

ADAPTIVE OPTIMIZED SCHWARZ METHODS

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SCHWARZ METHODS

Consider the following sample problem:

$$\Delta u(x, y) = f(x, y), \quad (x, y) \in \Omega = [-1, 1] \times [-1, 1]$$

$$u(x, y) = h(x, y), \quad (x, y) \in \partial\Omega$$

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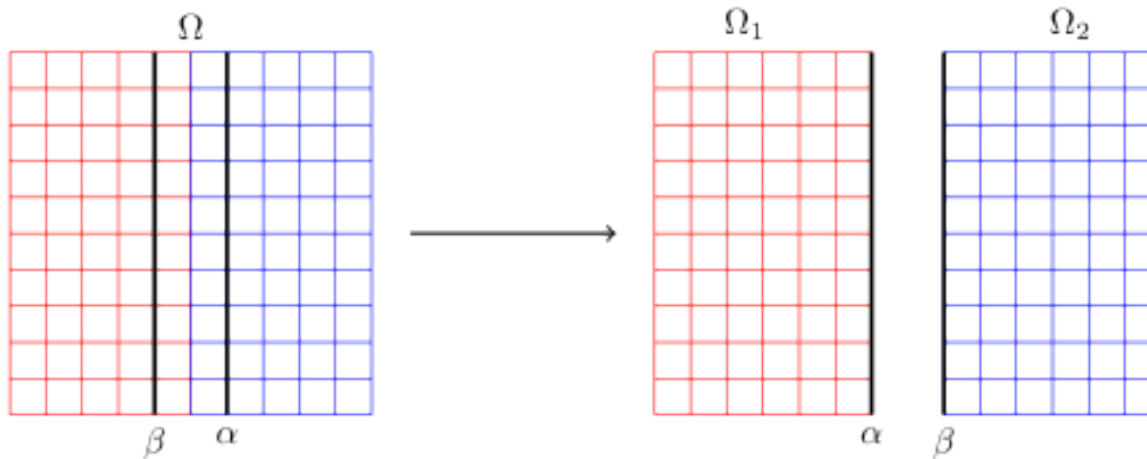
$$\Delta u_1^n(x, y) = f(x, y), \quad (x, y) \in \Omega_1 = [-1, \alpha] \times [-1, 1]$$

$$u_1^n(\alpha, y) = u_2^{n-1}(\alpha, y)$$

$$\Delta u_2^n(x, y) = f(x, y), \quad (x, y) \in \Omega_2 = [\beta, 1] \times [-1, 1]$$

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Additive Schwarz: solve both subdomains at the same time

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$$\begin{bmatrix} A_{11} & A_{1\Gamma} & \\ A_{\Gamma 1} & A_{\Gamma\Gamma} & A_{\Gamma 2} \\ & A_{2\Gamma} & A_{22} \end{bmatrix} \begin{bmatrix} \vec{u}_1 \\ \vec{u}_\Gamma \\ \vec{u}_2 \end{bmatrix} = \begin{bmatrix} \vec{f}_1 \\ \vec{f}_\Gamma \\ \vec{f}_2 \end{bmatrix}$$

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$$\begin{bmatrix} A_{11} & A_{1\Gamma} \\ A_{\Gamma 1} & A_{\Gamma\Gamma} + T_{2 \rightarrow 1} \end{bmatrix} \begin{bmatrix} \vec{u}_1^{n+1} \\ \vec{u}_{1\Gamma}^{n+1} \end{bmatrix} = \begin{bmatrix} \vec{f}_1 \\ \vec{f}_\Gamma \end{bmatrix} + \begin{bmatrix} -A_{\Gamma 2} \vec{u}_2^n + T_{2 \rightarrow 1} \vec{u}_{2\Gamma}^n \end{bmatrix}$$

$$\begin{bmatrix} A_{22} & A_{2\Gamma} \\ A_{\Gamma 2} & A_{\Gamma\Gamma} + T_{1 \rightarrow 2} \end{bmatrix} \begin{bmatrix} \vec{u}_2^{n+1} \\ \vec{u}_{2\Gamma}^{n+1} \end{bmatrix} = \begin{bmatrix} \vec{f}_2 \\ \vec{f}_\Gamma \end{bmatrix} + \begin{bmatrix} -A_{\Gamma 1} \vec{u}_1^n + T_{1 \rightarrow 2} \vec{u}_{1\Gamma}^n \end{bmatrix}$$

OPTIMIZED SCHWARZ METHODS

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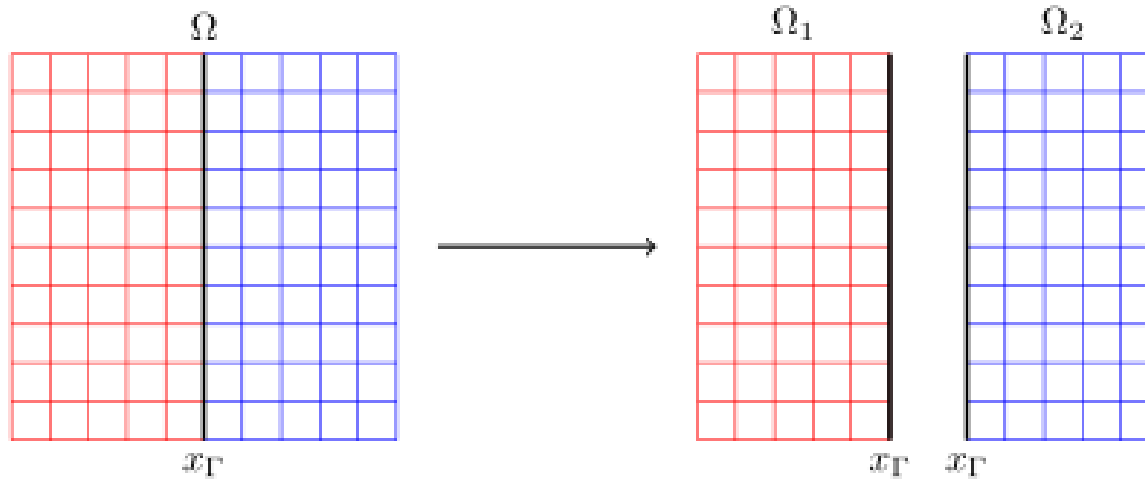
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If you have a specific Fourier mode in mind, you can also pick the best p for just that mode

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Tangential BCs are also a popular choice, and give a
second parameter q to optimize

$$\frac{\partial u_1^n}{\partial x} - pu_1^n(0, y) + q \frac{\partial u_1^n}{\partial y} =$$

$$\frac{\partial u_2^{n-1}}{\partial x} - pu_2^{n-1}(0, y) + q \frac{\partial u_2^n}{\partial y}$$

But the best BCs are absorbing BCs, which are used in perfectly matched layers

These are dense, and correspond to Schur complements

$$T_{2 \rightarrow 1} \rightarrow S_{2 \rightarrow 1} = -A_{\Gamma 2} A_{22}^{-1} A_{2\Gamma},$$

$$T_{1 \rightarrow 2} \rightarrow S_{1 \rightarrow 2} = -A_{\Gamma 1} A_{11}^{-1} A_{1\Gamma}$$

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This means they have about the same computation time as M iterations, where M is the size of the overlap

ADAPTIVE TRANSMISSION CONDITIONS

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To get them, we'll find them adaptively

Let's look at the differences between iterates for a single subdomain

$$\begin{aligned} & \begin{bmatrix} A_{11} & A_{1\Gamma} \\ A_{\Gamma 1} & A_{\Gamma\Gamma} + T_{2 \rightarrow 1} \end{bmatrix} \left(\begin{bmatrix} \vec{u}_1^{n+1} \\ \vec{u}_{1\Gamma}^{n+1} \end{bmatrix} - \begin{bmatrix} \vec{u}_1^n \\ \vec{u}_{1\Gamma}^n \end{bmatrix} \right) = \\ & \begin{bmatrix} \vec{f}_1 \\ \vec{f}_\Gamma \end{bmatrix} + \begin{bmatrix} -A_{\Gamma 2} \vec{u}_2^n + T_{2 \rightarrow 1} \vec{u}_{2\Gamma}^n \end{bmatrix} - \left(\begin{bmatrix} \vec{f}_1 \\ \vec{f}_\Gamma \end{bmatrix} + \begin{bmatrix} -A_{\Gamma 2} \vec{u}_2^{n-1} + T_{2 \rightarrow 1} \vec{u}_{2\Gamma}^{n-1} \end{bmatrix} \right) \end{aligned}$$

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$$\begin{bmatrix} A_{11} & A_{1\Gamma} \\ A_{\Gamma 1} & A_{\Gamma\Gamma} + T_{2 \rightarrow 1} \end{bmatrix} \begin{bmatrix} \vec{d}_1^{n+1} \\ \vec{d}_{1\Gamma}^{n+1} \end{bmatrix} = \begin{bmatrix} -A_{\Gamma 2} \vec{d}_2^n + T_{2 \rightarrow 1} \vec{d}_{2\Gamma}^n \end{bmatrix}$$

We then perform what's known as static condensation
by noting that

$$A_{11} \vec{d}_1^{n+1} = -A_{\Gamma 1} \vec{d}_{1\Gamma}^{n+1}$$

This leads to

$$(A_{\Gamma\Gamma} + \mathcal{S}_{1\rightarrow 2} + T_{2\rightarrow 1})\vec{d}_{1\Gamma}^{n+1} = (T_{2\rightarrow 1} - \mathcal{S}_{2\rightarrow 1})\vec{d}_{2\Gamma}^n$$

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$$\vec{y}^{n+1} = E_2\vec{d}_{2\Gamma}^n = -A_{\Gamma 2}\vec{d}_2^n + T_{2\rightarrow 1}\vec{d}_{2\Gamma}^n$$

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At every other iteration, we're going to update E_2

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$$E_2 \rightarrow E_2 - \frac{\vec{y} \vec{d}^\top}{\|\vec{d}\|^2}$$

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Through this process, the vectors \vec{y} get modified as well, to the vectors \vec{v}

$$E_2 \rightarrow E_2 - VW^T$$

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Since $V = E_2W$, this is equivalent to

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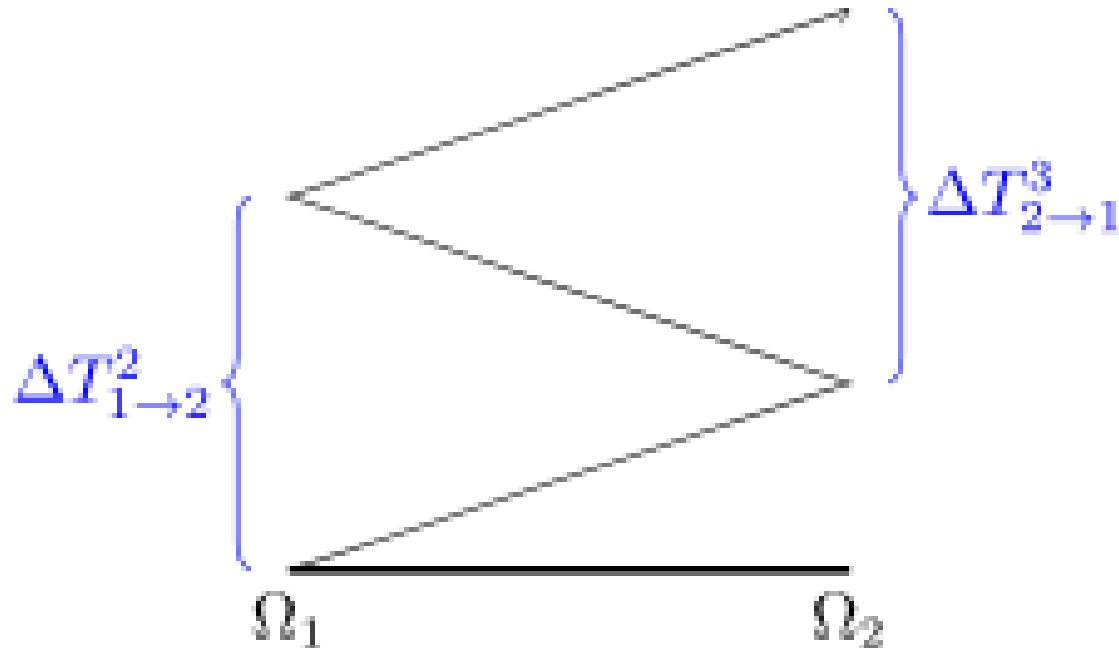
$$E_2 \rightarrow E_2 (I - WW^\top)$$

We generate a low rank approximation of E_2

To make the optimized BCs, we subtract this from

$$T_{2 \rightarrow 1}$$

The transmission conditions $T_{2 \rightarrow 1}$ and $T_{1 \rightarrow 2}$ now change iteratively



Recall:

$$(A_{\Gamma\Gamma} + S_{1 \rightarrow 2} + T_{2 \rightarrow 1}) \vec{d}_{1\Gamma}^{n+1} = (T_{2 \rightarrow 1} - S_{2 \rightarrow 1}) \vec{d}_{2\Gamma}^n$$

The vectors \vec{d} lie in a Krylov subspace

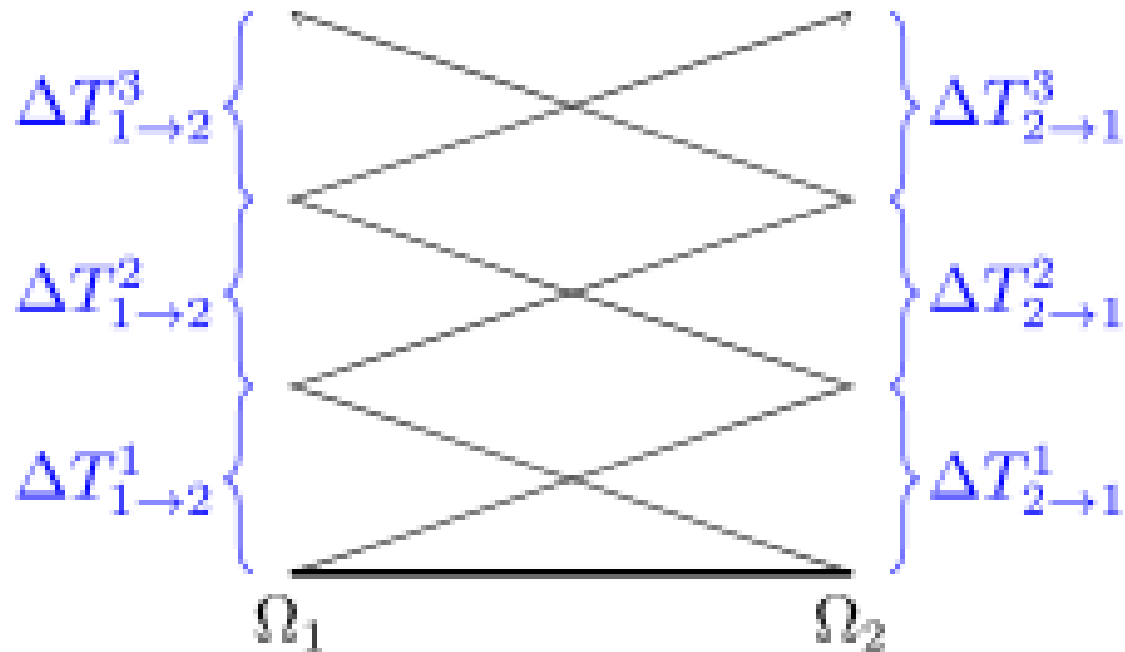
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The vectors \vec{d} lie in a Krylov subspace

They satisfy an implicit Galerkin condition

There's also the option to update the BCs at every iteration



ADAPTIVE OPTIMIZED SCHWARZ METHODS (AOSMS)

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Solve

$$\begin{bmatrix} A_{22} & A_{2\Gamma} \\ A_{\Gamma 2} & A_{\Gamma\Gamma} + T_{1\rightarrow 2}^1 \end{bmatrix} \begin{bmatrix} \vec{u}_2^1 \\ \vec{u}_{2\Gamma}^1 \end{bmatrix} = \begin{bmatrix} \vec{f}_2 \\ \vec{f}_\Gamma \end{bmatrix} + \begin{bmatrix} -A_{\Gamma 1} \vec{u}_1^0 + T_{1\rightarrow 2}^1 \vec{u}_{1\Gamma}^0 \end{bmatrix}$$

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Normalize $\vec{d}_{1\Gamma}^2$ using α_1^2 such that $\vec{w}_1^2 = \alpha_1^2 \vec{d}_{1\Gamma}^2$ and calculate

$$\vec{v}_1^2 = \alpha_1^2 \left(-A_{\Gamma 1} \vec{d}_1^2 + T_{1 \rightarrow 2}^1 \vec{d}_{1\Gamma}^2 \right)$$

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Update $T_{1 \rightarrow 2}^1$:

$$T_{1 \rightarrow 2}^2 = T_{1 \rightarrow 2}^1 + \Delta T_{1 \rightarrow 2}^2 = T_{1 \rightarrow 2}^1 - \vec{v}_1^2 (\vec{w}_1^2)^\top$$

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Solve

$$\begin{bmatrix} A_{22} & A_{2\Gamma} \\ A_{\Gamma 2} & A_{\Gamma\Gamma} + T_{1 \rightarrow 2}^2 \end{bmatrix} \begin{bmatrix} \vec{d}_2^3 \\ \vec{d}_{2\Gamma}^3 \end{bmatrix}$$

$$= \begin{bmatrix} -A_{\Gamma 1} \vec{d}_1^2 + T_{1 \rightarrow 2}^2 \vec{d}_{1\Gamma}^2 - \Delta T_{1 \rightarrow 2}^2 (\vec{u}_{2\Gamma}^1 - \vec{u}_{1\Gamma}^0) \end{bmatrix}$$

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$$= \langle \vec{w}_1^2, \vec{u}_{2\Gamma}^1 - \vec{u}_{1\Gamma}^0 \rangle \begin{bmatrix} \vec{v}_1^2 \end{bmatrix}$$

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$$\vec{v}_2^3 = \alpha_2^3 \left(-A_{\Gamma 2} \vec{d}_2^3 + T_{2 \rightarrow 1}^1 \vec{d}_{2\Gamma}^3 \right)$$

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Update $T_{i \rightarrow j}^n$ using $\vec{v}_i^n (\vec{w}_i^n)^\top$

WOODBURY MATRIX IDENTITY

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$$(A - VW^\top)\vec{u} = \vec{f},$$

$$\vec{u} = A^{-1}\vec{f} + A^{-1}V(I_{k \times k} - W^\top A^{-1}V)^{-1}W^\top A^{-1}\vec{f}$$

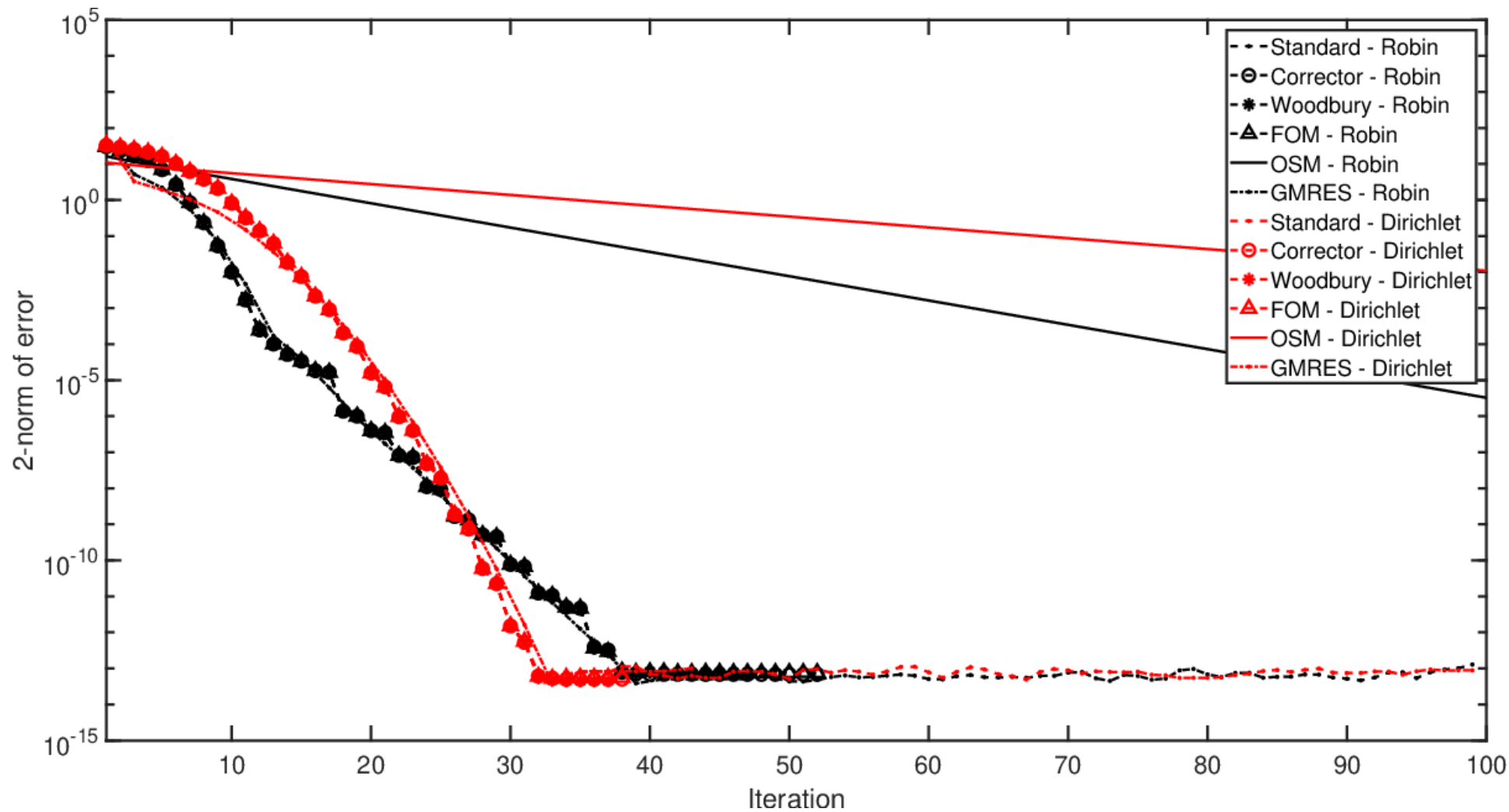
NUMERICAL EXPERIMENTS

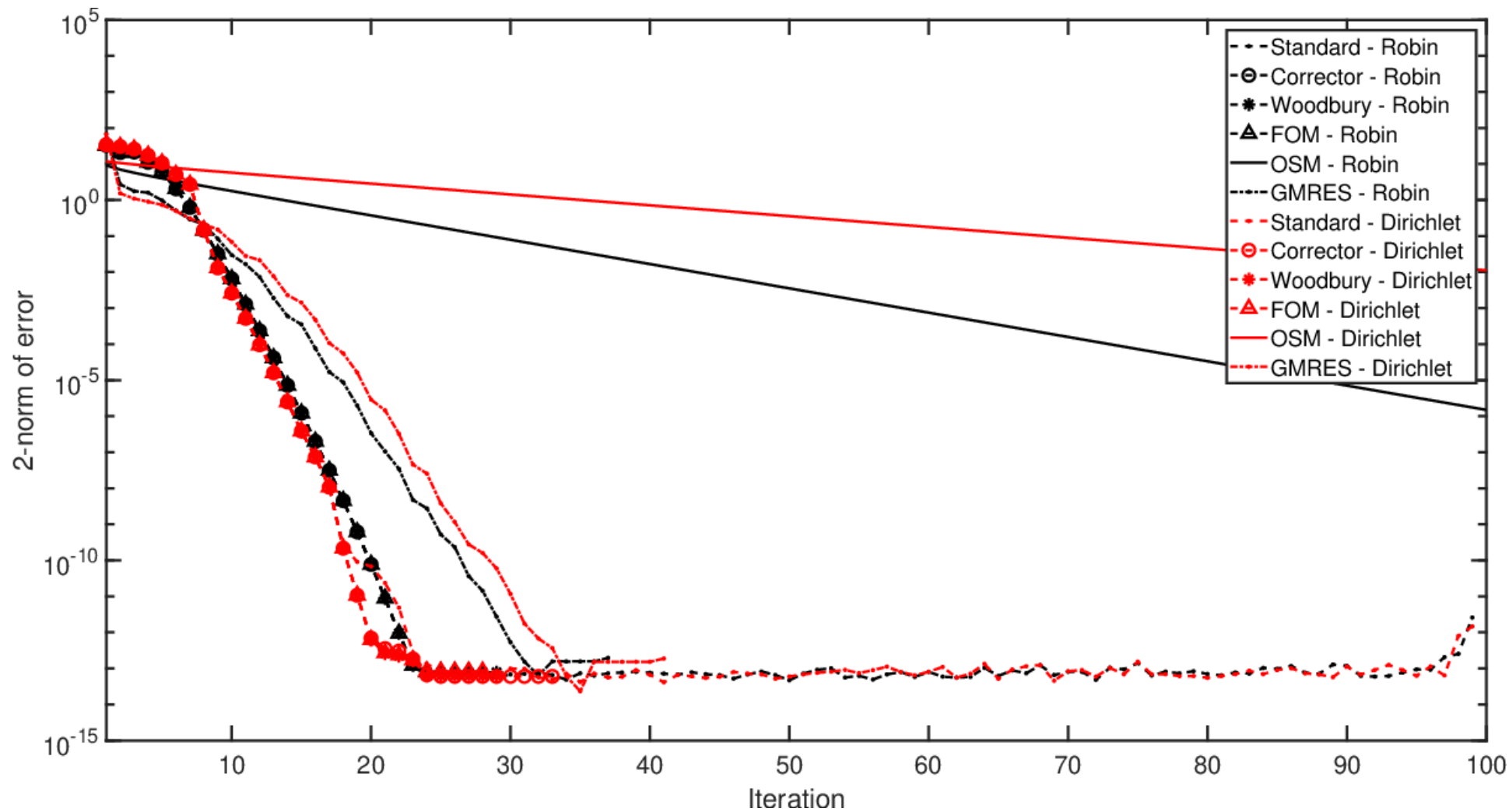
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Let's apply AOSMs to this problem





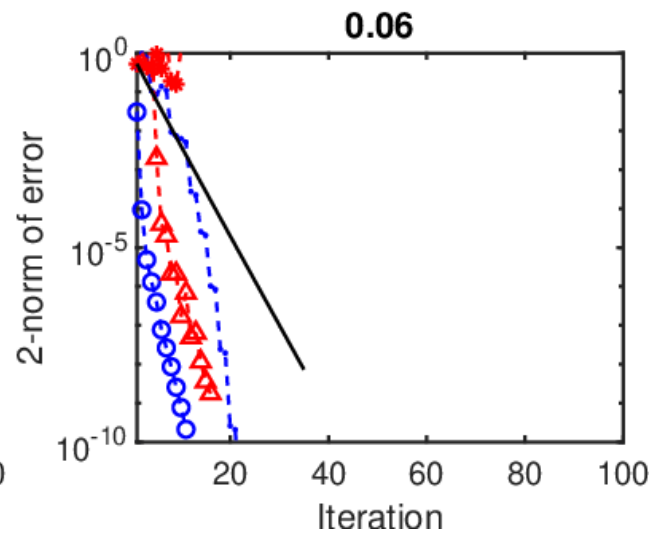
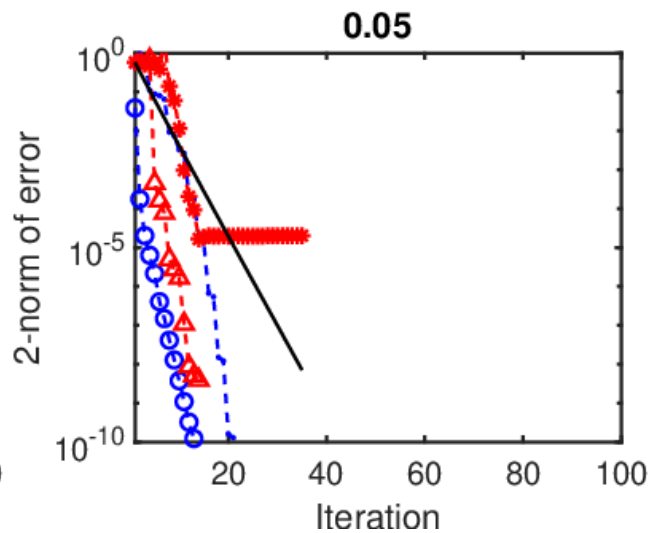
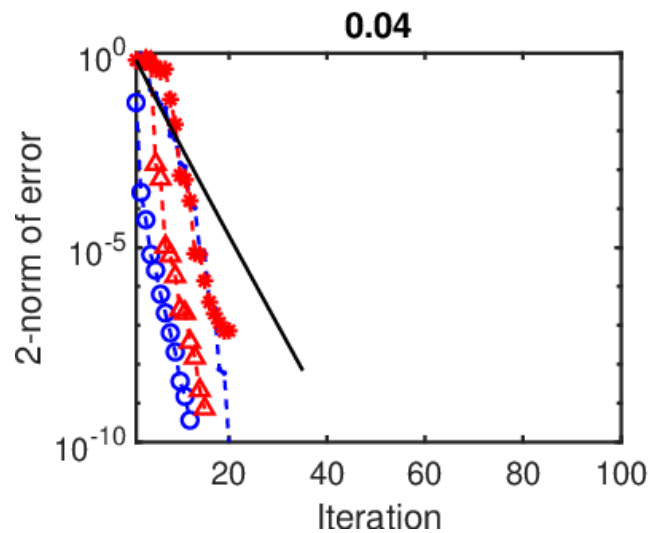
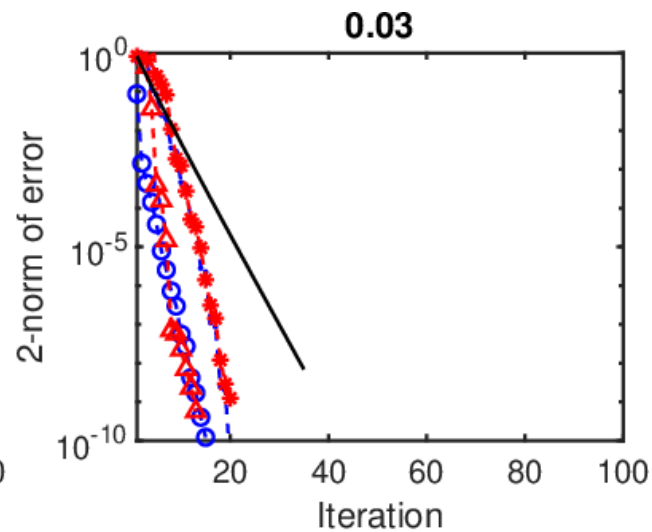
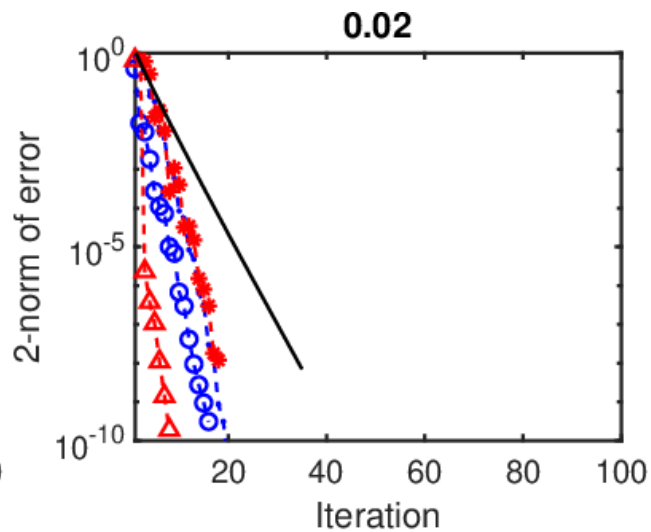
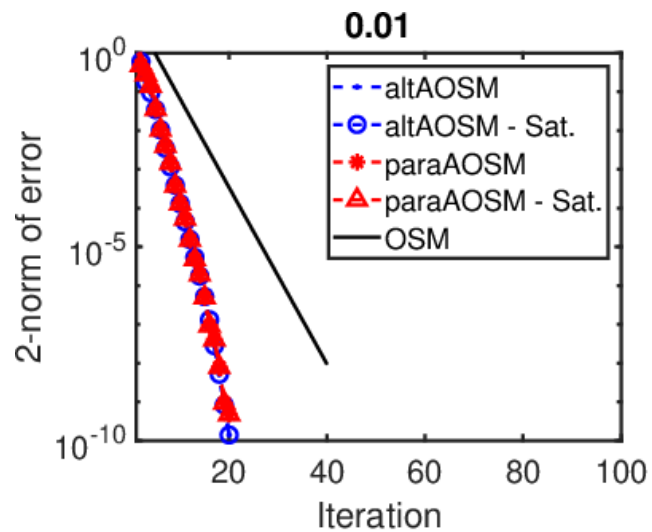
$$u_t(x, y, t) = \Delta u(x, y, t), \quad (x, y) \in \Omega = [-1, 1] \times [-1, 1], \quad t \in [0, T]$$

$$u(x, y, 0) = u_0(x, y), \quad (x, y) \in \Omega,$$

$$u(x, y, t) = h(x, y), \quad (x, y) \in \partial\Omega, \quad t \in [0, T]$$

$$\frac{u_{n+1} - u_n}{\Delta t} = Au_{n+1}$$

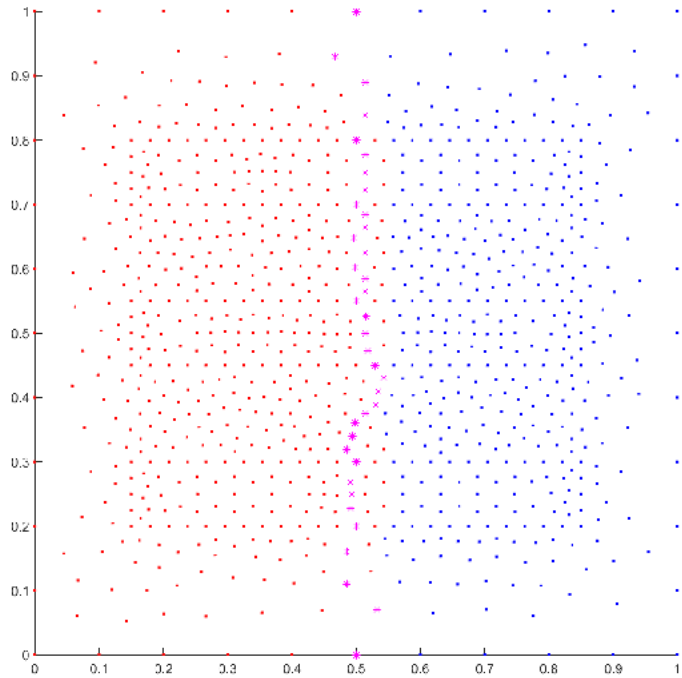
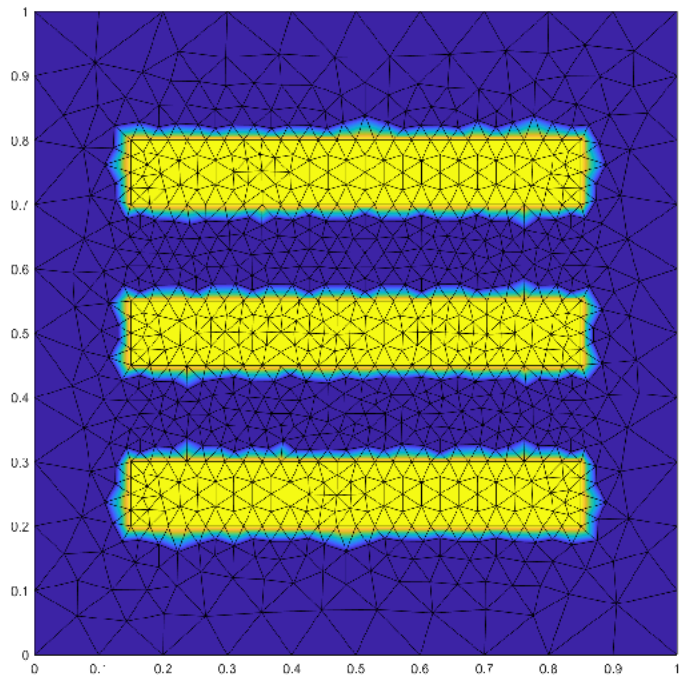
$$(I - \Delta t A)u_{n+1} = u_n$$

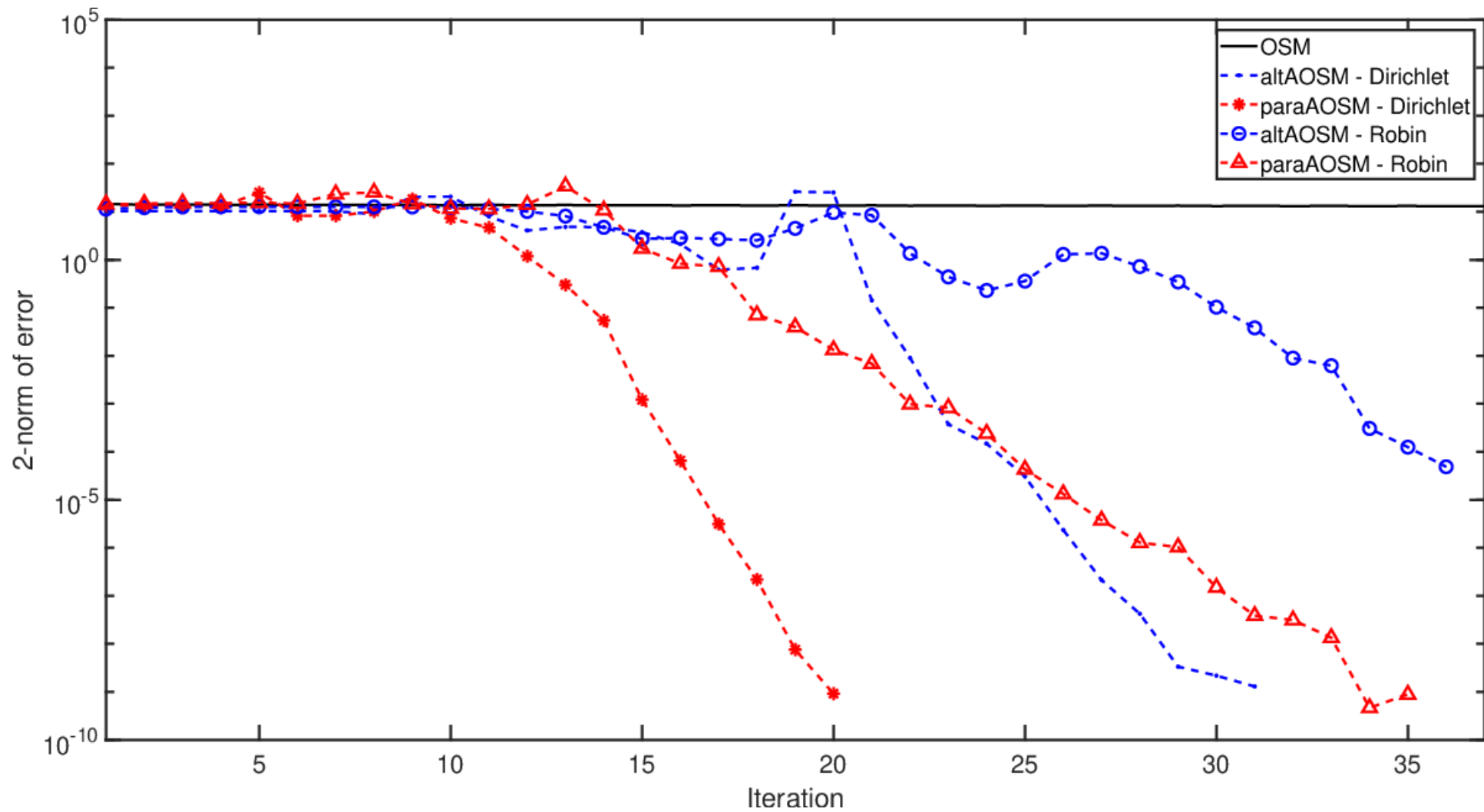


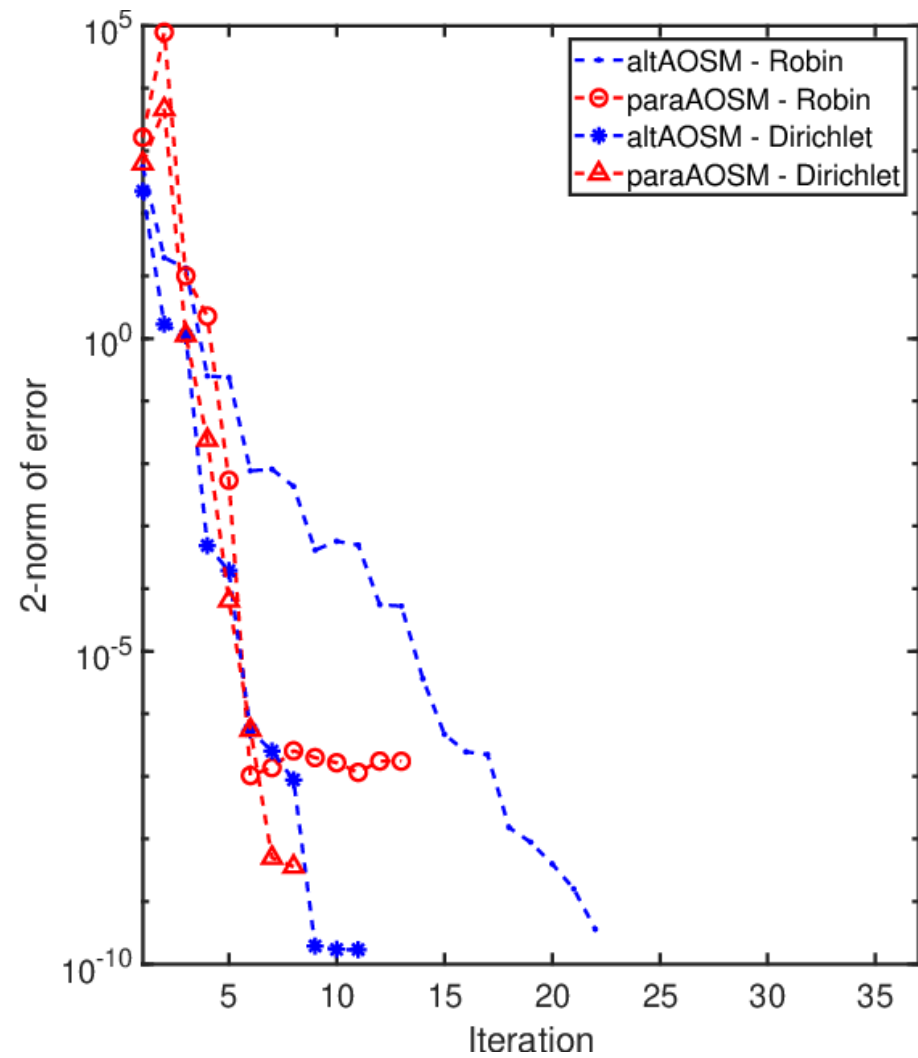
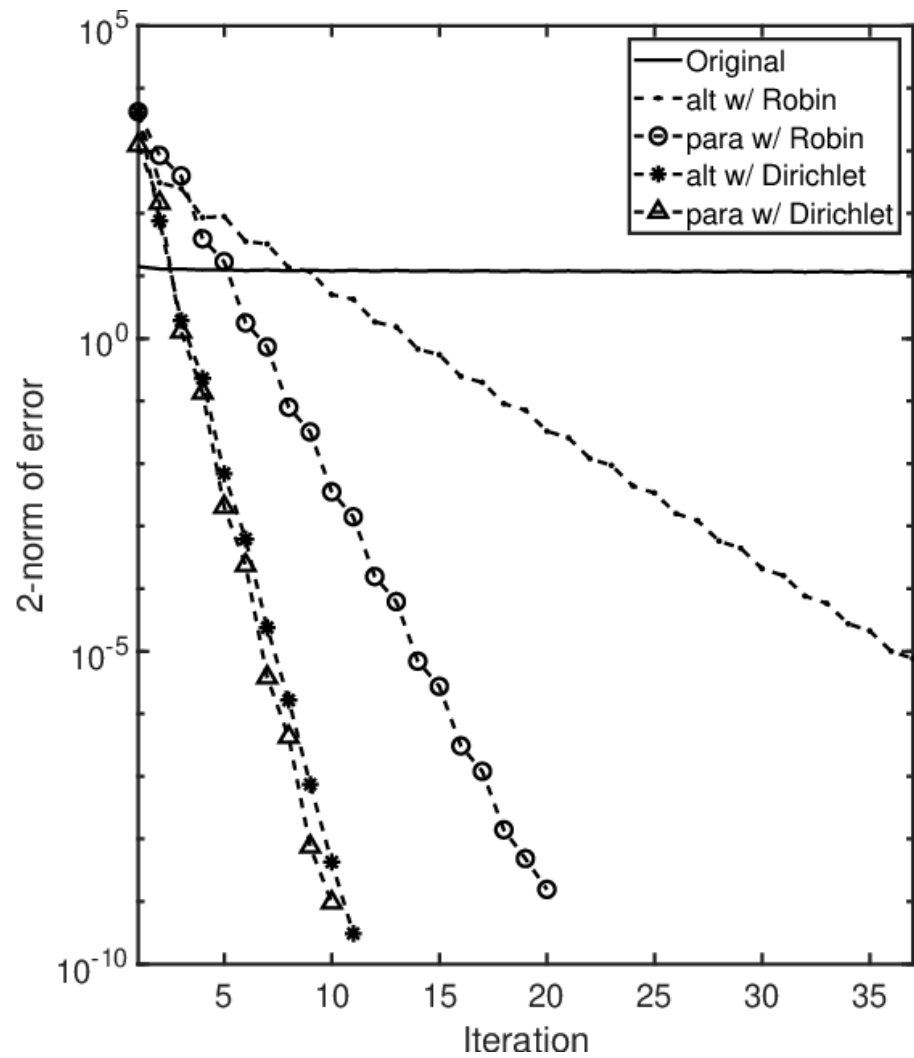
$$\nabla(\alpha(x, y) \cdot \nabla u(x, y)) = f(x, y), \quad (x, y) \in \Omega = [-1, 1] \times [-1, 1],$$

$$u(x, y) = h(x, y), \quad (x, y) \in \partial\Omega,$$

Solve this using FEM software







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- Track down stability issues
- Test out other choices of adaptive transmission conditions

