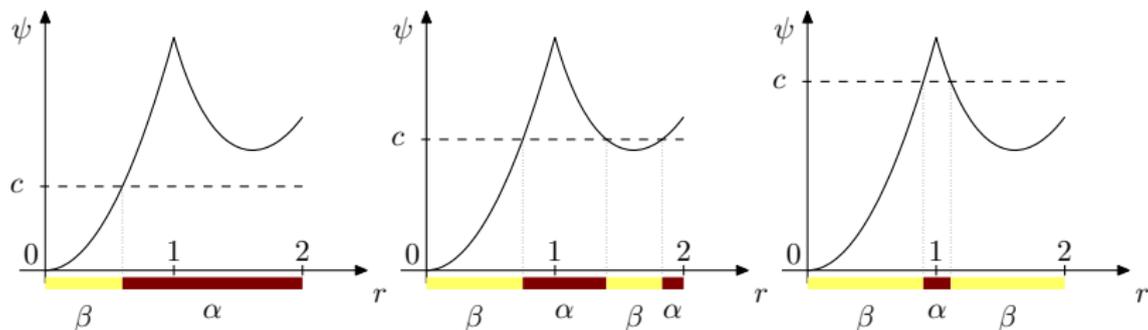
$$\psi(r) = \mu_1 (\sigma_1^*(r))^2 + (\sigma_2^*(r))^2.$$

The case $0 < \mu_1 < 3$ for $d = 2$, or $0 < \mu_1 < \frac{49}{15}$ for $d = 3$:

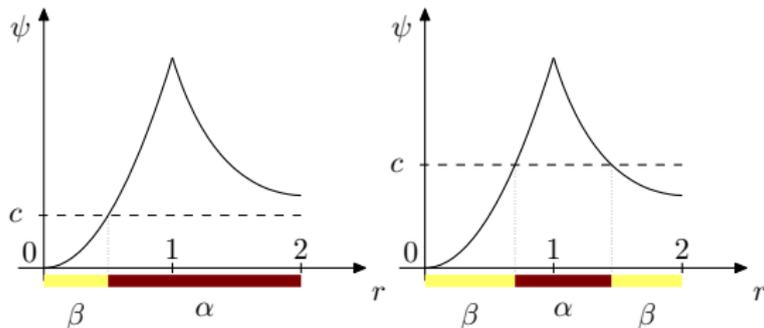


Example

The case $3 \leq \mu_1 < 15$ for $d = 2$, or $\frac{49}{15} \leq \mu_1 < 35$:

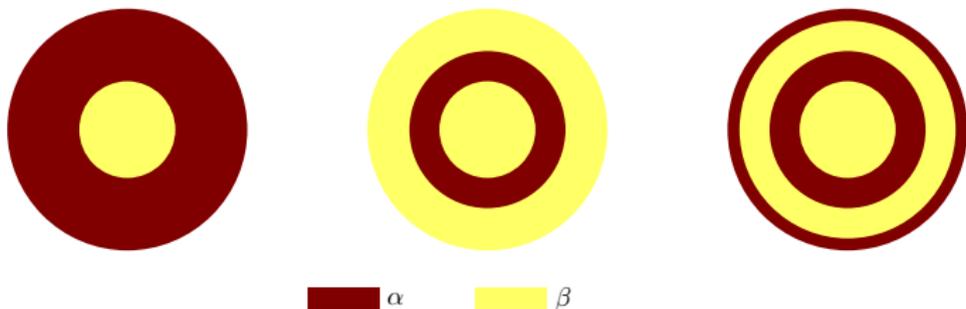


The case $\mu_1 \geq 15$ for $d = 2$, or $\mu_1 \geq 35$ for $d = 3$:



Multiple states

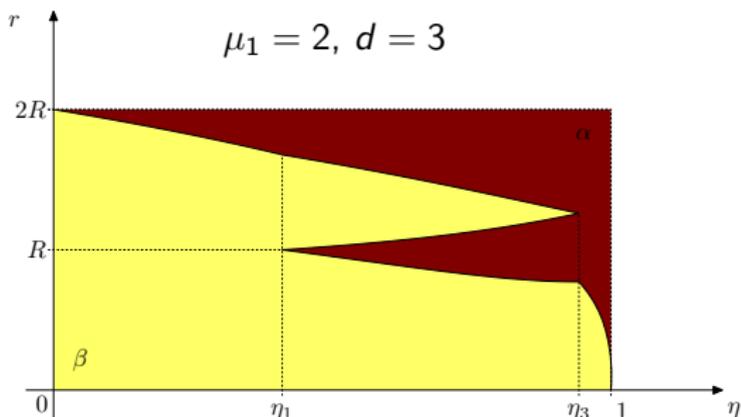
Three optimal configurations, depending on μ_1 and q_α :



Overall percentage of the first material: $\eta = \frac{q_\alpha}{|\Omega|}$.

Radii are obtained by solving algebraic equations in terms of μ_1 and η :

- $d = 2$ – explicitly
- $d = 3$ – numerically.



Conclusion

General strategy for solving $\max_{\mathcal{A}} J$ in **spherically symmetric case**:

- 1 Solve $-\operatorname{div} \sigma_i = f_i, i = 1..m$ – candidates for σ^* (in case of ball there is only one candidate).
- 2 Study conditions of optimality (they usually give unique solution θ^* – radial, but also **classical**).
- 3 Construct solution to $\max_{\mathcal{A}} J$ (commonly, it would be classical solution; for minimization problem the situation is quite different).

Thank you for your attention!