

Exploiting pHS when Preconditioning SPPs

Building Preconditioners for Saddle Point Problems
in port-Hamiltonian Systems

René H. P. Noffke

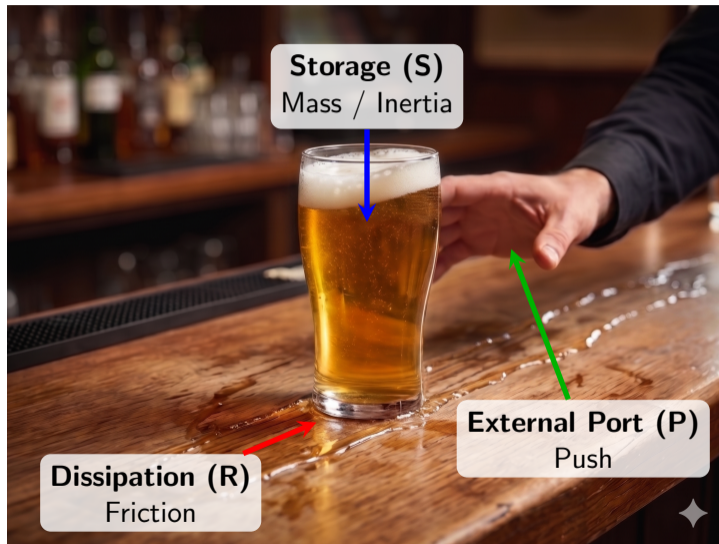
Edinburgh, May 28th 2026



A port-Hamiltonian Aperitif



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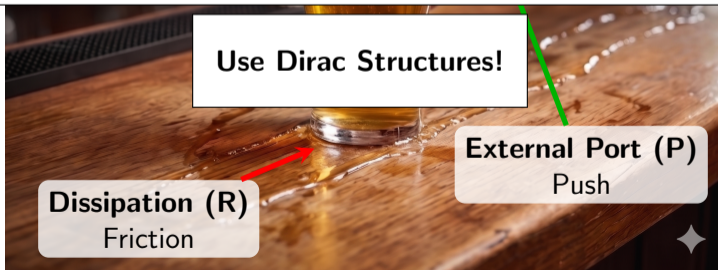
How to interconnect components by law of energy conservation?



A port-Hamiltonian Aperitif



How to interconnect components by law of energy conservation?



What? Foundations of pHS

What defines a port-Hamiltonian System (pHS) mathematically and physically?

Why? Connecting pHS and SPP

Why and when do port-Hamiltonian Systems translate into Saddle Point Problems (SPP)?

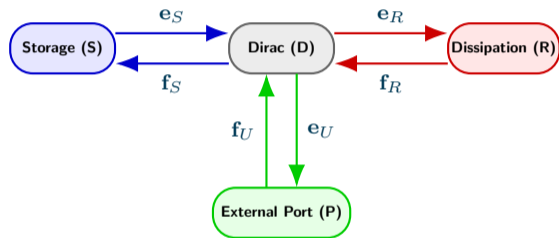
How? Preconditioning Strategies

How can we exploit the pHS structure to construct efficient SPP preconditioners?

port-Hamiltonian Systems (pHS)

Introduction to pHS I

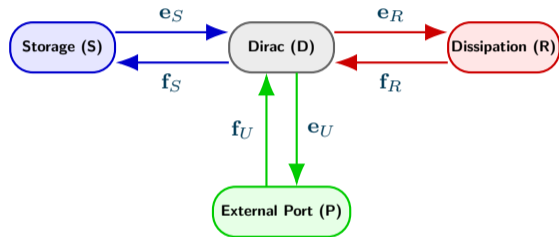
- ▶ Well-established framework in control engineering and mechatronics
- ▶ Deeply rooted in differential geometry (Dirac structures) and functional analysis
- ▶ *Relatively* new research area in numerical linear algebra and scientific computing



port-Hamiltonian Systems (pHS)

Introduction to pHS I

- Deeply rooted in differential geometry (**Dirac structures**) and functional analysis



port-Hamiltonian Systems (pHS)

Introduction to pHS II

Dirac Structure

$\mathcal{D} \subset \mathcal{F} \times \mathcal{F}^*$ with $\dim \mathcal{D} = \dim \mathcal{F} < \infty$ is called **Dirac structure**, iff for duality product $\langle \cdot, \cdot \rangle$ it holds that

$$\langle e, f \rangle = 0 \quad \text{for all } (e, f) \in \mathcal{D}.$$

Duality Product for $\mathcal{F} = \mathbb{R}^k$

For $\mathcal{F} = \mathbb{R}^k$, we get

$$\langle e, f \rangle = e^\top f.$$

For a pHS with $e = (e_R, e_S, e_P)^\top$ and $f = (f_R, f_S, f_P)^\top$, we get

$$\langle e, f \rangle = e_R f_R + e_S f_S + e_P f_P \stackrel{!}{=} 0.$$

Linear port-Hamiltonian System:
Linear differential equation system

$$M\dot{x}(t) = (J - R)x(t) + Bu(t)$$

with

- ▶ coupling matrix J **skew symmetric**,
- ▶ resistive matrix R , s.t. $R + R^\top \succeq 0$,
- ▶ material matrix $M = M^\top \succeq 0$ and
- ▶ external port $Bu(t)$.



port-Hamiltonian Systems (pHS)

Why should we use pHS?

- ▶ **Physical Energy Conservation**
Energy changes only through internal dissipation or exchange via ports
- ▶ **Structure-Preserving Interconnection**
Modular coupling of multi-physical domains results in new pHS
- ▶ **Natural Stability**
Physical energy bounds naturally prevent unbounded system growth

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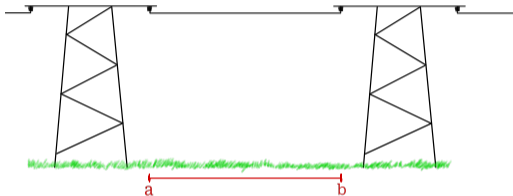
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A port-Hamiltonian Example

The 1D Transmission Line Model I

Continuous Formulation:



Telegrapher's Equations

$$R'i(z, t) + L' \frac{\partial i(z, t)}{\partial t} + \frac{\partial u(z, t)}{\partial z} = 0,$$

$$\frac{\partial i(z, t)}{\partial z} + G'u(z, t) + C' \frac{\partial u(z, t)}{\partial t} = 0,$$

with suitable boundary and initial conditions.

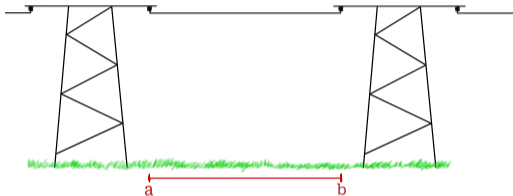
Properties:

- ▶ Describes voltage $u(z, t)$ and current $i(z, t)$ in space $z \in [a, b]$ and time $t \in [0, T]$
- ▶ Can be formulated as an infinite-dimensional port-Hamiltonian System

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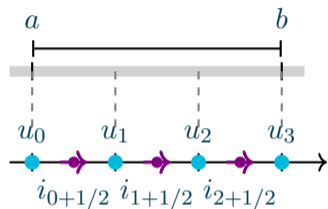
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Need a discretization that keeps pHS structure as well as energy properties!

A port-Hamiltonian Example

The 1D Transmission Line Model II

Space Discretization:



$$\mathbf{u} = (u_1, \dots, u_N)^\top, \quad \mathbf{i} = (i_{1/2}, \dots, i_{N+1/2})^\top, \quad B\mathbf{v} = (0_N, u_0, 0_N, u_{N+1})^\top$$

$$\frac{\partial}{\partial t} \underbrace{\begin{bmatrix} C' & 0 \\ 0 & L' \end{bmatrix}}_M \underbrace{\begin{bmatrix} \mathbf{u} \\ \mathbf{i} \end{bmatrix}}_{\mathbf{x}} = \left(\underbrace{\begin{bmatrix} 0 & -D \\ D^\top & 0 \end{bmatrix}}_J - \underbrace{\begin{bmatrix} G' & 0 \\ 0 & R' \end{bmatrix}}_R \right) \underbrace{\begin{bmatrix} \mathbf{u} \\ \mathbf{i} \end{bmatrix}}_{\mathbf{x}} + B\mathbf{v}$$

Time Discretization:

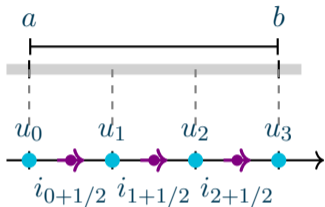
For $\mathbf{x}_k = \mathbf{x}(t_k)$, $t_k = k\tau$ and $\Gamma = \text{diag}(\mathbf{I}_N, -\mathbf{I}_{N+1})$, implicit midpoint rule yields

$$\Gamma A \mathbf{x}_{k+1} = \begin{bmatrix} \mathbf{I}_N (C' + \frac{\tau}{2} G') & \frac{\tau}{2} D \\ \frac{\tau}{2} D^\top & -\mathbf{I}_{N+1} (L' + \frac{\tau}{2} R') \end{bmatrix} \mathbf{x}_{k+1} = \Gamma b(\mathbf{x}_k)$$

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We get a Saddle Point Problem! – Coincidence? –

From pHS to SPP

- ▶ A space discrete port-Hamiltonian System **always** gives $M\dot{x}(t) = (J - R)x(t) + Bu(t)$, with

$$M = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} = M^\top \succeq 0, \quad J = \begin{bmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{bmatrix} = -J^\top, \quad R = \begin{bmatrix} R_{11} & R_{12} \\ R_{21} & R_{22} \end{bmatrix}$$

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- ▶ Need for symplectic and locally and globally energy consistent time discretization
→ Implicit Midpoint Rule



From pHS to SPP

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Proposition:

Applying implicit midpoint rule to a real valued linear pHS always yields

$$\mathcal{A} = M - \frac{\tau}{2}(J - R) = \begin{bmatrix} M_{11} - \frac{\tau}{2}J_{11} + \frac{\tau}{2}R_{11} & M_{12} - \frac{\tau}{2}J_{12} + \frac{\tau}{2}R_{12} \\ M_{12}^\top + \frac{\tau}{2}J_{12}^\top + \frac{\tau}{2}R_{21} & M_{22} - \frac{\tau}{2}J_{22} + \frac{\tau}{2}R_{22} \end{bmatrix}.$$

This fits the definition of a **generalized Saddle Point Problem** w.l.o.g.

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Preconditioning port-Hamiltonian Systems

Starting Point

What we have:

- ▶ 2×2 block-structure in the system matrix
- ▶ Generalized Saddle Point Problem
→ Under reasonable assumptions, even classic SPP



Preconditioning port-Hamiltonian Systems

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What we have:

- ▶ 2×2 block-structure in the system matrix
- ▶ Generalized Saddle Point Problem
→ Under reasonable assumptions, even classic SPP

What we want:

- ▶ Apply well known preconditioners for Saddle Point Problems on pHS
- ▶ Develop new preconditioners exploiting the pHS properties

A novel pH-Constraint Preconditioner

Classic Constraint Preconditioner:

Solve

$$Av = b \Leftrightarrow \begin{bmatrix} A & B_1 \\ B_2 & -C \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} f \\ g \end{bmatrix}$$

in two steps:

1. $y = (C + B_2 A^{-1} B_1)^{-1} (B_2 A^{-1} f - g)$
2. $x = A^{-1} (f - B_1 y)$

Implicit Midpoint Formulation:

For a linear pHS we always get

$$\mathcal{A} = \begin{bmatrix} M_{11} - \frac{\tau}{2} J_{11} + \frac{\tau}{2} R_{11} & M_{12} - \frac{\tau}{2} J_{12} + \frac{\tau}{2} R_{12} \\ M_{12}^\top + \frac{\tau}{2} J_{12}^\top + \frac{\tau}{2} R_{21} & M_{22} - \frac{\tau}{2} J_{22} + \frac{\tau}{2} R_{22} \end{bmatrix}$$

Proposition:

Writing the Schur Complement as

$$S = C + B_2 A^{-1} B_1 =: S_1 + S_2,$$

we see that for an underlying pHS

$$-S_1 = \underbrace{M_{22} + \frac{\tau}{2} R_{22}^{\text{sym}}}_{S_1^{\text{sym}}} + \underbrace{\frac{\tau}{2} (R_{22}^{\text{skew}} - J_{22})}_{S_1^{\text{skew}}}$$

with $R_{22}^{\text{skew/sym}} = \frac{1}{2} (R_{22} \pm R_{22}^\top)$.

Unique HSS Splitting:

No explicit J, M, R needed!



A novel pH-Constraint Preconditioner

We have to solve:

1. $y = (C + B_2 A^{-1} B_1)^{-1} (B_2 A^{-1} f - g)$
2. $x = A^{-1} (f - B_1 y)$

Outer Solver:

Take e.g. AMG solver to approximate A^{-1}

Inner Solver:

- ▶ Approximate just S_1 instead of S
- ▶ **Widlund method** to approximate S_1^{-1}
- ▶ Use e.g. AMG to approximate $(S_1^{\text{sym}})^{-1}$

Algorithm:

1. **Inner Solve I (AMG):**
 $\tilde{f} = \text{AMG}(A).\text{matvec}(f)$
2. **Schur RHS:**
 $r_S = B_2 \tilde{f} - g$
3. **Inner Solve II (Widlund):**
 $y = \text{Widlund}(S_1, r_S)$
4. **Outer Solve (AMG):**
 $x = \text{AMG}(A).\text{matvec}(f - B_1 y)$

Preconditioning port-Hamiltonian Systems

Considered Candidates

Baselines & General-Purpose:

- ▶ No Preconditioner – Pure GMRES
- ▶ Incomplete LU Decomposition

pHS related:

- ▶ Widlund
- ▶ Rapoport

SPP related:

- ▶ SIMPLE Block-Triangular
- ▶ Constraint (AMG/ILU inner solver)

pHS & SPP related:

- ▶ Novel constraint preconditioning approach

Preconditioning port-Hamiltonian Systems

Test Problems

Stabilized Stokes Problem

(cf. Gdc et al., 2022)

- ▶ Discretization of unsteady incompressible Stokes equations yields $\mathcal{A} = H + S$
- ▶ The Hermitian part $H = H^\top \succeq 0$ and skew-Hermitian part $S = -S^\top$

$$\mathcal{A} = \begin{bmatrix} M - \frac{\tau}{2} A_H & -\frac{\tau}{2} B \\ \frac{\tau}{2} B^* & -\frac{\tau}{2} C \end{bmatrix}$$

with C stabilization term

Transmission Line & Maxwell pHS

(cf. Kasolis et al., in prep.)

- ▶ Discrete pH-coupling of Transmission Line Model and Maxwell's equations
- ▶ With impl. midpoint rule pH-System $M\dot{x} = (J - R)x + Bf$ yields

$$\mathcal{A} = \begin{bmatrix} M^L + \frac{\tau}{2} M^R & -\frac{\tau}{2} \Theta & 0 \\ \frac{\tau}{2} \Theta^\top & M^\epsilon + \frac{\tau}{2} (M^\sigma + Z^\eta) & -\frac{\tau}{2} K^\top \\ 0 & \frac{\tau}{2} K & M^\mu \end{bmatrix}$$

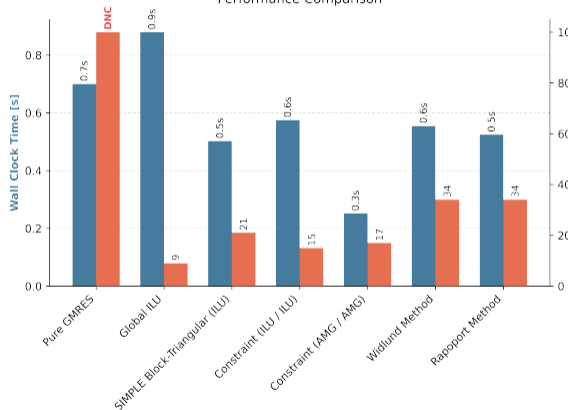


A novel pH-Constraint Preconditioner

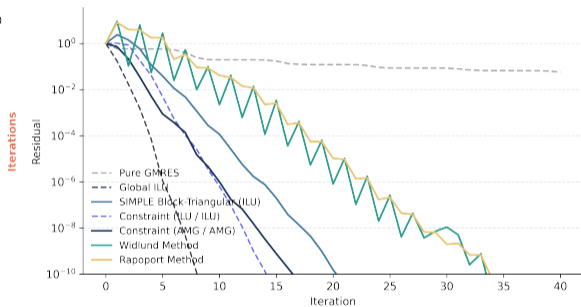
Numerical Results – Stabilized Stokes I

Stabilized Stokes (49923 x 49923) Acc. 1.0e-10

Performance Comparison



Residual Evolution

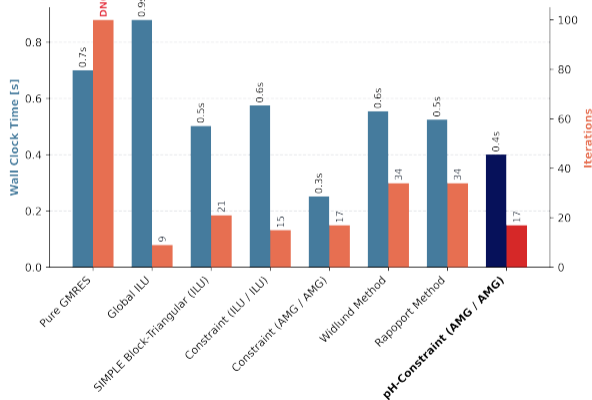


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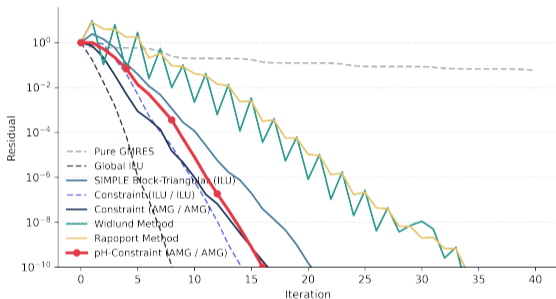
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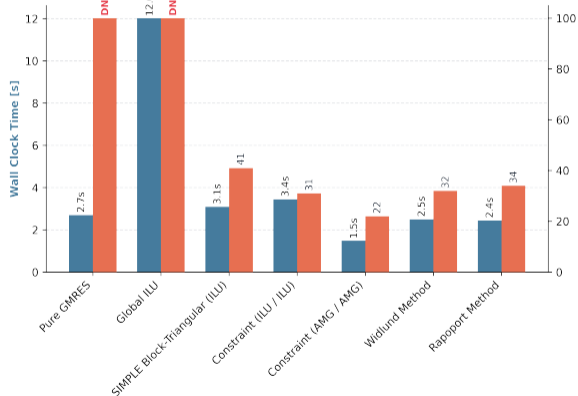


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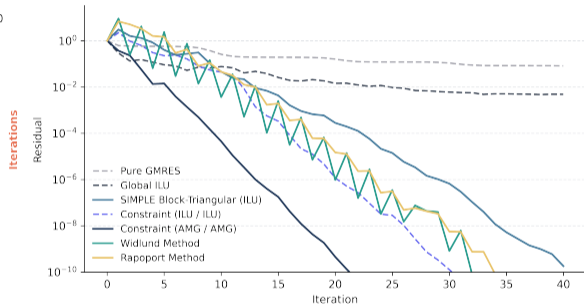
Numerical Results – Stabilized Stokes II

Stabilized Stokes (198147 x 198147) Acc. 1.0e-10

Performance Comparison



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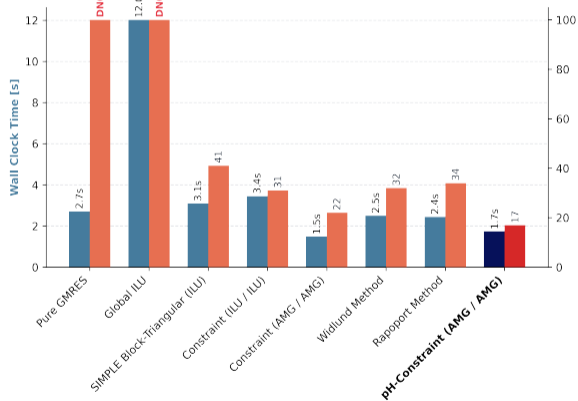


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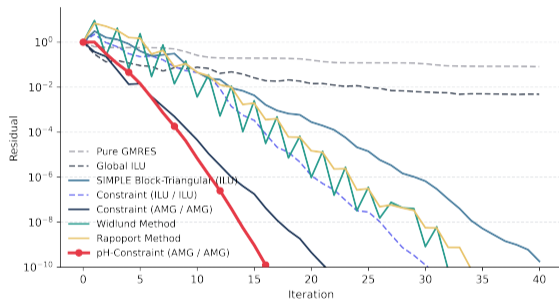
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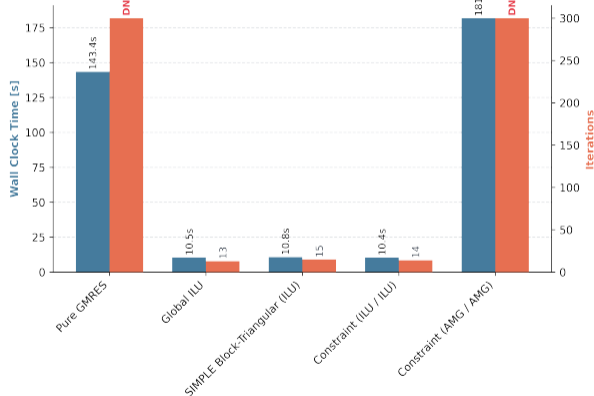
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A novel pH-Constraint Preconditioner

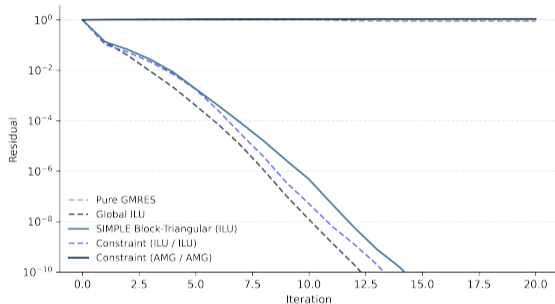
Numerical Results – Coupled Transmission Line

Antenna 2D (1203424 x 1203424) Acc. 1.0e-10

Performance Comparison



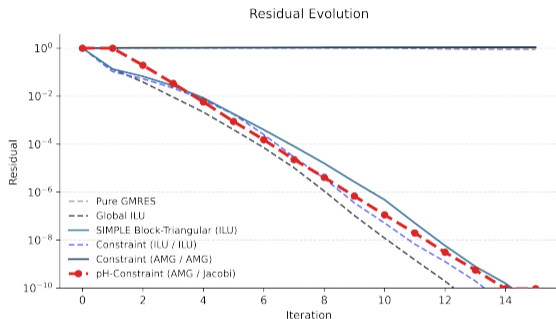
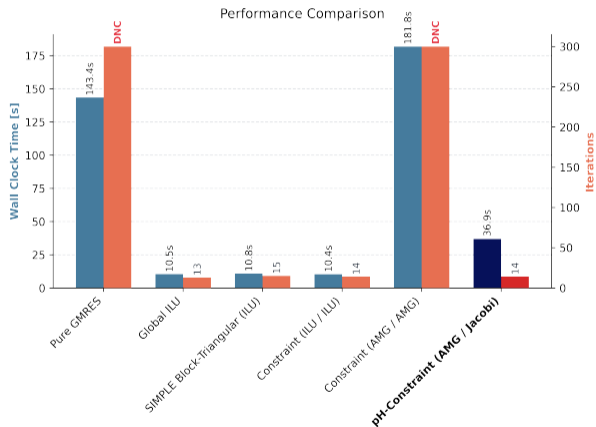
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How? Preconditioning Strategies

How can we exploit the pHS structure to construct efficient SPP preconditioners?

- ▶ Implicit midpoint rule transforms any linear port-Hamiltonian System into a generalized Saddle Point Problem
- ▶ Established preconditioners for Saddle Point Problems also work for port-Hamiltonian Systems
- ▶ Novel pH-Constraint preconditioner exploits both SPP and pHS structures, overcoming the non-scalability and null-space issues of standard approaches



Thanks for your Attention!

Slides and Contact:



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There's More!

port-Hamiltonian Systems (pHS)

Definition Dirac Structure

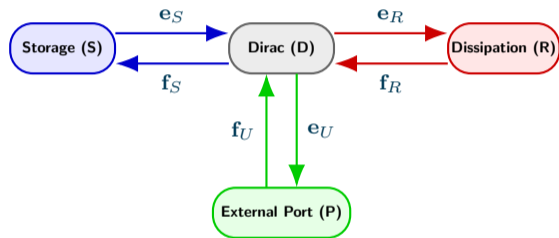
Definition Dirac Structure

Let there be:

- ▶ A finite-dimensional linear space \mathcal{F} ,
- ▶ its dual space $\mathcal{E} = \mathcal{F}^*$ and
- ▶ the duality product $\langle e, f \rangle$ for $(e, f) \in \mathcal{E} \times \mathcal{F}$.

Then, $\mathcal{D} \subset \mathcal{F} \times \mathcal{E}$ with $\dim \mathcal{D} = \dim \mathcal{F}$ is called **Dirac structure**, iff

$$\langle e, f \rangle = 0 \quad \text{for all } (e, f) \in \mathcal{D}.$$



From pHS to SPP

Proof I

We know that for a real valued linear pHS implicit midpoint rule gives

$$A = M - \frac{\tau}{2}(J - R) = \begin{bmatrix} M_{11} - \frac{\tau}{2}J_{11} + \frac{\tau}{2}R_{11} & M_{12} - \frac{\tau}{2}J_{12} + \frac{\tau}{2}R_{12} \\ M_{12}^\top + \frac{\tau}{2}J_{12}^\top + \frac{\tau}{2}R_{21} & M_{22} - \frac{\tau}{2}J_{22} + \frac{\tau}{2}R_{22} \end{bmatrix}.$$

A **generalized Saddle Point Problem**, requires at least one of the following conditions to hold:

C1 A is symmetric.

C2 The symmetric part $H = \frac{1}{2}(A + A^\top)$ is positive semidefinite.

C3 $B_1 = B_2 = B$.

C4 C is symmetric positive definite.

C5 $C = 0$.



From pHS to SPP

Proof II

We use C2. We have

$$A = M_{11} - \frac{\tau}{2}J_{11} + \frac{\tau}{2}R_{11}.$$

This gives

$$\frac{1}{2}(A + A^T) = \frac{1}{2} \left((M_{11} - \frac{\tau}{2}J_{11} + \frac{\tau}{2}R_{11}) + (M_{11}^T - \frac{\tau}{2}J_{11}^T + \frac{\tau}{2}R_{11}^T) \right)$$

due to symmetry of M and skew symmetry of J

$$\begin{aligned} &= \frac{1}{2} \left((M_{11} - \frac{\tau}{2}J_{11} + \frac{\tau}{2}R_{11}) + (M_{11} + \frac{\tau}{2}J_{11} + \frac{\tau}{2}R_{11}^T) \right) \\ &= M_{11} + \frac{\tau}{4}(R_{11} + R_{11}^T). \end{aligned}$$

Since $M \succeq 0$ and $R + R^T \succeq 0$ this is also positive semi-definite.

Motivation for Approximation of S

We have

$$S = \underbrace{C}_{S_1} + \underbrace{B_2 A^{-1} B_1}_{S_2}.$$

From the pHS structure, we know that:

$$S_1 = C = \frac{\tau}{2}(J_{22} - R_{22}) - M_{22}$$

$$S_2 = B_2 A^{-1} B_1 = \left[M_{21} - \frac{\tau}{2}(J_{21} - R_{21}) \right] \left[M_{11} - \frac{\tau}{2}(J_{11} - R_{11}) \right]^{-1} \left[M_{12} - \frac{\tau}{2}(J_{12} - R_{12}) \right]$$

Making the reasonable assumption that the non-diagonal blocks of M are zero, we get:

$$S_1 \sim -M_{22} + \mathcal{O}(\tau), \quad S_2 \sim \mathcal{O}(\tau^2)$$

→ **For small τ S_2 becomes neglectable!**

Used Solvers/Preconditioners

Global Preconditioners/Solvers

GMRES:

- ▶ Custom implementation of Full GMRES
- ▶ Computes x explicitly in each iteration to determine the residual exactly

Jacobi:

- ▶ **Jacobi:** Diagonal inverse applied to the whole system A

Global ILU:

- ▶ BlackBox SciPy implementation of sparse ILU decomposition applied to whole A

Used Solvers/Preconditioners

SIMPLE Preconditioners

SIMPLE Diagonal:

- ▶ Approximation of A -block by inverse diagonal
- ▶ Approximation of Schur complement $S \approx C + B_2(\text{diag}(A))^{-1}B_1$ by SciPy implementation of sparse ILU decomposition

SIMPLE Tridiagonal:

- ▶ SIMPLE diagonal approach with substitution step for x
- ▶ Schur complement approximation by SciPy implementation of sparse ILU decomposition

Used Solvers/Preconditioners

Constraint Preconditioners

Constraint ILU / ILU:

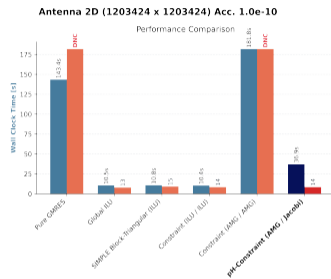
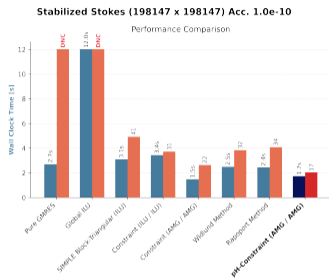
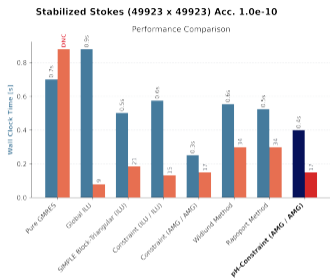
- ▶ A^{-1} approximation by SciPy implementation of sparse ILU decomposition
- ▶ Approximation of inverse Schur complement S^{-1} by SciPy implementation of sparse ILU decomposition

Constraint AMG / AMG:

- ▶ A^{-1} approximation by pyAMG implementation of smoothed aggregation AMG
- ▶ Approximation of inverse Schur complement S^{-1} by pyAMG implementation of smoothed aggregation AMG



Performance Comparison



- ▶ Global ILU scales poorly and fails to converge for large-scale SPPs
- ▶ AMG struggles with large null spaces → pH-Constraint + Jacobi does not
- New solver is scalable and addresses the AMG problem with exchangeable inner solvers!