



The Iterative Solution of Systems from PDE Constrained Optimization: An Overview

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Alright to turn the central heating
down a notch dear?

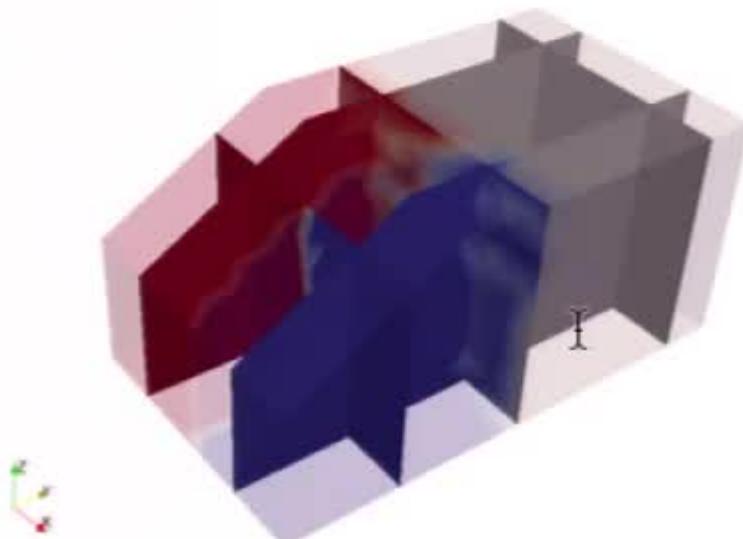


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How does this work?



y: temperature (state)

u: control

$$\min_{\mathbf{y}, \mathbf{u}} \frac{1}{2} \|\mathbf{y} - \hat{\mathbf{y}}\|_*^2 + \frac{\beta}{2} \|\mathbf{u}\|_*^2$$

$$\text{s.t. } \mathcal{L}\mathbf{y} = \mathbf{f}(\mathbf{u})$$

$$\mathbf{u}_l \leq \mathbf{u} \leq \mathbf{u}_u$$

$$\mathbf{y}_l \leq \mathbf{y} \leq \mathbf{y}_u$$



The 'mother problem'

$$\min_{y,u} \frac{1}{2} \|y - \hat{y}\|_{L_2(\Omega_1)}^2 + \frac{\beta}{2} \|u\|_{L_2(\Omega_2)}^2$$

s.t.
$$-\nabla^2 y = \begin{cases} u, & \text{for } x \in \Omega_2 \\ 0, & \text{for } x \in \Omega \setminus \Omega_2, \end{cases}$$

$$y = f \text{ on } \partial\Omega$$

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$$\min_{y,u} \frac{1}{2} \mathbf{y}^T Q_y \mathbf{y} - \mathbf{y}^T \mathbf{b} + \frac{\beta}{2} \mathbf{u}^T Q_u \mathbf{u}$$

s.t. $K\mathbf{y} = \hat{Q}\mathbf{u} + \mathbf{f}$

$$\begin{bmatrix} \beta Q_u & 0 & -\hat{Q}^T \\ 0 & Q_y & K^T \\ -\hat{Q} & K & 0 \end{bmatrix} \begin{bmatrix} \mathbf{u} \\ \mathbf{y} \\ \mathbf{p} \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \mathbf{b} \\ \mathbf{f} \end{bmatrix}$$



The linear system

$$\begin{bmatrix} \beta Q_u & 0 & -\hat{Q}^T \\ 0 & Q_y & K^T \\ -\hat{Q} & K & 0 \end{bmatrix} \begin{bmatrix} \mathbf{u} \\ \mathbf{y} \\ \mathbf{p} \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \mathbf{b} \\ \mathbf{f} \end{bmatrix}$$

The linear system is:

- ▶ symmetric, but indefinite
- ▶ very large scale
- ▶ sparse

Solve with a Krylov subspace method.



Preconditioning

$$\begin{bmatrix} \beta Q_u & 0 & -\hat{Q}^T \\ 0 & Q_y & K^T \\ -\hat{Q} & K & 0 \end{bmatrix} \quad \text{saddle point system}$$

Ideal preconditioner:

$$P = \begin{bmatrix} \beta Q_u & 0 & 0 \\ 0 & Q_y & 0 \\ 0 & 0 & \frac{1}{\beta} \hat{Q} Q_u^{-1} \hat{Q}^T + K^T Q_y^{-1} K \end{bmatrix}$$

Three distinct eigenvalues – MINRES will converge in three iterations.

[Murphy, Golub, Wathen, 1999]



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Preconditioning

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Three distinct eigenvalues – MINRES will converge in three iterations.

[Murphy, Golub, Wathen, 1999]



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Approximating $\begin{bmatrix} \beta Q_u & 0 \\ 0 & Q_y \end{bmatrix}$

The diagonal is a good approximation to the mass matrix: e.g., if we have a 3D tetrahedral mesh of P1 elements we have

$$\lambda(D^{-1}Q) \in [1/2, 5/2].$$

[Wathen, 1987]

Can do better – Chebyshev semi-iteration applied to relaxed Jacobi.

[Wathen, R., 2008] , [R., Dollar, Wathen, 2008]



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Approximating $\frac{1}{\beta} \hat{Q} Q_u^{-1} \hat{Q}^T + K^T Q_y^{-1} K$

Approximation 1: $S \approx K^T Q_y^{-1} K$

Eigenvalues of the preconditioned system satisfy:

$$\begin{aligned} \lambda &= 1, \\ \frac{1}{2} \left(1 + \sqrt{5 + \frac{2\alpha_1 h^4}{\beta}} \right) &\leq \lambda \leq \frac{1}{2} \left(1 + \sqrt{5 + \frac{2\alpha_2}{\beta}} \right) \\ \text{or } \frac{1}{2} \left(1 - \sqrt{5 + \frac{2\alpha_2}{\beta}} \right) &\leq \lambda \leq \frac{1}{2} \left(1 - \sqrt{5 + \frac{2\alpha_1 h^4}{\beta}} \right). \end{aligned}$$

(h mesh size, α_1, α_2 constants)

[R., Dollar, Wathen, 2008]



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Approximating $\frac{1}{\beta} \hat{Q} Q_u^{-1} \hat{Q}^T + K^T Q_y^{-1} K$

Approximation 2: $S \approx (K^T + L^T) Q_y^{-1} (K + L)$, where

$$L^T = \frac{1}{\sqrt{\beta}} \hat{Q} Q_u^{-1/2} Q_y^{1/2}$$

Eigenvalues of the preconditioned system satisfy:

$$\frac{1}{2} \leq \lambda \leq 1$$

[Pearson, Wathen, 2011]



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Control constraints

To make the problem a little harder...

$$\begin{aligned} \min_{y,u} \quad & \frac{1}{2} \|y - \hat{y}\|_{L_2(\Omega_1)}^2 + \frac{\beta}{2} \|u\|_{L_2(\Omega_2)}^2 \\ \text{s.t.} \quad & -\nabla^2 y = u \text{ in } \Omega_2 \\ & y = f \text{ on } \partial\Omega \\ & u_l \leq u \leq u_u \end{aligned}$$

Can be solved using an active set method (semi-smooth Newton).

Linear system at each step looks like:

$$\begin{bmatrix} \beta Q_u & 0 & -\hat{Q}^T \\ 0 & Q_y & K^T \\ -\hat{Q} & K & 0 \end{bmatrix} \begin{bmatrix} \mathbf{u} \\ \mathbf{y} \\ \mathbf{p} \end{bmatrix} = \begin{bmatrix} \mu_k \\ \mathbf{b} \\ \mathbf{f} \end{bmatrix}$$

[Stoll, Wathen, 2012]



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State constraints

$$\begin{aligned} \min_{y,u} \quad & \frac{1}{2} \|y - \hat{y}\|_{L_2(\Omega_1)}^2 + \frac{\beta}{2} \|u\|_{L_2(\Omega_2)}^2 + \frac{1}{2\epsilon} \|\max\{0, y - y_u\}\|_{L_2(\Omega)}^2 + \frac{1}{2\epsilon} \|\min\{0, y - y_l\}\|_{L_2(\Omega)}^2 \\ \text{s.t.} \quad & -\nabla^2 y = u \text{ in } \Omega_2 \\ & y = f \text{ on } \partial\Omega_2 \end{aligned}$$

Need to solve a linear system of the form

$$\begin{bmatrix} \beta Q_u & 0 & -\hat{Q}^T \\ 0 & Q_y + \epsilon^{-1} G_A Q_y G_A & K^T \\ -\hat{Q} & K & 0 \end{bmatrix} \begin{bmatrix} \mathbf{u} \\ \mathbf{y} \\ \mathbf{p} \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \mathbf{b} - \mathbf{z} \\ \mathbf{f} \end{bmatrix}$$

where G is a projection onto the active set \mathcal{A}

[Ito, Kunisch, 2003] , [Pearson, Stoll, Wathen, 2014]



Time-dependent problems

$$\begin{aligned} \min_{y,u} \quad & \frac{1}{2} \int_0^T \int_{\Omega_1} (y - \hat{y})^2 dx dt + \frac{\beta}{2} \int_0^T \int_{\Omega_2} u^2 dx dt \\ \text{s.t.} \quad & y_t - \Delta y = \begin{cases} u, & \text{for } (\mathbf{x}, t) \in \Omega_2 \times [0, T], \\ 0, & \text{for } (\mathbf{x}, t) \in \Omega \setminus \Omega_2 \times [0, T], \end{cases} \\ & y = g, \quad \text{on } \partial\Omega, \\ & y = y_0, \quad \text{at } t = 0, \end{aligned}$$



Transformed into linear algebra...

$$\begin{bmatrix} \tau\beta\mathcal{M}_u & 0 & -\tau\mathcal{M} \\ 0 & \tau\mathcal{M}_y & \mathcal{K}^T \\ -\tau\mathcal{M} & \mathcal{K} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{u} \\ \mathbf{y} \\ \mathbf{p} \end{bmatrix} = \begin{bmatrix} 0 \\ \tau\hat{\mathbf{b}} \\ \mathbf{d} \end{bmatrix},$$

$$\mathcal{M} = \text{blkdiag}(\hat{Q}, \dots, \hat{Q}),$$

$$\mathcal{M}_y = \text{blkdiag}(1/2Q_y, Q_y, \dots, Q_y, 1/2Q_y),$$

$$\mathcal{M}_u = \text{blkdiag}(1/2Q_u, Q_u, \dots, Q_u, 1/2Q_u), \text{ and}$$

$$\mathcal{K} = \begin{bmatrix} Q_u + \tau K & & & \\ -Q_u & Q_u + \tau K & & \\ & \ddots & \ddots & \\ & & -Q_u & Q_u + \tau K \end{bmatrix}.$$

[Pearson, Stoll, Wathen, 2012]



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Other norms?

$$\begin{aligned} \min_{y,u} \quad & \frac{1}{2} \|y - \hat{y}\|_{L_2(\Omega_1)}^2 + \frac{\beta}{2} \|u\|_{\mathcal{H}_1(\Omega_2)}^2 \\ \text{s.t.} \quad & -\nabla^2 y = u \text{ in } \Omega_2 \\ & y = f \text{ on } \partial\Omega \end{aligned}$$



Time-dependent formulation

$$\min_{y,u} \frac{1}{2} \int_0^T \int_{\Omega_1} (y - \bar{y})^2 dx dt + \frac{\beta}{2} \int_0^T \int_{\Omega_2} u^2 dx dt + \frac{\beta}{2} \int_0^T \int_{\Omega_2} (\nabla u)^2 dx dt$$

$$y_t - \nabla^2 y = \begin{cases} u, & \text{for } (\mathbf{x}, t) \in \Omega_2 \times [0, T], \\ 0, & \text{for } (\mathbf{x}, t) \in \Omega \setminus \Omega_2 \times [0, T], \end{cases}$$

$$y = g, \quad \text{on } \partial\Omega,$$

$$y = y_0, \quad \text{at } t = 0,$$



The linear system

$$\begin{bmatrix} \tau\mathcal{M}_y & 0 & -\mathcal{K}^T \\ 0 & \tau\beta(\mathcal{M}_u + \mathcal{K}_u) & \tau\widehat{\mathcal{M}} \\ -\mathcal{K} & \tau\widehat{\mathcal{M}} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{y} \\ \mathbf{u} \\ \mathbf{p} \end{bmatrix} = \begin{bmatrix} \tau\widehat{\mathbf{b}} \\ 0 \\ \mathbf{d} \end{bmatrix}$$

where $\mathcal{K}_u = \text{blkdiag}(1/2K_u, K_u, \dots, K_u, 1/2K_u)$, K_u is a Neumann Laplacian.



Approximation to

$$S = \tau^{-1} \mathcal{K} \mathcal{M}_y^{-1} \mathcal{K} + \tau \beta^{-1} \widehat{\mathcal{M}} (\mathcal{M}_u + \mathcal{K}_u)^{-1} \widehat{\mathcal{M}}^T.$$

Look for a (non-symmetric) approximation

$$\hat{S} = \tau^{-1} (\mathcal{K} + \mathcal{L}_1) \mathcal{M}_y^{-1} (\mathcal{K} + \mathcal{L}_2)^T$$

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Approximation to

$$S = \tau^{-1} \mathcal{K} \mathcal{M}_y^{-1} \mathcal{K} + \tau \beta^{-1} \widehat{\mathcal{M}} (\mathcal{M}_u + \mathcal{K}_u)^{-1} \widehat{\mathcal{M}}^T.$$

Look for a (non-symmetric) approximation

$$\hat{S} = \tau^{-1} \left(\mathcal{K} + \frac{\tau}{\sqrt{\beta}} \widehat{\mathcal{M}} (\mathcal{M}_u + \mathcal{K}_u)^{-1} \mathcal{M}_y \right) \mathcal{M}_y^{-1} \left(\mathcal{K} + \frac{\tau}{\sqrt{\beta}} \widehat{\mathcal{M}} \right)^T$$



Approximation to

$$S = \tau^{-1} \mathcal{K} \mathcal{M}_y^{-1} \mathcal{K} + \tau \beta^{-1} \widehat{\mathcal{M}} (\mathcal{M}_u + \mathcal{K}_u)^{-1} \widehat{\mathcal{M}}^T.$$

Look for a (non-symmetric) approximation

$$\hat{S} = \tau^{-1} \left(\mathcal{K} + \frac{\tau}{\sqrt{\beta}} \widehat{\mathcal{M}} (\mathcal{M}_u + \mathcal{K}_u)^{-1} \mathcal{M}_y \right) \mathcal{M}_y^{-1} \left(\mathcal{K} + \frac{\tau}{\sqrt{\beta}} \widehat{\mathcal{M}} \right)^T$$

Solving a system with $\mathcal{K} + \frac{\tau}{\sqrt{\beta}} \widehat{\mathcal{M}} (\mathcal{M}_u + \mathcal{K}_u)^{-1} \mathcal{M}_y \mathbf{u} = \mathbf{f}$ is equivalent to solving

$$\begin{bmatrix} \mathcal{K} & \widehat{\mathcal{M}} \\ \mathcal{M}_y & -\frac{\sqrt{\beta}}{\tau} (\mathcal{M}_u + \mathcal{K}_u) \end{bmatrix} \begin{bmatrix} \mathbf{u} \\ * \end{bmatrix} = \begin{bmatrix} \mathbf{f} \\ \mathbf{0} \end{bmatrix}.$$

Treat this as a sub-problem.



Approximating a solve with

$$\begin{bmatrix} \mathcal{K} & \widehat{\mathcal{M}} \\ \mathcal{M}_y & -\frac{\sqrt{\beta}}{\tau} (\mathcal{M}_u + \mathcal{K}_u) \end{bmatrix}$$

Recall this involves the solution of diagonal blocks of the form

$$\begin{bmatrix} Q_u + \tau K & \widehat{Q} \\ I & Q_y - \frac{\sqrt{\beta}}{\tau} (Q_u + K_u) \end{bmatrix}$$

Approximate this by a **simple iteration** of the form

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \omega W^{-1} \mathbf{r}_k$$

where $W = \begin{bmatrix} \widehat{M + \tau K} & 0 \\ 0 & -\frac{\sqrt{\beta}}{\tau} (\widehat{M}_u + \widehat{K}_u) \end{bmatrix}$



Numerical results

Example:

$$\hat{y} = \exp\left(-64\left((x_0 - 0.5)^2 + (x_1 - 0.5)^2\right)\right),$$

$\Omega = [0, 1]^2$, $\tau = 0.05$. In the preconditioner $\omega = 0.1$, 10 steps of simple iteration taken. Outer tolerance is 10^{-6} .

DoF	\mathbb{I}		
	$\beta = 10^{-2}$	$\beta = 10^{-4}$	$\beta = 10^{-6}$
	# it(t)	# it(t)	# it(t)
1089	13(35.1)	13(35.2)	22(57.3)
4225	13(112.6)	15(128.8)	22(184.8)
16641	15(462.3)	15(462.2)	25(756.1)
66049	17(1442.6)	20(1691.4)	31(2578.7)
263169	19(4928.3)	22(5843.9)	34(8368.3)

[Barker, R., Stoll, to appear]



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