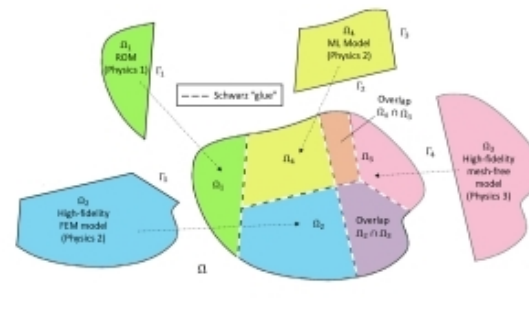
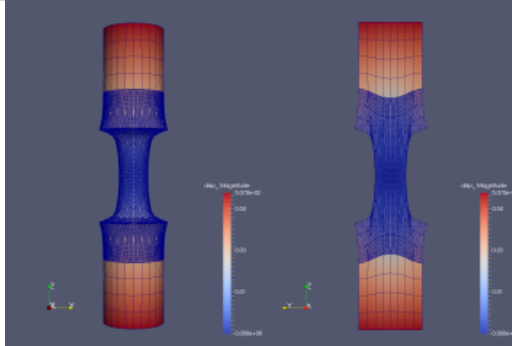
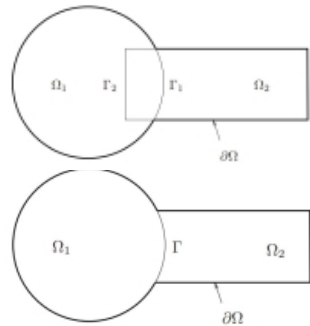




Application of the Schwarz alternating method for the coupling of nonlinear solid mechanics-based and fluids-based full order models to nonlinear reduced order models



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¹Sandia National Laboratories, ²Stanford University

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Cannes, France. April 28, 2023



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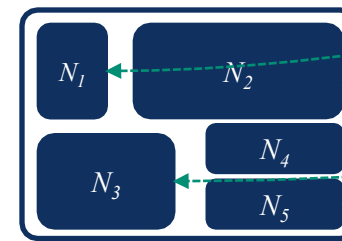
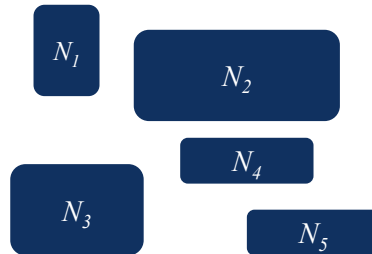
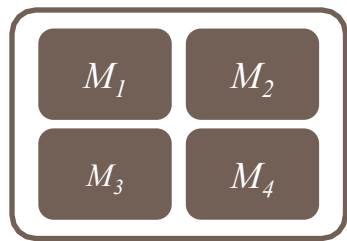


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Motivation

The past decades have seen tremendous investment in **simulation frameworks for coupled multi-scale and multi-physics problems**.

- Frameworks rely on **established mathematical theories** to couple physics components.
- Most existing coupling frameworks are based on **traditional discretization methods**.



Complex System Model

- PDEs, ODEs
- Nonlocal integral
- Classical DFT
- Atomistic, ...

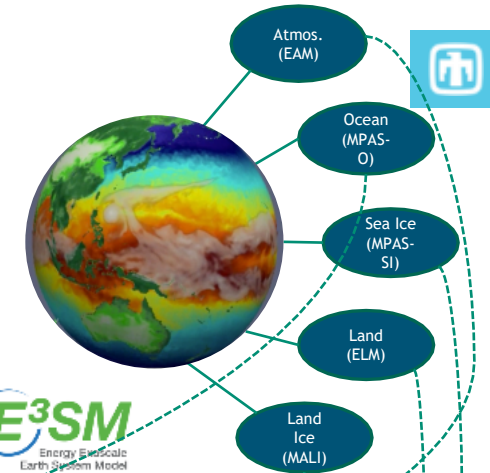
Traditional Methods

- Mesh-based (FE, FV, FD)
- Meshless (SPH, MLS)
- Implicit, explicit
- Eulerian, Lagrangian...

Coupled Numerical Model

- Monolithic (Lagrange multipliers)
- Partitioned (loose) coupling
- Iterative (Schwarz, optimization)

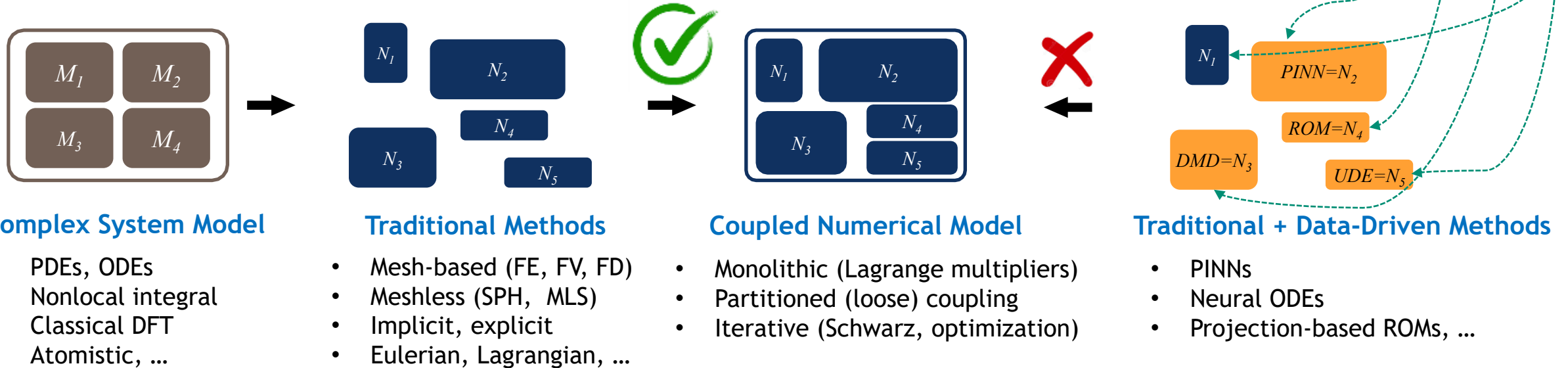
E³SM
Energy-Euscale
Earth System Model



Motivation

The past decades have seen tremendous investment in **simulation frameworks for coupled multi-scale and multi-physics problems**.

- Frameworks rely on **established mathematical theories** to couple physics components.
- Most existing coupling frameworks are based on **traditional discretization methods**.



- There is currently a big push to integrate **data-driven methods** into modeling & simulation toolchains.

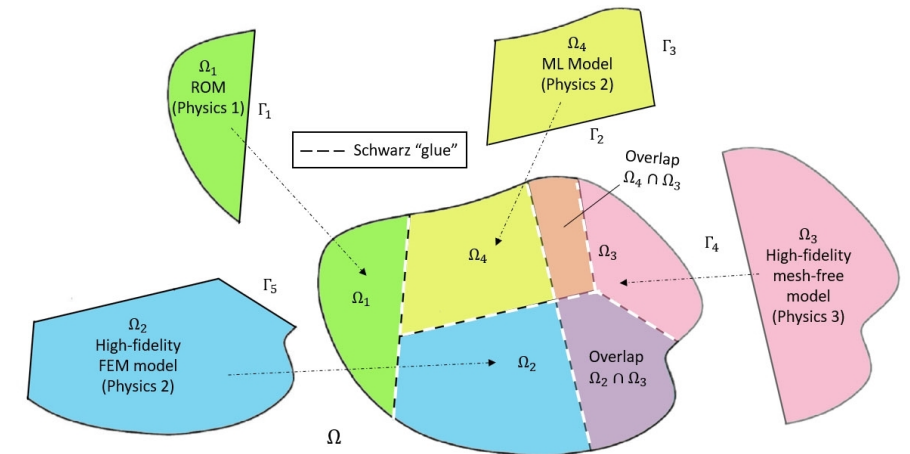
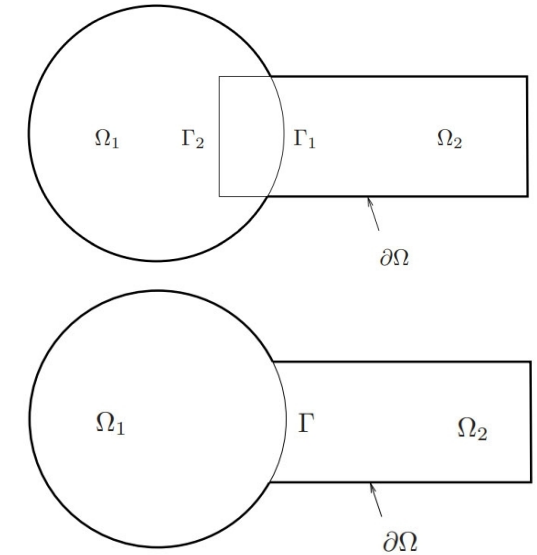
Unfortunately, existing algorithmic and software infrastructures are **ill-equipped** to handle plug-and-play integration of **non-traditional, data-driven models**!

1. The Alternating Schwarz Method for FOM*-ROM[#] and ROM-ROM Coupling

- Method Formulation
- ROM Construction and Implementation
- Numerical Example: Solid Mechanics
- Numerical Example: Fluid Mechanics

2. Summary and Comparison of Methods

3. Future Work

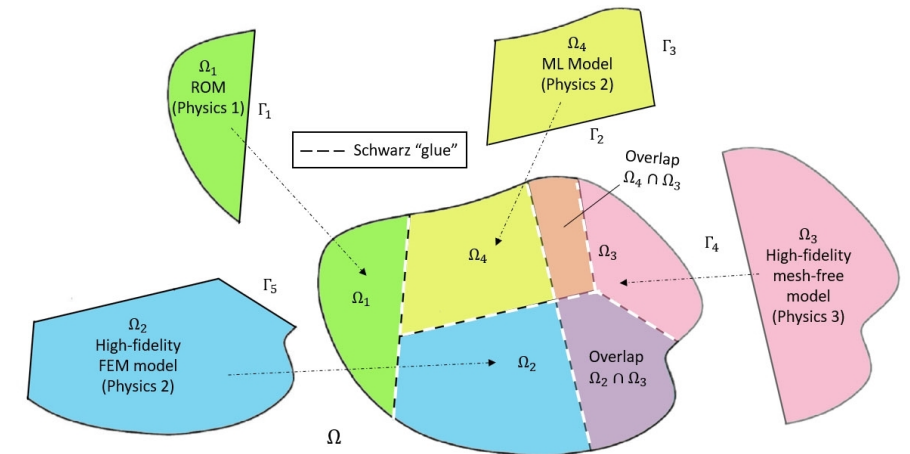
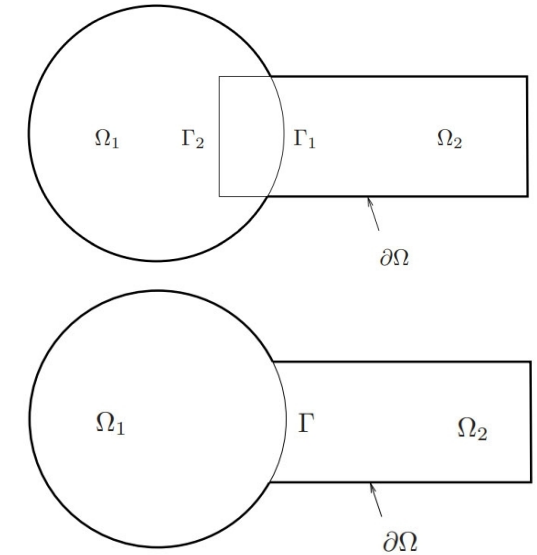


1. The Alternating Schwarz Method for FOM*-ROM[#] and ROM-ROM Coupling

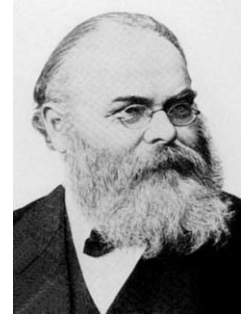
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Schwarz Alternating Method for Domain Decomposition



H. Schwarz (1843-1921)

- Proposed in 1870 by H. Schwarz for solving Laplace PDE on irregular domains.

Crux of Method: if the solution is known in regularly shaped domains, use those as pieces to iteratively build a solution for the more complex domain.

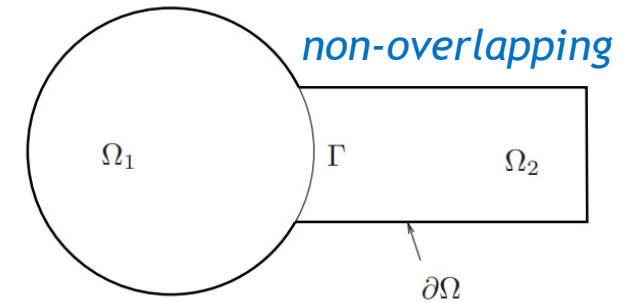
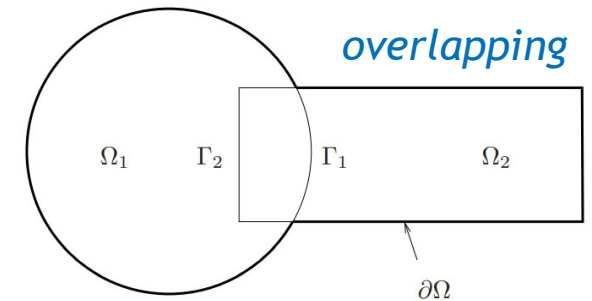
Basic Schwarz Algorithm

Initialize:

- Solve PDE by any method on Ω_1 w/ initial guess for transmission BCs on Γ_1 .

Iterate until convergence:

- Solve PDE by any method on Ω_2 w/ transmission BCs on Γ_2 based on values just obtained for Ω_1 .
- Solve PDE by any method on Ω_1 w/ transmission BCs on Γ_1 based on values just obtained for Ω_2 .



- Schwarz alternating method most commonly used as a **preconditioner** for Krylov iterative methods to solve linear algebraic equations.

Idea behind this work: using the Schwarz alternating method as a **discretization method** for solving multi-scale or multi-physics partial differential equations (PDEs).

How We Use the Schwarz Alternating Method



AS A *PRECONDITIONER*
FOR THE LINEARIZED
SYSTEM

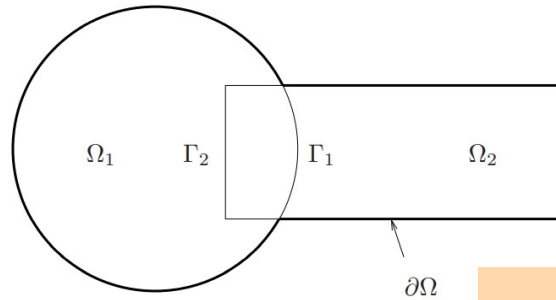


AS A *SOLVER* FOR THE
COUPLED
FULLY NONLINEAR
PROBLEM

Overlapping Domain Decomposition

$$\begin{cases} N(\mathbf{u}_1^{(n+1)}) = f, & \text{in } \Omega_1 \\ \mathbf{u}_1^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_1 \setminus \Gamma_1 \\ \mathbf{u}_1^{(n+1)} = \mathbf{u}_2^{(n)} & \text{on } \Gamma_1 \end{cases}$$

$$\begin{cases} N(\mathbf{u}_2^{(n+1)}) = f, & \text{in } \Omega_2 \\ \mathbf{u}_2^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_2 \setminus \Gamma_2 \\ \mathbf{u}_2^{(n+1)} = \mathbf{u}_1^{(n+1)} & \text{on } \Gamma_2 \end{cases}$$



$$\text{Model PDE: } \begin{cases} N(\mathbf{u}) = \mathbf{f}, & \text{in } \Omega \\ \mathbf{u} = \mathbf{g}, & \text{on } \partial\Omega \end{cases}$$

- Dirichlet-Dirichlet transmission BCs [Schwarz 1870; Lions 1988; Mota *et al.* 2017; Mota *et al.* 2022]

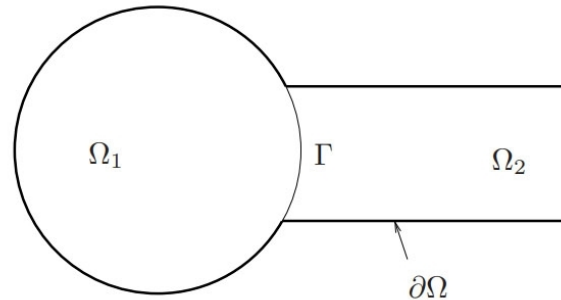
This talk: sequential subdomain solves (*multiplicative Schwarz*). Parallel subdomain solves (*additive Schwarz*) also possible.

Non-overlapping Domain Decomposition

$$\begin{cases} N(\mathbf{u}_1^{(n+1)}) = f, & \text{in } \Omega_1 \\ \mathbf{u}_1^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_1 \setminus \Gamma \\ \mathbf{u}_1^{(n+1)} = \lambda_{n+1}, & \text{on } \Gamma \end{cases}$$

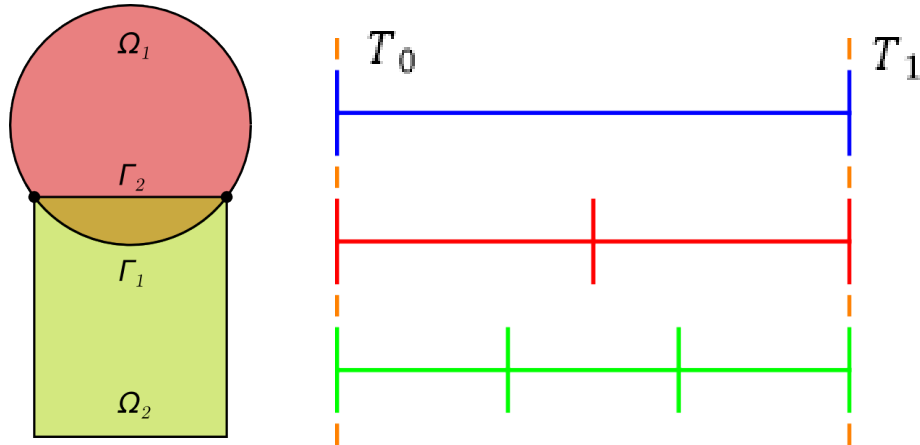
$$\begin{cases} N(\mathbf{u}_2^{(n+1)}) = f, & \text{in } \Omega_2 \\ \mathbf{u}_2^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_2 \setminus \Gamma \\ \nabla \mathbf{u}_2^{(n+1)} \cdot \mathbf{n} = \nabla \mathbf{u}_1^{(n+1)} \cdot \mathbf{n}, & \text{on } \Gamma \end{cases}$$

$$\lambda_{n+1} = \theta \varphi_2^{(n)} + (1 - \theta) \lambda_n, \text{ on } \Gamma, \text{ for } n \geq 1$$



- Relevant for multi-material and multi-physics coupling
- Alternating Dirichlet-Neumann transmission BCs [Zanolli *et al.* 1987]
- Robin-Robin transmission BCs also lead to convergence [Lions 1990]
- $\theta \in [0,1]$: relaxation parameter (can help convergence)

Time-Advancement Within the Schwarz Framework



Controller time stepper

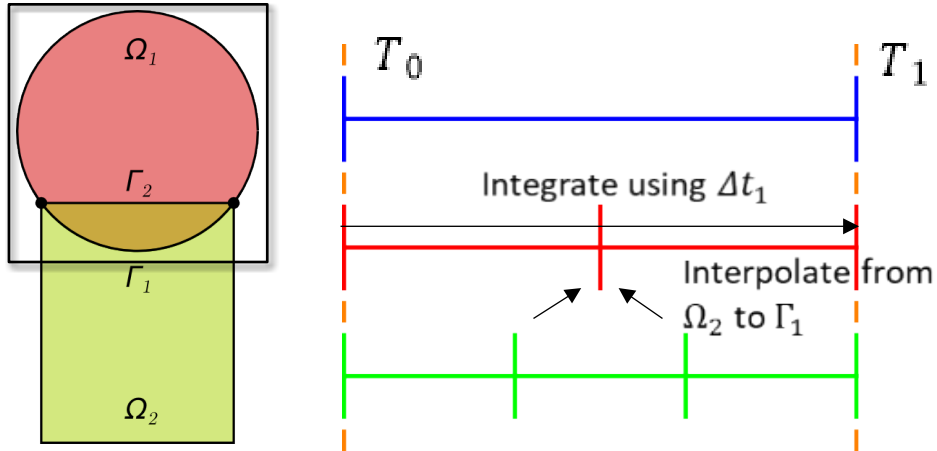
Time integrator for Ω_1

Time integrator for Ω_2

Step 0: Initialize $i = 0$ (controller time index).

$$\text{Model PDE: } \begin{cases} \dot{\mathbf{u}} + N(\mathbf{u}) = \mathbf{f}, & \text{in } \Omega \\ \mathbf{u}(\mathbf{x}, t) = \mathbf{g}(t), & \text{on } \partial\Omega \\ \mathbf{u}(\mathbf{x}, 0) = \mathbf{u}_0, & \text{in } \Omega \end{cases}$$

Time-Advancement Within the Schwarz Framework



Controller time stepper

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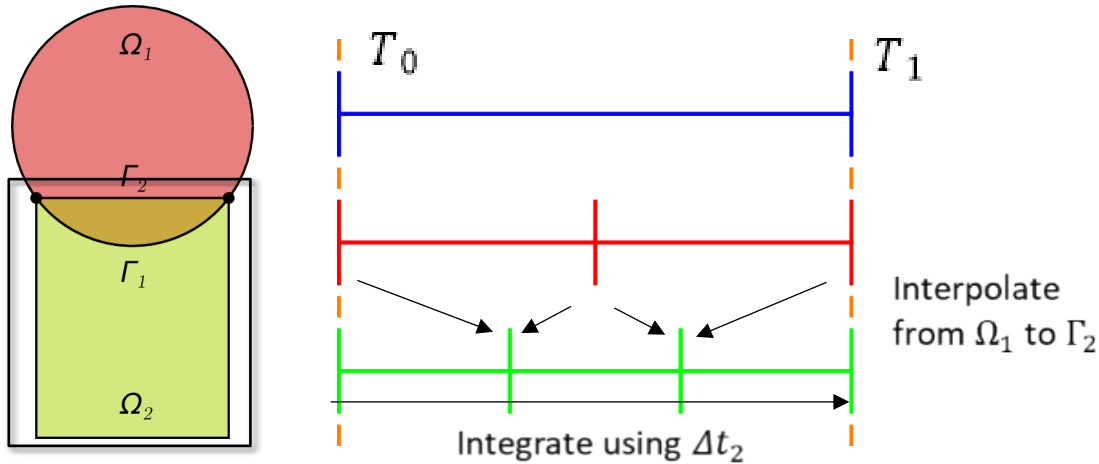
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Step 1: Advance Ω_1 solution from time T_i to time T_{i+1} using time-stepper in Ω_1 with time-step Δt_1 , using solution in Ω_2 interpolated to Γ_1 at times $T_i + n\Delta t_1$.

Model PDE:

$$\begin{cases} \dot{\mathbf{u}} + N(\mathbf{u}) = \mathbf{f}, & \text{in } \Omega \\ \mathbf{u}(\mathbf{x}, t) = \mathbf{g}(t), & \text{on } \partial\Omega \\ \mathbf{u}(\mathbf{x}, 0) = \mathbf{u}_0, & \text{in } \Omega \end{cases}$$

Time-Advancement Within the Schwarz Framework



Controller time stepper

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Time integrator for Ω_2

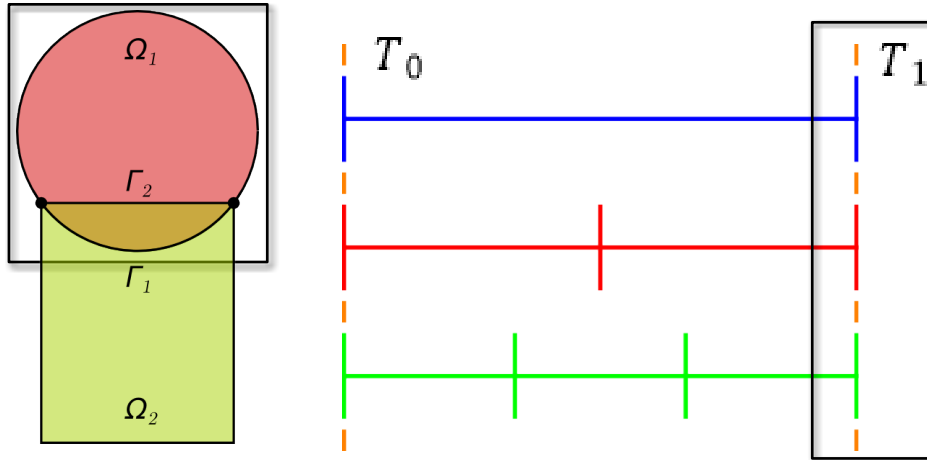
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Step 2: Advance Ω_2 solution from time T_i to time T_{i+1} using time-stepper in Ω_2 with time-step Δt_2 , using solution in Ω_1 interpolated to Γ_2 at times $T_i + n\Delta t_2$.

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Time-Advancement Within the Schwarz Framework



Controller time stepper

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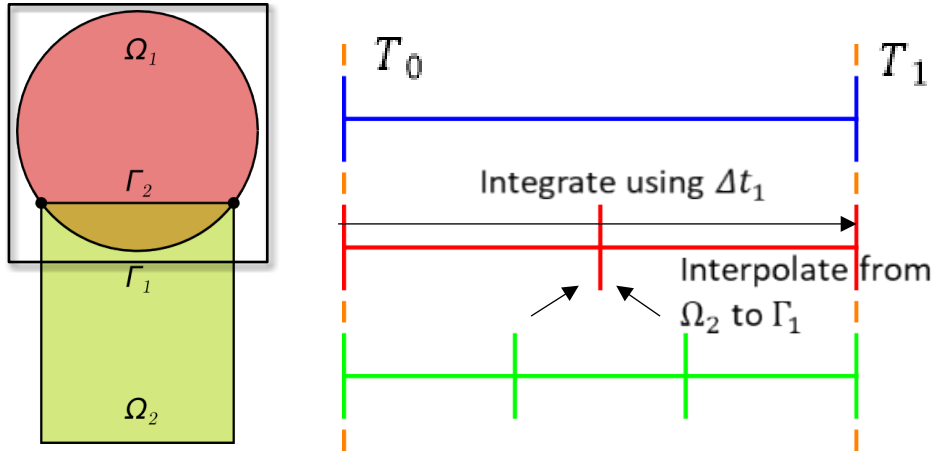
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Step 3: Check for convergence at time T_{i+1} .

$$\text{Model PDE: } \begin{cases} \dot{\mathbf{u}} + N(\mathbf{u}) = \mathbf{f}, & \text{in } \Omega \\ \mathbf{u}(\mathbf{x}, t) = \mathbf{g}(t), & \text{on } \partial\Omega \\ \mathbf{u}(\mathbf{x}, 0) = \mathbf{u}_0, & \text{in } \Omega \end{cases}$$

Time-Advancement Within the Schwarz Framework



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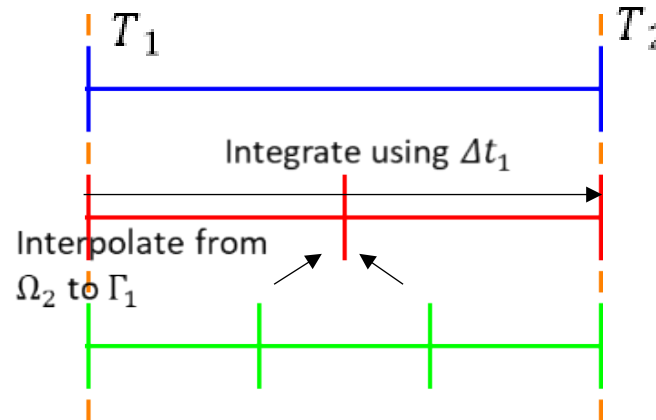
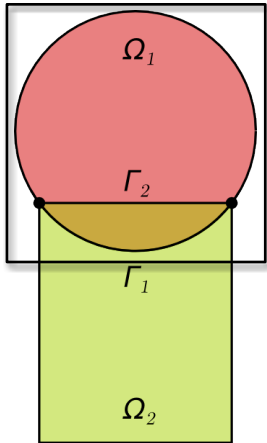
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Step 3: Check for convergence at time T_{i+1} .

➤ If unconverged, return to Step 1.

Model PDE:

$$\begin{cases} \dot{\mathbf{u}} + N(\mathbf{u}) = \mathbf{f}, & \text{in } \Omega \\ \mathbf{u}(\mathbf{x}, t) = \mathbf{g}(t), & \text{on } \partial\Omega \\ \mathbf{u}(\mathbf{x}, 0) = \mathbf{u}_0, & \text{in } \Omega \end{cases}$$



Controller time stepper

Time integrator for Ω_1

Time integrator for Ω_2

Can use ***different integrators*** with ***different time steps*** within each domain!

Step 0: Initialize $i = 0$ (controller time index).

Step 1: Advance Ω_1 solution from time T_i to time T_{i+1} using time-stepper in Ω_1 with time-step Δt_1 , using solution in Ω_2 interpolated to Γ_1 at times $T_i + n\Delta t_1$.

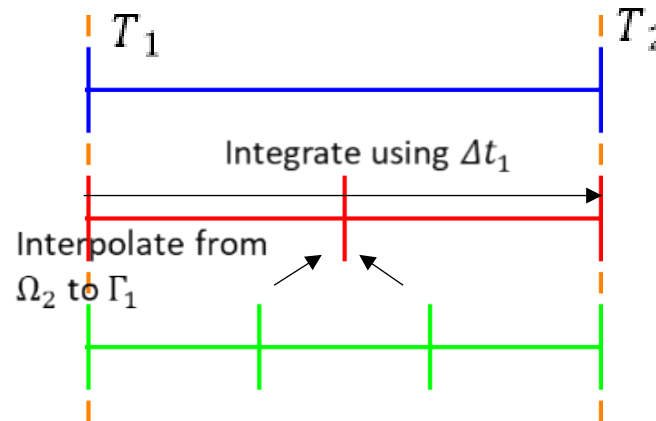
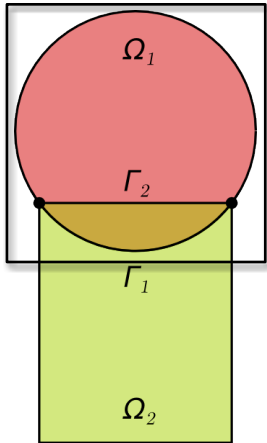
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Step 3: Check for convergence at time T_{i+1} .

- If unconverged, return to Step 1.
- If converged, set $i = i + 1$ and return to Step 1.

Model PDE:

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Controller time stepper

Time integrator for Ω_1

Time integrator for Ω_2

Time-stepping procedure is **equivalent** to doing Schwarz on **space-time domain** [Mota *et al.* 2022].

Step 0: Initialize $i = 0$ (controller time index).

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Schwarz for Multiscale FOM-FOM Coupling in Solid Mechanics¹

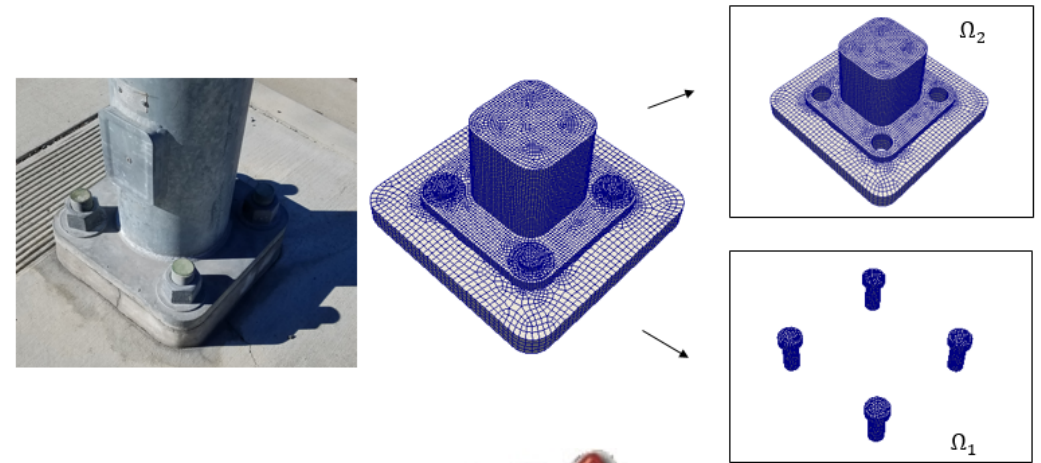


Model Solid Mechanics PDEs:

Quasistatic: $\text{Div } \mathbf{P} + \rho_0 \mathbf{B} = \mathbf{0} \quad \text{in } \Omega$

Dynamic: $\text{Div } \mathbf{P} + \rho_0 \mathbf{B} = \rho_0 \ddot{\boldsymbol{\varphi}} \quad \text{in } \Omega \times I$

- Coupling is **concurrent** (two-way).
- **Ease of implementation** into existing massively-parallel HPC codes.
- **Scalable, fast, robust** (we target **real** engineering problems, e.g., analyses involving failure of bolted components!).
- Coupling does not introduce **nonphysical artifacts**.
- **Theoretical** convergence properties/guarantees¹.
- “**Plug-and-play**” framework:
 - Ability to couple regions with **different non-conformal meshes**, **different element types** and **different levels of refinement** to simplify task of **meshing complex geometries**.
 - Ability to use **different solvers/time-integrators** in different regions.

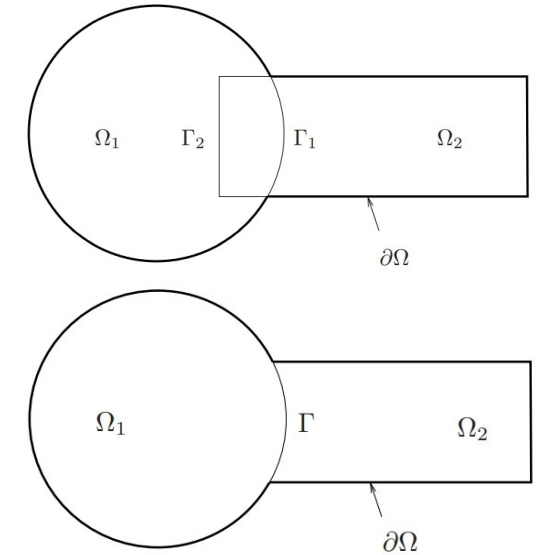


¹ Mota et al. 2017; Mota et al. 2022. ² <https://github.com/sandialabs/LCM>.



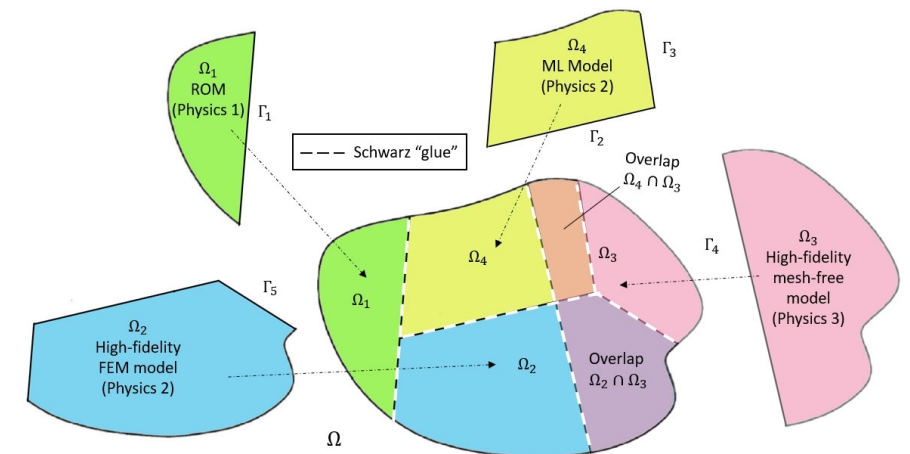
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2. Summary and Comparison of Methods

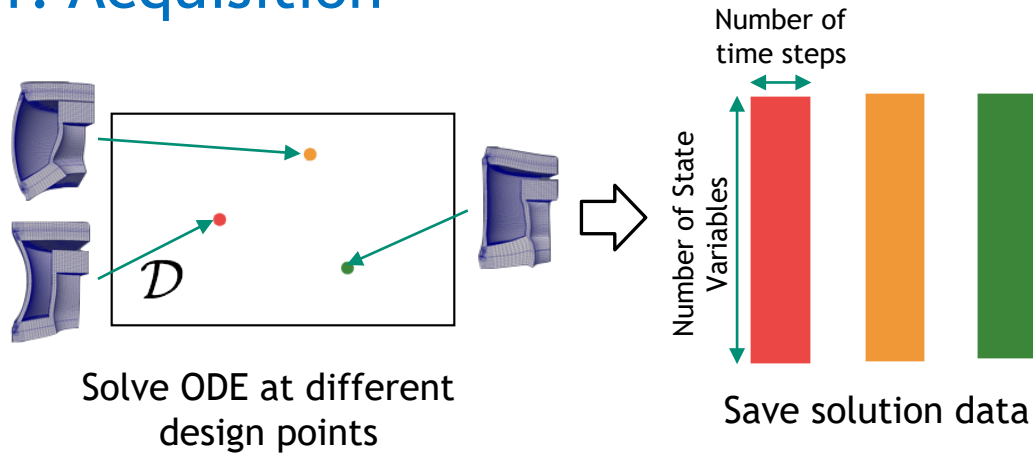
3. Future Work



Projection-Based Model Order Reduction via the POD/Galerkin Method

Full Order Model (FOM): $M \frac{d^2 u}{dt^2} + f_{\text{int}}(u) = f_{\text{ext}}$

1. Acquisition



2. Learning

Proper Orthogonal Decomposition (POD):

$$X = \begin{bmatrix} \text{red} & \text{orange} & \text{green} \end{bmatrix} = \Phi \begin{bmatrix} \text{brown} & \text{blue} \end{bmatrix} \begin{matrix} \Sigma \\ \text{blue box } v^T \end{matrix}$$

ROM = projection-based Reduced Order Model

3. Projection-Based Reduction

Reduce the number of unknowns

$$u(t) \approx \tilde{u}(t) = \Phi \hat{u}(t)$$

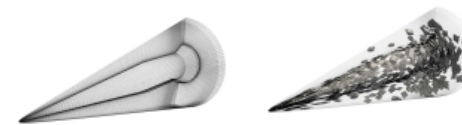


Perform Galerkin projection

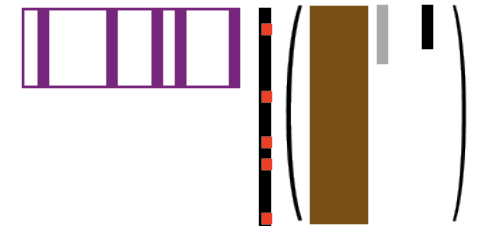
$$\Phi^T M \Phi \frac{d^2 \hat{u}}{dt^2} + \Phi^T f_{\text{int}}(\Phi \hat{u}) = \Phi^T f_{\text{ext}}$$

Hyper-reduce nonlinear terms

$$f_{\text{int}}(\Phi \hat{u}) \approx A f_{\text{int}}(\Phi \hat{u})$$



Hyper-reduction/sample mesh



HROM = Hyper-reduced ROM

Schwarz Extensions to FOM-ROM and ROM-ROM Couplings

Enforcement of Dirichlet boundary conditions (DBC) in ROM at indices i_{Dir}

- Method I in [Gunzburger *et al.* 2007] is employed

$$\mathbf{u}(t) \approx \bar{\mathbf{u}} + \Phi \hat{\mathbf{u}}(t), \quad \mathbf{v}(t) \approx \bar{\mathbf{v}} + \Phi \hat{\mathbf{v}}(t), \quad \mathbf{a}(t) \approx \bar{\mathbf{a}} + \Phi \hat{\mathbf{a}}(t)$$

- POD modes made to satisfy homogeneous DBCs: $\Phi(i_{\text{Dir}}, :) = \mathbf{0}$
- BCs imposed by modifying $\bar{\mathbf{u}}, \bar{\mathbf{v}}, \bar{\mathbf{a}}$: $\bar{\mathbf{u}}(i_{\text{Dir}}) \leftarrow \chi_u, \bar{\mathbf{v}}(i_{\text{Dir}}) \leftarrow \chi_v, \bar{\mathbf{a}}(i_{\text{Dir}}) \leftarrow \chi_a$

Choice of domain decomposition

- Error-based indicators that help decide in what region of the domain a ROM can be viable should drive domain decomposition [Bergmann *et al.* 2018] (future work)

Snapshot collection and reduced basis construction

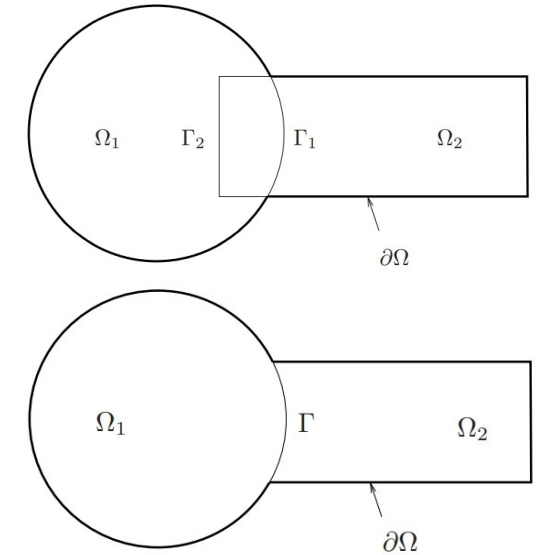
- POD results presented herein use snapshots obtained via FOM-FOM coupling on $\Omega = \bigcup_i \Omega_i$
- Scenario I*: generate snapshots/bases separately in each Ω_i [Hoang *et al.* 2021, Smetana *et al.* 2022]

For nonlinear solid mechanics, hyper-reduction methods need to preserve Hamiltonian structure

- We employ the Energy-Conserving Sampling & Weighting Method (ECSW) [Farhat *et al.* 2015]
- Boundary points must be included in sample mesh for DBC enforcement

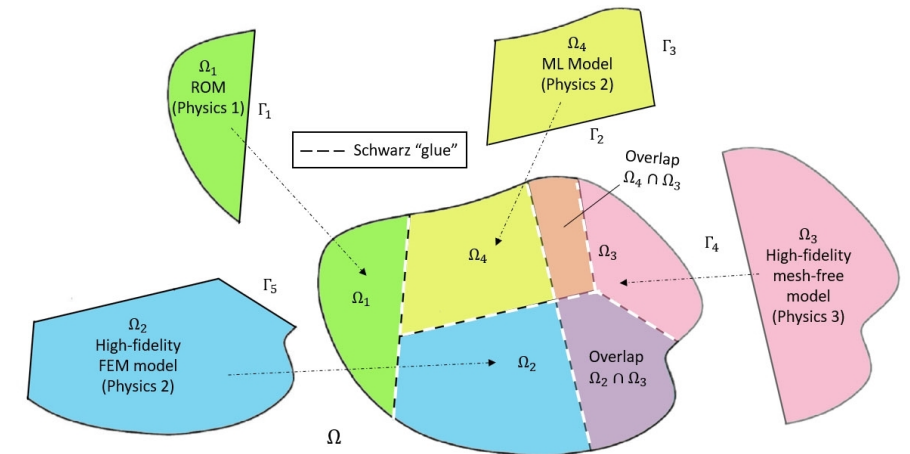
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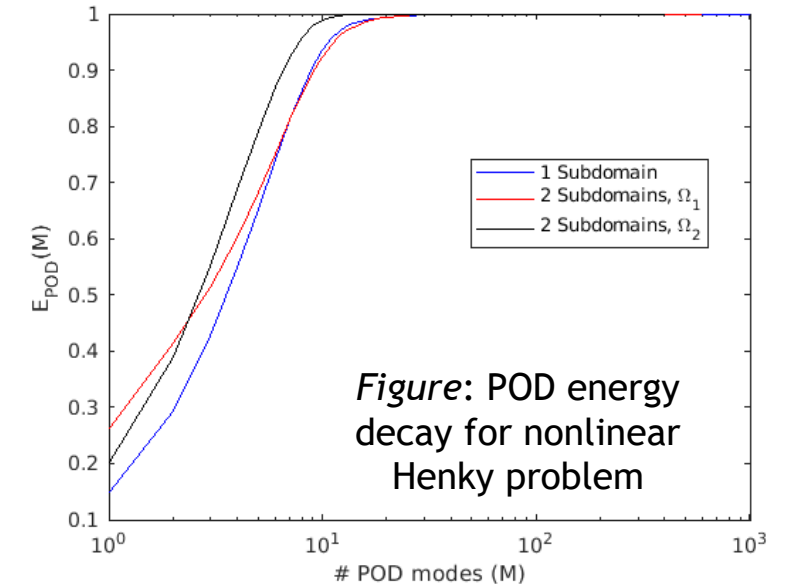


Numerical Example: 1D Dynamic Wave Propagation



Problem

- **1D beam** geometry $\Omega = (0,1)$, clamped at both ends, with prescribed initial condition discretized using FEM + Newmark- β
- Simple problem but very **stringent test** for discretization/coupling methods.
- Two **constitutive models** considered:
 - Linear elastic (problem has exact analytical solution)
 - Nonlinear hyperelastic Henky **This talk**
- ROMs results are **reproductive** and **predictive**, and are based on the **POD/Galerkin** method, with POD calculated from FOM-FOM coupled model.
 - 50 POD modes capture $\sim 100\%$ snapshot energy for linear variant of this problem.
 - 536 POD modes capture $\sim 100\%$ snapshot energy for Henky variant of this problem.
- Hyper-reduced ROMs (HROMs) perform **hyper-reduction** using ECSW [Farhat *et al.*, 2015]
 - Ensures that **Lagrangian structure** of problem is preserved in HROM.
- **Couplings tested:** overlapping, non-overlapping, FOM-FOM, FOM-ROM, ROM-ROM, FOM-HROM, HROM-HROM, implicit-explicit, implicit-implicit, explicit-explicit. **This talk**



Numerical Example: 1D Dynamic Wave Propagation



Problem

- Two variants of problem, with different initial conditions (ICs):
 - Symmetric Gaussian IC (top right)
 - Rounded Square IC (bottom right)
- Non-overlapping domain decomposition (DD)** of $\Omega = \Omega_1 \cup \Omega_2$, where $\Omega_1 = [0, 0.6]$ and $\Omega_2 = [0.6, 1.0]$
 - DD is based on heuristics: during time-interval considered ($0 \leq t \leq 1 \times 10^3$), sharper gradient forms in Ω_1 , suggesting FOM or larger ROM is needed there.
- Reproductive problem:**
 - Displacement snapshots collected using FOM-FOM non-overlapping coupling with **Symmetric Gaussian IC**
 - FOM-ROM, FOM-HROM, ROM-ROM and HROM-HROM run with **Symmetric Gaussian IC**
- Predictive problem:**
 - Displacement snapshots collected using FOM-FOM non-overlapping coupling with **Symmetric Gaussian IC**
 - FOM-ROM, FOM-HROM, ROM-ROM and HROM-HROM run with **Rounded Square IC**

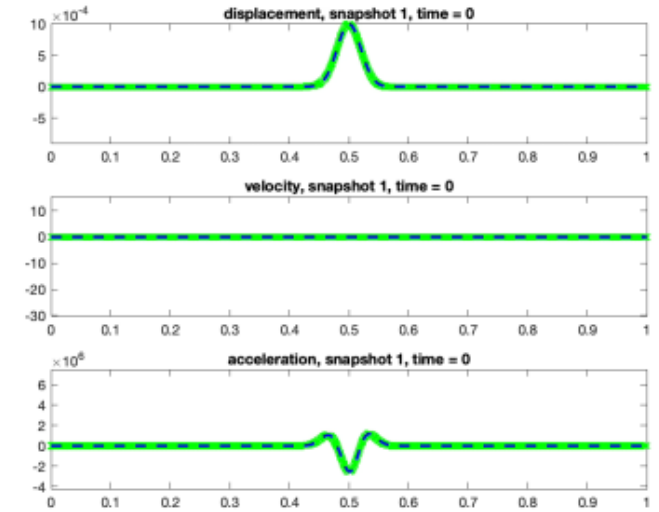
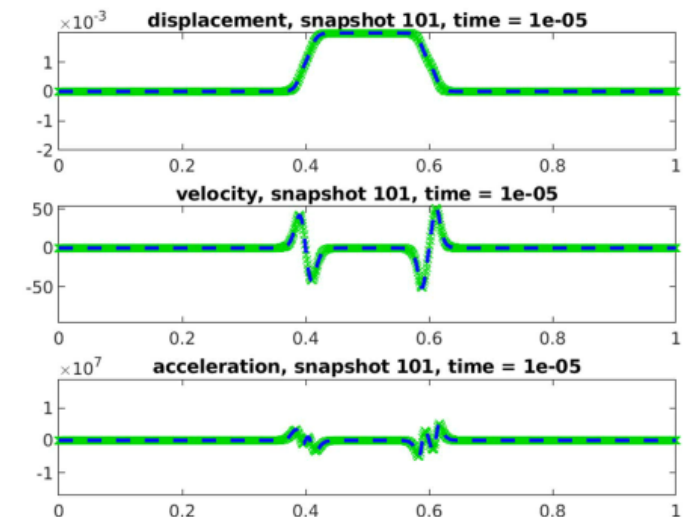


Figure above: Symmetric Gaussian IC problem solution

Figure below: Rounded Square IC problem solution



Numerical Example: Reproductive Problem Results

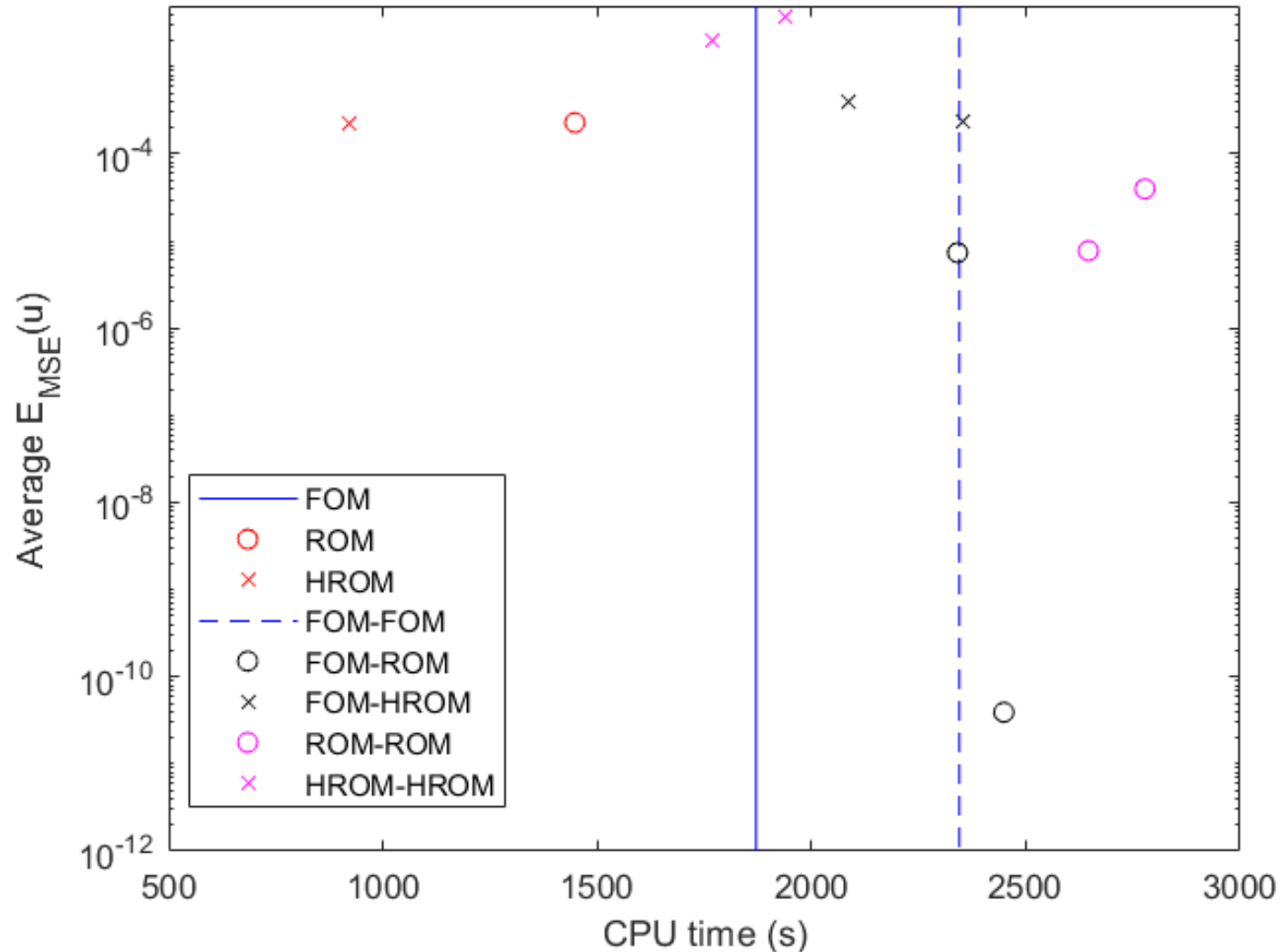


Model	M_1/M_2	$N_{e,1}/N_{e,2}$	CPU time (s)	$\frac{\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{u}}_1)}{\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{u}}_2)}$	$\frac{\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{v}}_1)}{\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{v}}_2)}$	$\frac{\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{a}}_1)}{\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{a}}_2)}$	N_S
FOM	—/—	—/—	1.871×10^3	—/—	—/—	—/—	—
ROM	60/—	—/—	1.398×10^3	1.659×10^{-2} /—	1.037×10^{-1}	4.681×10^{-1} /—	—
HROM	60/—	155/—	5.878×10^2	1.730×10^{-2} /—	1.063×10^{-1} /—	4.741×10^{-1} /—	—
ROM	200/—	—/—	1.448×10^3	2.287×10^{-4} /—	4.038×10^{-3} /—	4.542×10^{-2} /—	—
HROM	200/—	428/—	9.229×10^2	8.396×10^{-4} /—	8.947×10^{-3} /—	7.462×10^{-2} /—	—
FOM-FOM	—/—	—/—	2.345×10^3	—	—	—	24,630
FOM-ROM	—/80	—/—	2.341×10^3	2.171×10^{-6} / 1.253×10^{-5}	3.884×10^{-5} / 2.401×10^{-4}	2.982×10^{-4} / 2.805×10^{-3}	25,227
FOM-HROM	—/80	—/130	2.085×10^3	2.022×10^{-4} / 5.734×10^{-4}	1.723×10^{-3} / 5.776×10^{-3}	7.421×10^{-3} / 3.791×10^{-2}	29,678
FOM-ROM	—/200	—/—	2.449×10^3	4.754×10^{-12} / 7.357×10^{-11}	1.835×10^{-10} / 4.027×10^{-9}	5.550×10^{-9} / 1.401×10^{-7}	24,630
FOM-HROM	—/200	—/252	2.352×10^3	1.421×10^{-5} / 4.563×10^{-4}	1.724×10^{-4} / 2.243×10^{-3}	9.567×10^{-4} / 1.364×10^{-2}	27,156
ROM-ROM	200/80	—/—	2.778×10^3	4.861×10^{-5} / 3.093×10^{-5}	1.219×10^{-3} / 4.177×10^{-4}	1.586×10^{-2} / 3.936×10^{-3}	27,810
HROM-HROM	200/80	315/130	1.769×10^3	3.410×10^{-3} / 6.662×10^{-4}	4.110×10^{-2} / 6.432×10^{-3}	2.485×10^{-1} / 4.307×10^{-2}	29,860
ROM-ROM	300/80	—/—	2.646×10^3	2.580×10^{-6} / 1.292×10^{-5}	6.226×10^{-5} / 2.483×10^{-4}	9.470×10^{-4} / 2.906×10^{-3}	25,059
HROM-HROM	300/80	405/130	1.938×10^3	6.960×10^{-3} / 7.230×10^{-4}	6.328×10^{-2} / 7.403×10^{-3}	3.137×10^{-1} / 4.960×10^{-2}	29,896

Green shading highlights most competitive coupled models

- All coupled models evaluated converged on average in <3 Schwarz iterations per time-step
- Larger FOM-ROM coupling has **same total # Schwarz iters** (N_S) as FOM-FOM coupling
- Other couplings require more Schwarz iters than FOM-FOM coupling to converge
 - **More Schwarz iters** required when coupling **less accurate models**
 - Larger 300/80 mode ROM-ROM takes less wall-clock time than smaller 200/80 mode ROM-ROM
- **FOM-HROM** and **HROM-HROM** couplings **outperform** the **FOM-FOM** coupling in terms of CPU time by 12.5-32.6%
- All couplings involving ROMs/HROMs are **at least as accurate** as single-domain ROMs/HROMs

Numerical Example: Reproductive Problem Results



- **Single-domain ROM and HROM are most efficient**
- Couplings involving ROMs and HROMs enable one to achieve **smaller errors**
- Benefits of **hyper-reduction** are **limited on 1D problem**

Numerical Example: Reproductive Problem Results

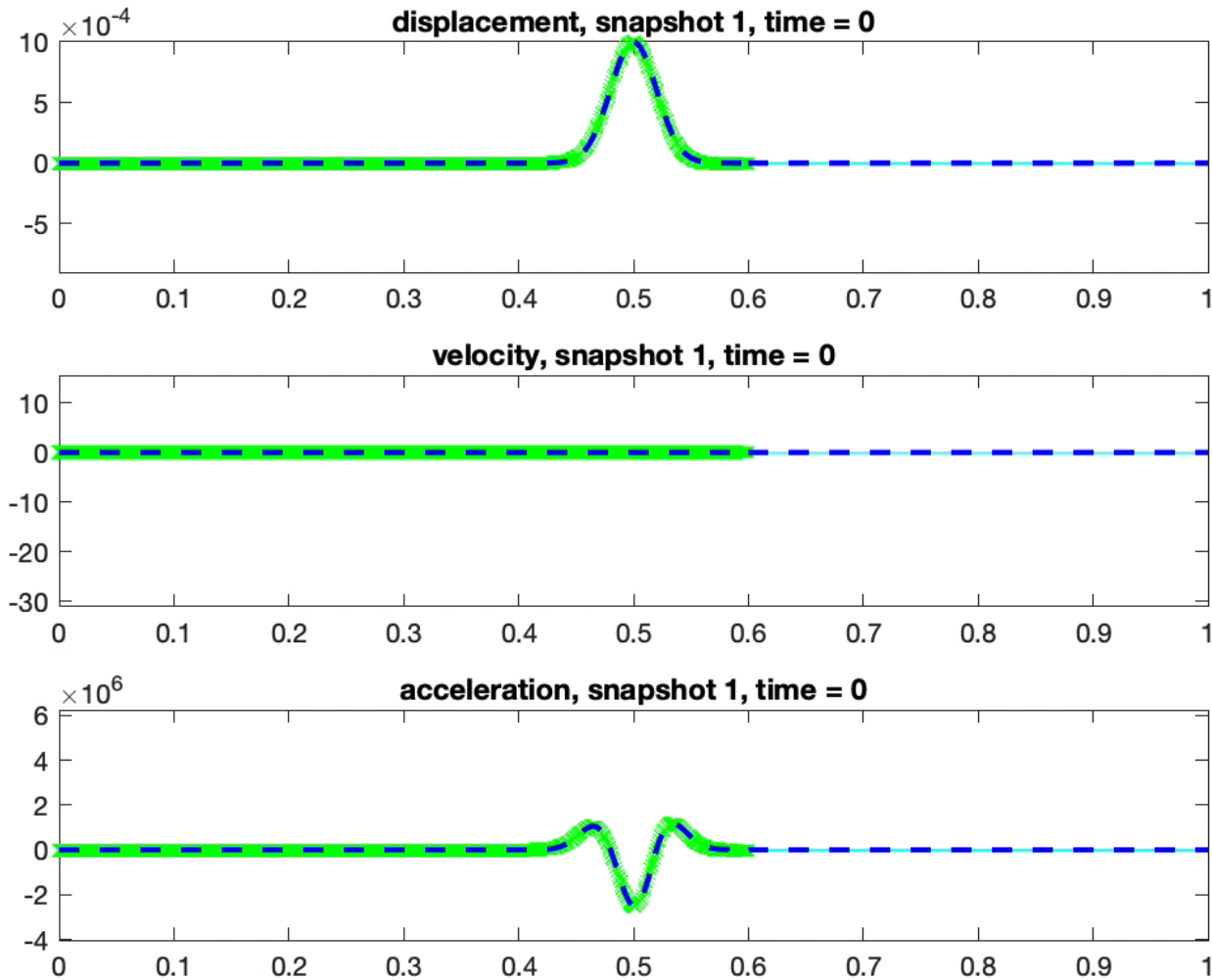
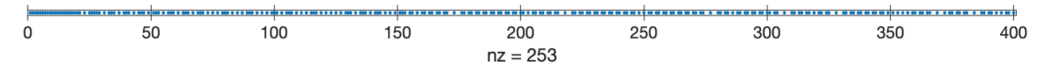


Figure left: FOM (green) - HROM (cyan) coupling compared with single-domain FOM solution (blue). HROM has 200 modes.

Figure below: ECSW algorithm samples 253/400 elements

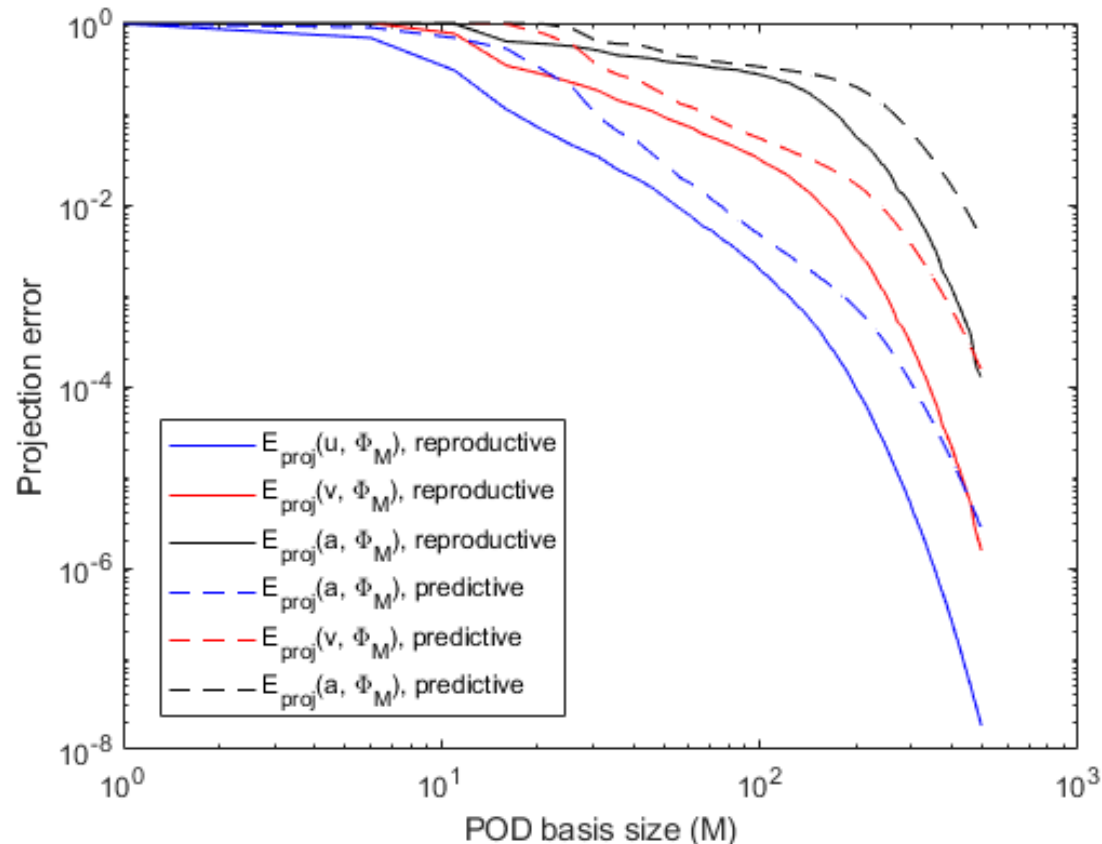


Numerical Example: Predictive Problem Results



- Start by calculating **projection error** for reproductive and predictive version of the Rounded Square IC problem:

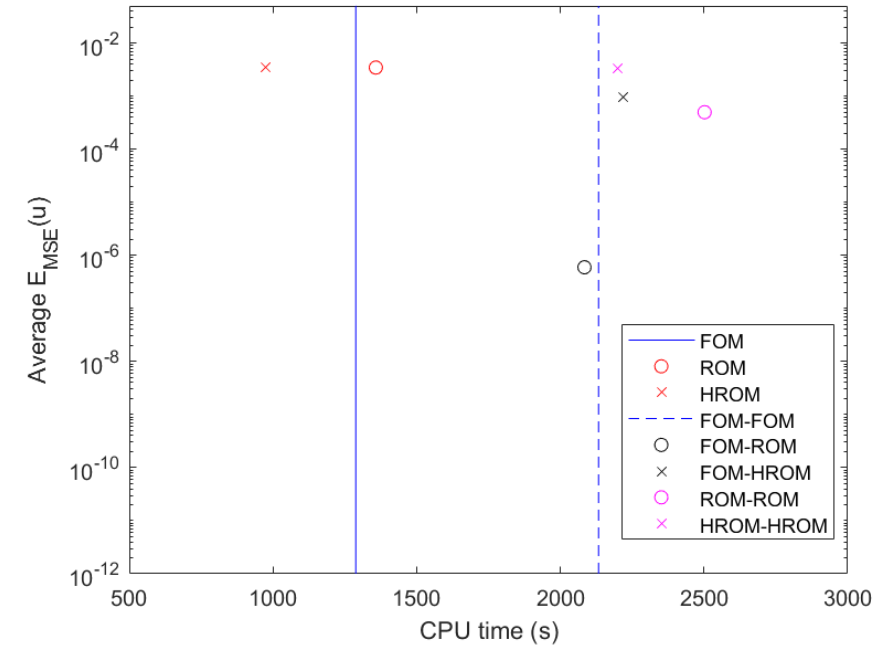
$$\mathcal{E}_{\text{proj}}(\mathbf{u}, \Phi_M) := \frac{\|\mathbf{u} - \Phi_M(\Phi_M^T \Phi_M)^{-1} \Phi_M^T \mathbf{u}\|_2}{\|\mathbf{u}\|_2}$$



- Projection error suggests **predictive ROM** can achieve **accuracy** and **convergence** with **basis refinement**
- O(100) modes** are needed to achieve sufficiently accurate ROM
 - Larger ROMs containing O(100) modes considered in our coupling experiments: $M_1 = 300$, $M_2 = 200$

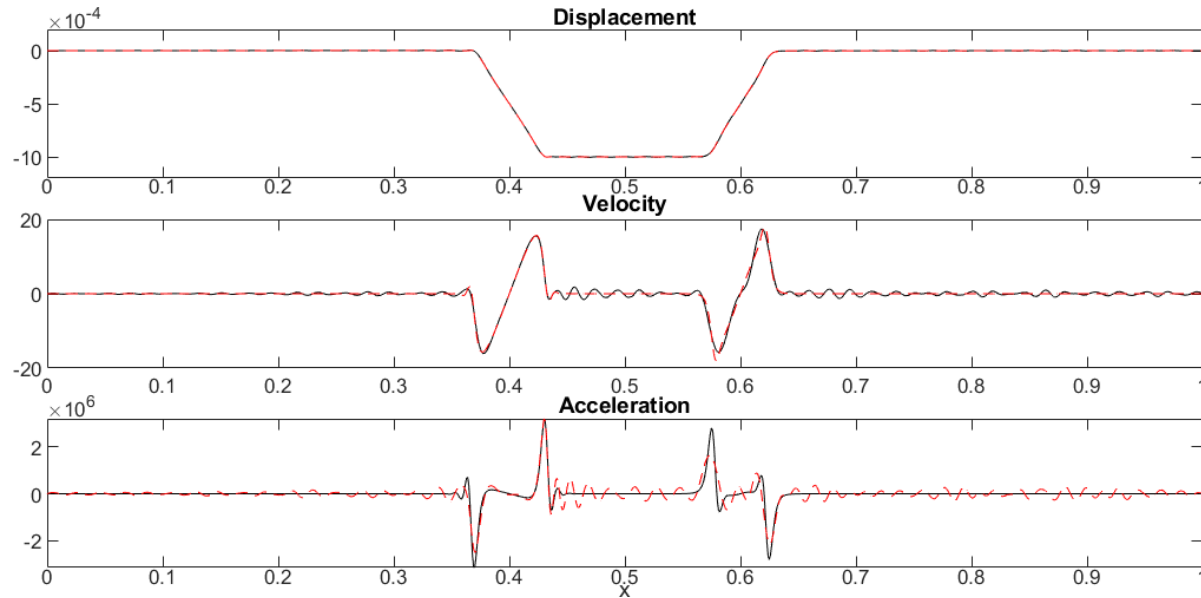
Numerical Example: Predictive Problem Results

Model	CPU time (s)	$N_{e,1}/N_{e,2}$	$\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{u}}_1)/\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{u}}_2)$	$\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{v}}_1)/\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{v}}_2)$	$\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{a}}_1)/\mathcal{E}_{\text{MSE}}(\tilde{\mathbf{a}}_2)$	N_S
FOM	1.288×10^3	—/—	—/—	—/—	—/—	—
ROM	1.358×10^3	—/—	$3.451 \times 10^{-3}/-$	$6.750 \times 10^{-2}/-$	$3.021 \times 10^{-1}/-$	—
HROM	9.759×10^2	614/—	$3.463 \times 10^{-3}/-$	$6.750 \times 10^{-2}/-$	$3.021 \times 10^{-1}/-$	—
FOM-FOM	2.133×10^3	—/—	—/—	—/—	—/—	23,280
FOM-ROM	2.084×10^3	—/—	$1.907 \times 10^{-8}/1.170 \times 10^{-6}$	$1.461 \times 10^{-6}/9.882 \times 10^{-5}$	$3.973 \times 10^{-5}/1.757 \times 10^{-3}$	23,288
FOM-HROM	2.219×10^3	—/253	$1.967 \times 10^{-4}/1.720 \times 10^{-3}$	$4.986 \times 10^{-3}/4.185 \times 10^{-2}$	$2.768 \times 10^{-2}/2.388 \times 10^{-1}$	29,700
ROM-ROM	2.502×10^3	—/—	$5.592 \times 10^{-4}/4.346 \times 10^{-4}$	$1.575 \times 10^{-2}/1.001 \times 10^{-2}$	$9.197 \times 10^{-2}/5.304 \times 10^{-2}$	26,220
HROM-HROM	2.200×10^3	405/253	$4.802 \times 10^{-3}/1.960 \times 10^{-3}$	$8.500 \times 10^{-2}/4.630 \times 10^{-2}$	$3.744 \times 10^{-1}/2.580 \times 10^{-1}$	30,067

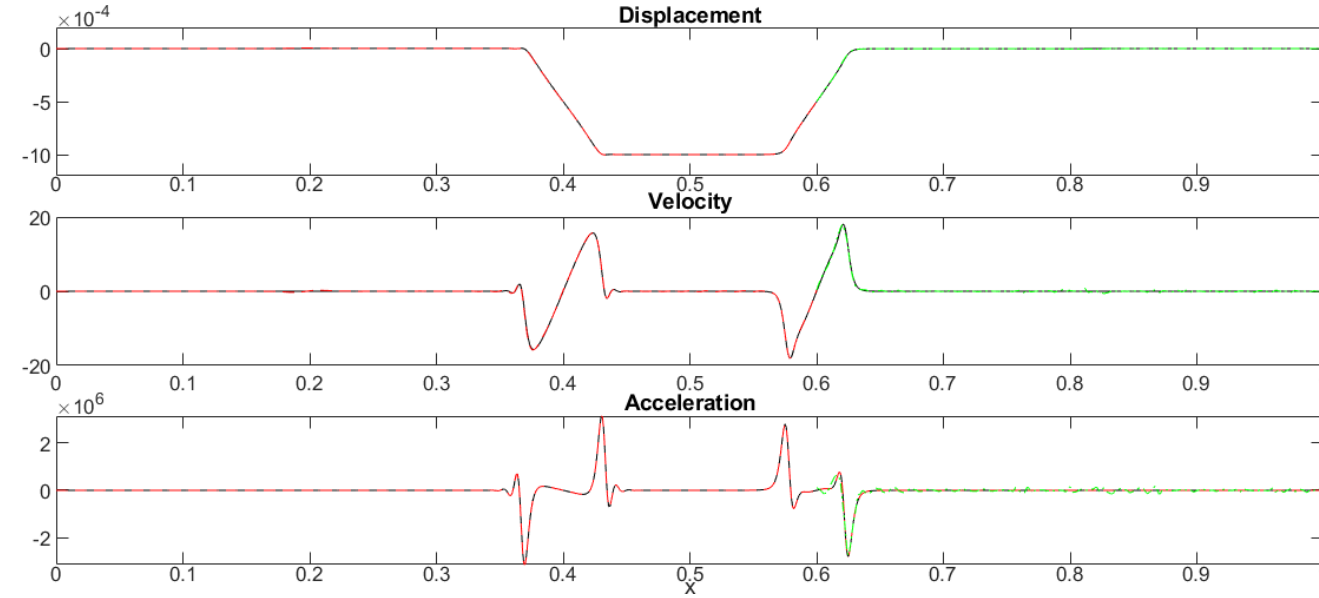


- Results indicate that **predictive accuracy/robustness can be improved by coupling ROM or HROM to FOM**
 - FOM-ROM coupling is **remarkably accurate**, achieving displacement error $O(1 \times 10^{-8})$
 - FOM-HROM and ROM-ROM couplings are **more accurate** than single-domain ROMs
 - HROM-HROM **on par** with single-domain HROM in terms of accuracy
- Wall-clock times of coupled models can be improved**
 - FOM-HROM, ROM-ROM and HROM-HROM models are **slower** than FOM-FOM model as **more Schwarz iterations** required to achieve convergence
 - Hyper-reduction** samples $\sim 60\%$ of total mesh points for this 1D traveling wave problem
 - ❖ Greater gains from hyper-reduction anticipated for 2D/3D problems

Numerical Example: Predictive Problem Results



Predictive single-domain ROM ($M_1 = 300$)
solution at final time



Predictive FOM-HROM ($M_2 = 200$)
solution at final time

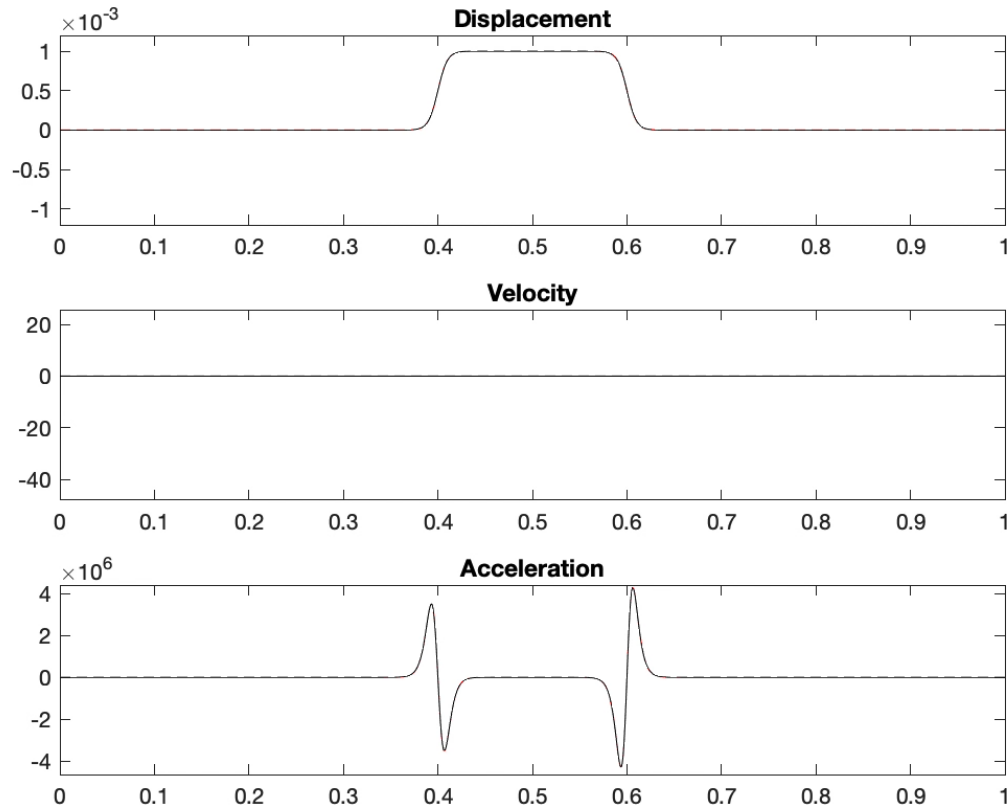
— Single-domain FOM solution

— Solution in Ω_1

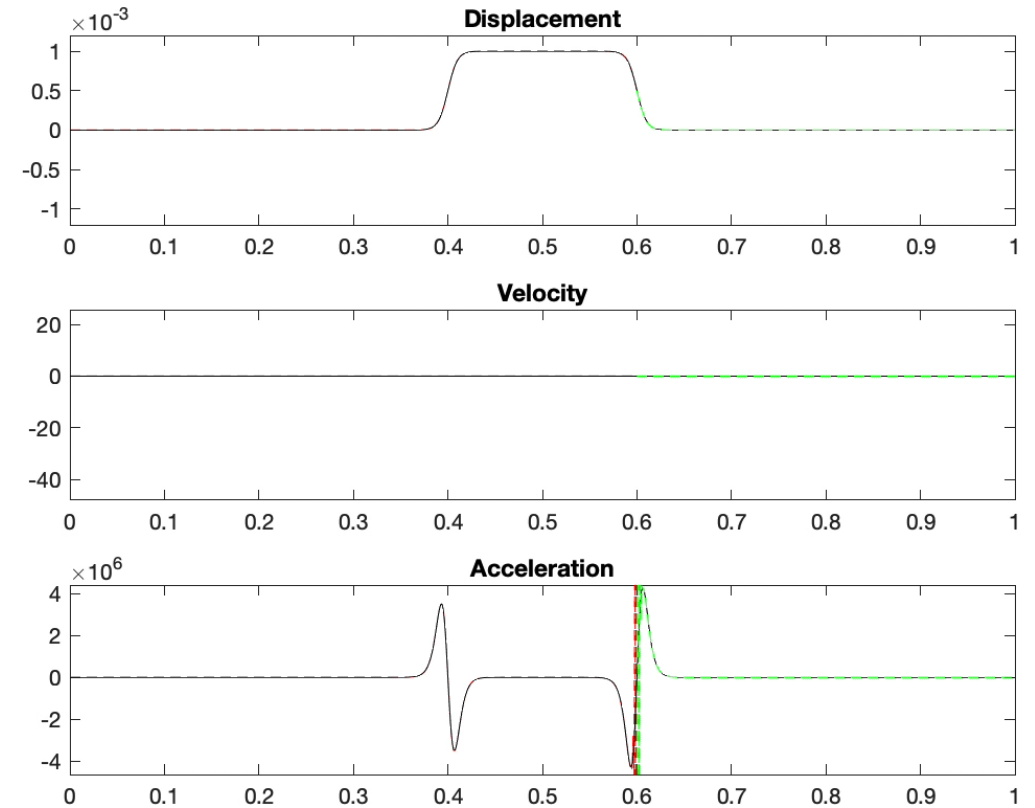
— Solution in Ω_2

- Predictive **single-domain ROM** solution exhibits **spurious oscillations** in velocity and acceleration
- Predictive **FOM-HROM** solution is **smooth** and **oscillation-free**
 - Highlights coupling method's ability to improve ROM predictive accuracy

Numerical Example: Predictive Problem Results



Predictive single-domain ROM ($M_1 = 300$)



Predictive FOM-HROM ($M_2 = 200$)

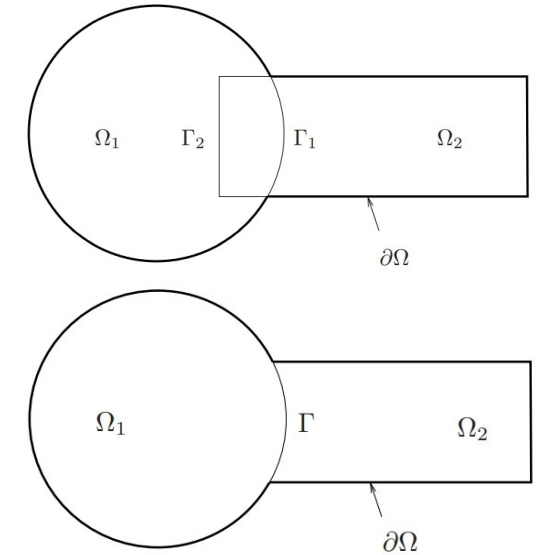
— Single-domain FOM solution

— Solution in Ω_1

— Solution in Ω_2

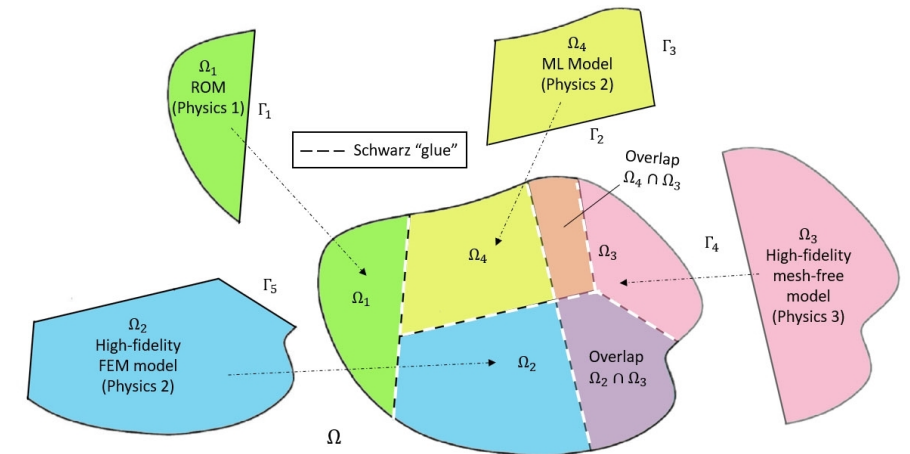
1. The Alternating Schwarz Method for FOM*-ROM[#] and ROM-ROM Coupling

- Method Formulation
- ROM Construction and Implementation
- Numerical Example: Solid Mechanics
- **Numerical Example: Fluid Mechanics**



2. Summary and Comparison of Methods

3. Future Work



Numerical Example: 2D Inviscid Burgers Problem

$$\frac{\partial u}{\partial t} + \frac{1}{2} \left(\frac{\partial u^2}{\partial x} + \frac{\partial uv}{\partial y} \right) = 0.02 \exp(\mu_2 x)$$

$$\frac{\partial v}{\partial t} + \frac{1}{2} \left(\frac{\partial vu}{\partial x} + \frac{\partial v^2}{\partial y} \right) = 0$$

$$u(x=0, y, t; \mu) = \mu_1$$

$$u(x, y, t=0) = v(x, y, t=0) = 1$$

$$x, y \in [0, 100], t \in [0, T_f]$$

- Spatial discretization given by a **Godunov-type scheme** with $N = 250$ elements in each dimension
- Temporal discretization given by the **trapezoidal method** with fixed $\Delta t = 0.05$ where $T_f = 25.0$ for a total of 500 time steps
- Following coupled subdomains will occupy the same geometric footprint as the FOM with different solvers, resolution, and subdomain decomposition

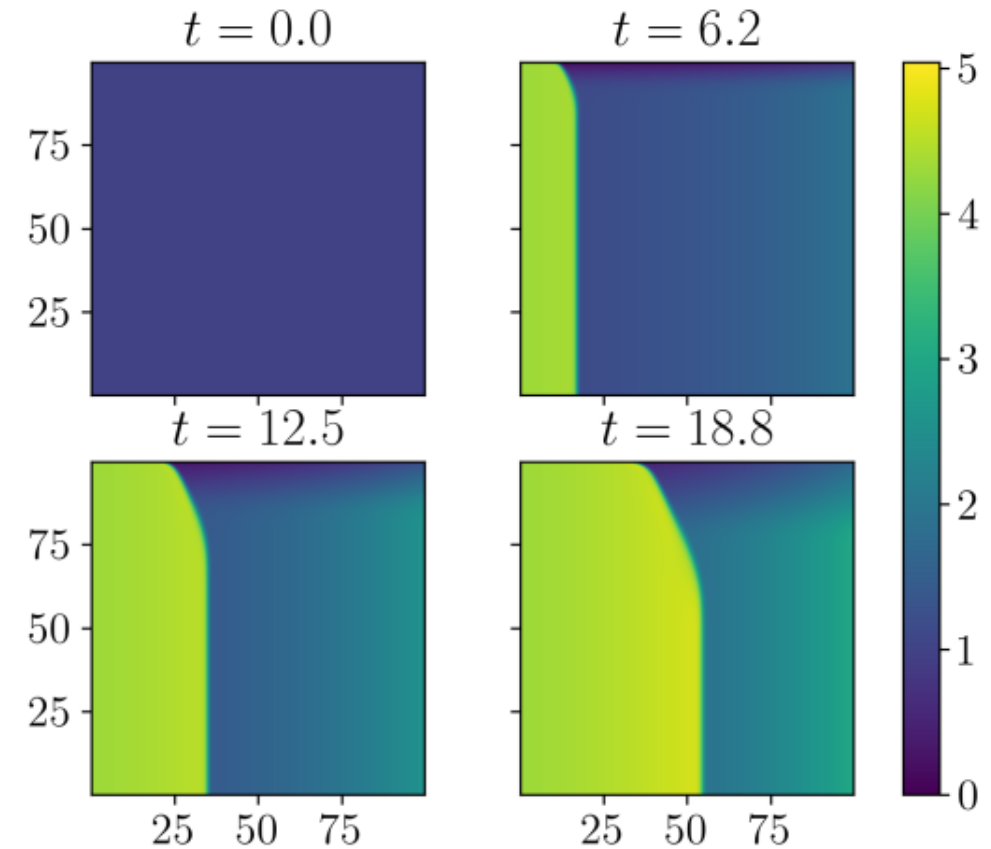
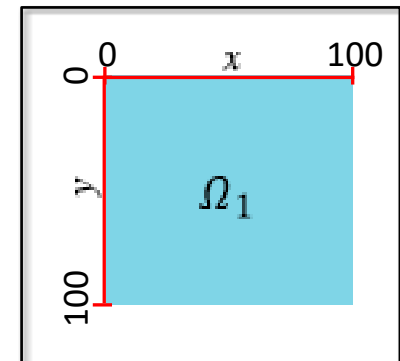


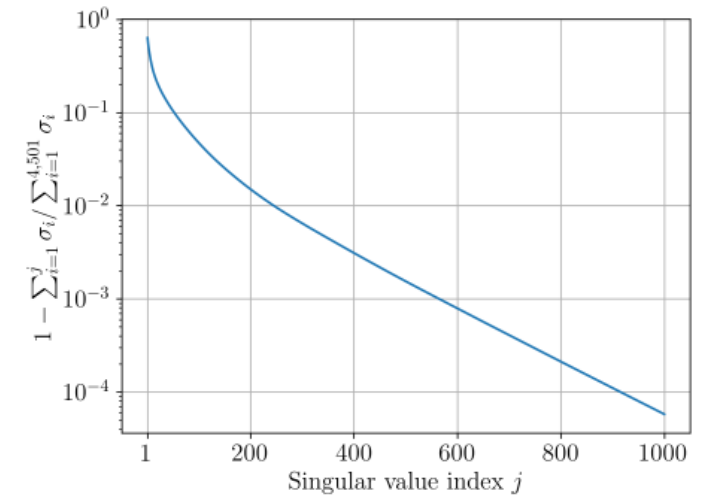
Figure above: solution of u component at various times



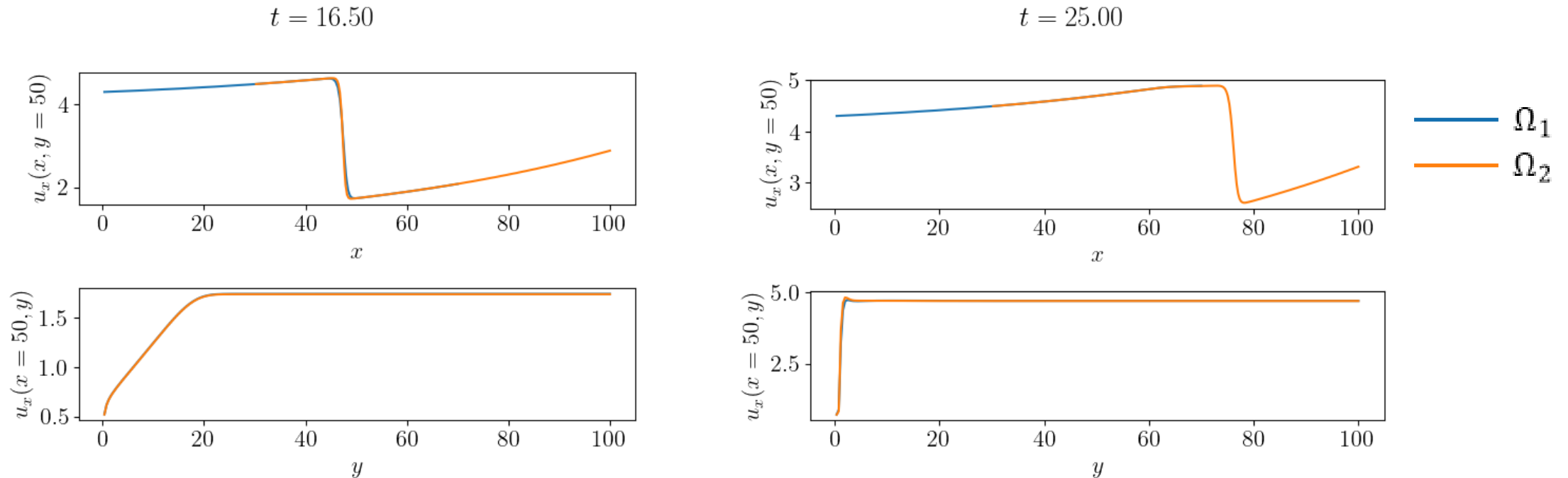
Numerical Example: 2D Inviscid Burgers Problem



- **2D** makes for a more appropriate testing of potential speedups from coupling subdomains to ROMs
- The **inviscid Burgers' equation** is a popular analog for fluid problems where shocks are possible, particularly difficult for conventional projection-based ROMs
- Two **parameters** considered:
 - Dirichlet BC parameterization μ_1
 - Source term parameterization μ_2
- ROMs results are **predictive and** are based on the **Least Squares Petrov-Galerkin (LSPG)** method, with POD calculated from FOM coupling models.
 - Greater than 200 POD modes required to capture 99% snapshot energy for when sampling 9 $\mu = [\mu_1, \mu_2]$ values
- Hyper-reduced ROMs (HROMs) perform **hyper-reduction** using ECSW [Farhat *et al.*, 2015]
- **Couplings tested:** overlapping, FOM-FOM, FOM-ROM, ROM-ROM, FOM-HROM, HROM-HROM, implicit-explicit, implicit-implicit, explicit-explicit.



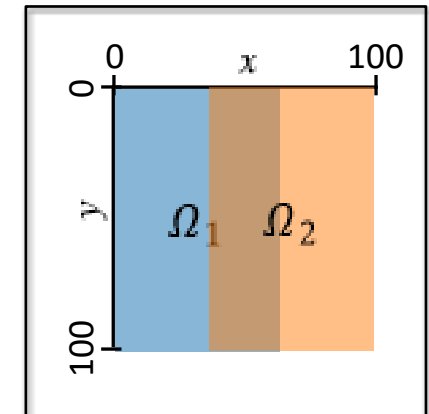
FOM-FOM Coupling: Differing Resolution



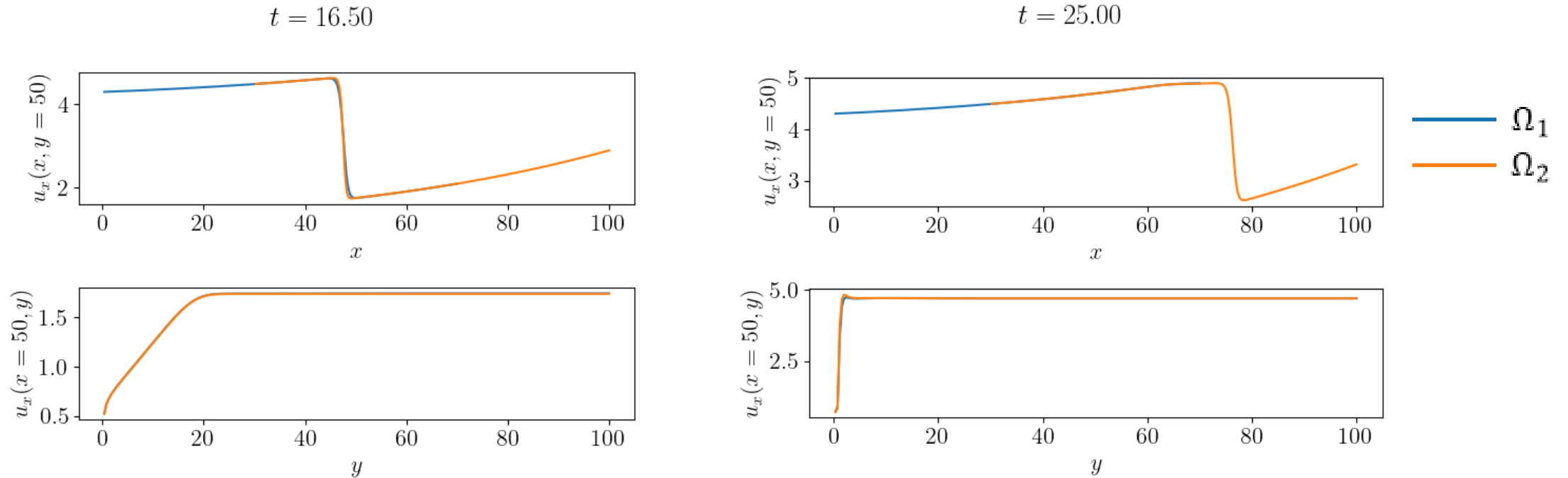
Figures above: Two-subdomain explicit-explicit overlapping coupling in x -axis $[0, 70] \cup [30, 100]$ where $\mu = [4.3, 0.021]$, $\Delta t = 0.005$, $\Delta x_1 = 0.4$, $\Delta x_2 = 0.3$

- Figures show the mid-plane slice of the solution for u_x at various times
- The right subdomain is a finer mesh, and the difference in how the shock is resolved can be seen
- $\Omega_1 \rightarrow \Omega_2$ ordering gives 2 Schwarz iterations per global time step
- $\Omega_2 \rightarrow \Omega_1$ ordering gives 3 Schwarz iterations per global time step

Order can be important!

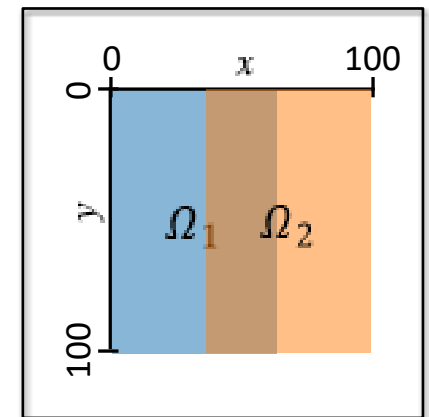


FOM-FOM Coupling: Differing Solvers

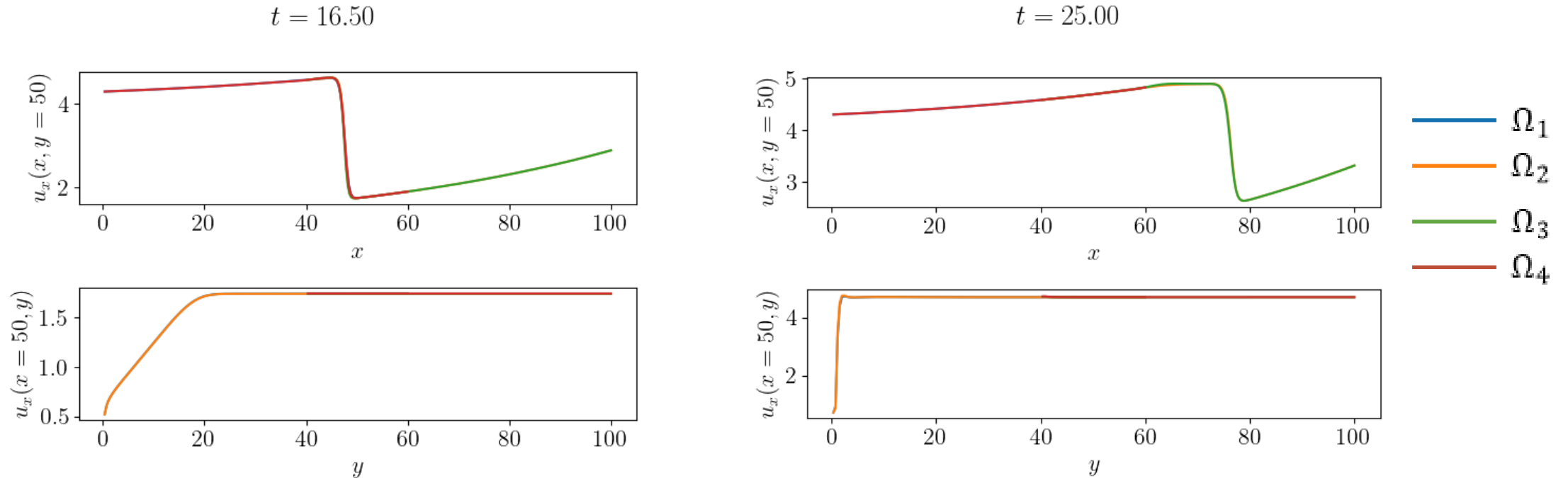


*Figures above: Two-subdomain implicit-explicit overlapping coupling in x-axis $[0, 70]$
 $U [30, 100]$, $\mu = [4.3, 0.021]$, $\Delta t_1 = 0.05$, $\Delta t_2 = 0.005$, $\Delta x_1 = 0.4$, $\Delta x_2 = 0.3$*

- Introducing a different time stepper in Ω_1 has not introduced artifacts and produces visually identical solution
- Choosing $\Omega_1 \rightarrow \Omega_2$ still only requires 2 Schwarz iterations per global time step

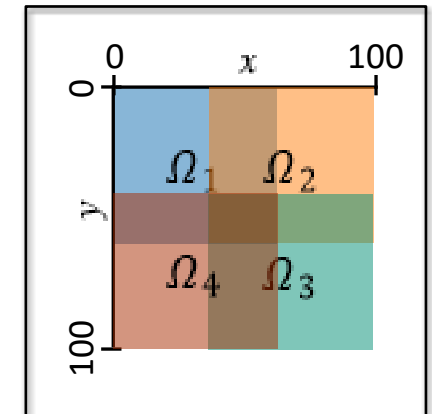


FOM-FOM Coupling: >2 Subdomains



Figures above: Four-subdomain implicit-explicit-implicit-explicit overlapping coupling in x-axis $[0, 60] \cup [40, 100]$ and y-axis $[0, 60] \cup [40, 100]$, $\mu = [4.3, 0.021]$, $\Delta t_1 = \Delta t_3 = 0.05$, $\Delta t_2 = \Delta t_4 = 0.005$, $\Delta x_1 = \Delta x_4 = 0.4$, $\Delta x_2 = \Delta x_3 = 0.3$

- Despite a heterogeneous mixture of different subdomains coupled in multiple dimensions with different solvers, resolutions, etc. the solution is still consistent
- Choosing $\Omega_1 \rightarrow \Omega_2 \rightarrow \Omega_3 \rightarrow \Omega_4$ requires 3 Schwarz iterations per global time step



Single Domain ROM

- Uniform sampling of $\mathcal{D} = [4.25, 5.50] \times [0.015, 0.03]$ by a 3×3 grid \Rightarrow 9 training parameter points characterized by $\Delta\mu_1 = 0.625$ and $\Delta\mu_2 = 0.0075$
- Queried but unsampled parameter point $\mu = [4.75, 0.02]$ with reduced dimension of $n = 95$
- Reduced mesh resulting from solving non-negative least squares problem formulate by ECSW gives $n_e = 5\,689$ elements (9.1% of $N_e = 62\,500$ elements).

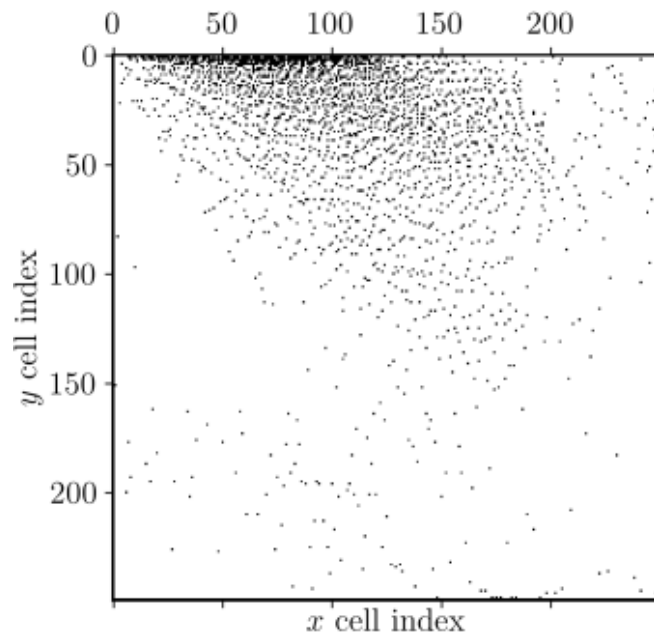


Figure above: Reduced mesh of single domain HROM

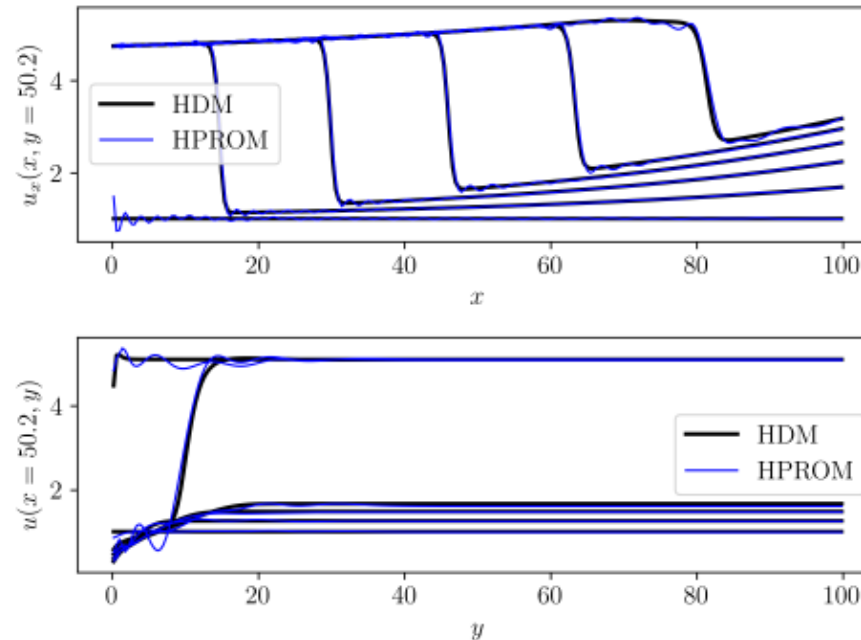
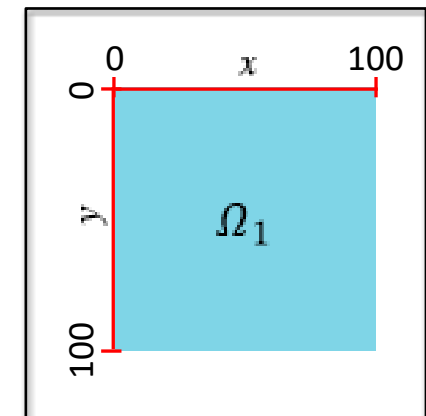


Figure above: HROM and FOM results at various time steps



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New Postdoc



Pavel Bochev



Amy De Castro



Paul Kuberry



$$\int \mathcal{M}^2 dt$$



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This talk

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Start of Backup Slides

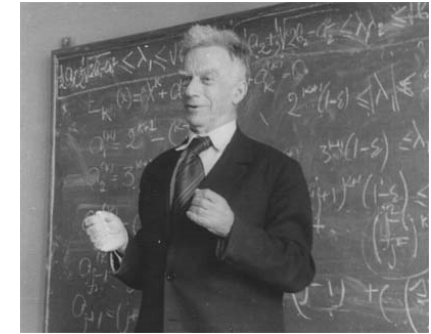
Theoretical Foundation

Using the Schwarz alternating as a **discretization method** for PDEs is natural idea with a sound **theoretical foundation**.

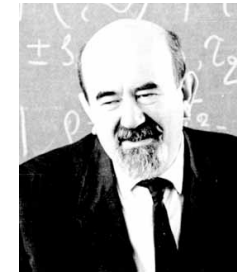
- **S.L. Sobolev (1936)**: posed Schwarz method for **linear elasticity** in variational form and **proved method's convergence** by proposing a convergent sequence of energy functionals.
- **S.G. Mikhlin (1951)**: **proved convergence** of Schwarz method for general linear elliptic PDEs.
- **P.-L. Lions (1988)**: studied convergence of Schwarz for **nonlinear monotone elliptic problems** using max principle.
- **A. Mota, I. Tezaur, C. Alleman (2017)**: proved **convergence** of the alternating Schwarz method for **finite deformation quasi-static nonlinear PDEs** (with energy functional $\Phi[\varphi]$) with a **geometric convergence rate**.

$$\Phi[\varphi] = \int_B A(F, Z) dV - \int_B B \cdot \varphi dV$$

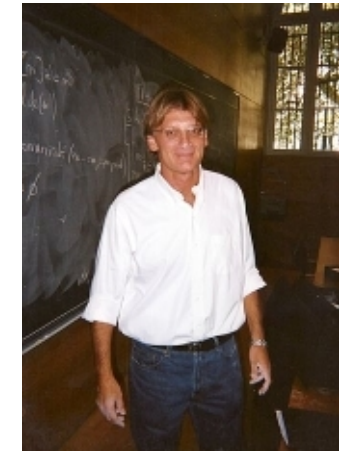
$$\nabla \cdot P + B = 0$$



S.L. Sobolev (1908 – 1989)



S.G. Mikhlin
(1908 – 1990)



P.-L. Lions (1956-)



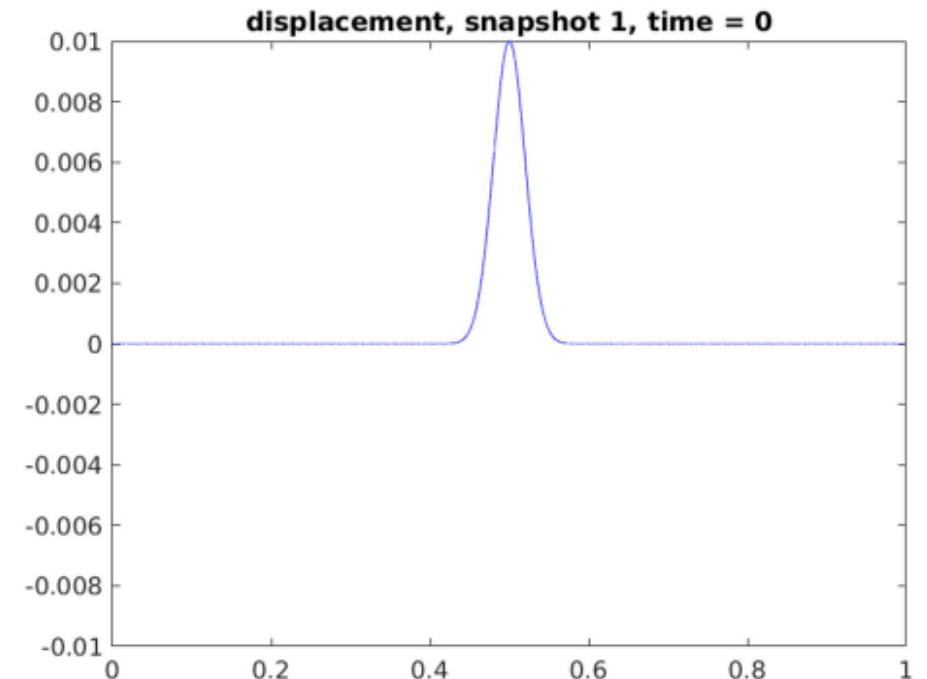
A. Mota, I. Tezaur, C. Alleman

Numerical Example: Linear Elastic Wave Propagation Problem

- Linear elastic **clamped beam** with Gaussian initial condition.
- Simple problem with analytical exact solution but very **stringent test** for discretization/coupling methods.
- **Couplings tested:** FOM-FOM, FOM-ROM, ROM-ROM, implicit-explicit, implicit-implicit, explicit-explicit.
- ROMs are **reproductive** and based on the **POD/Galerkin** method.
 - 50 POD modes capture ~100% snapshot energy



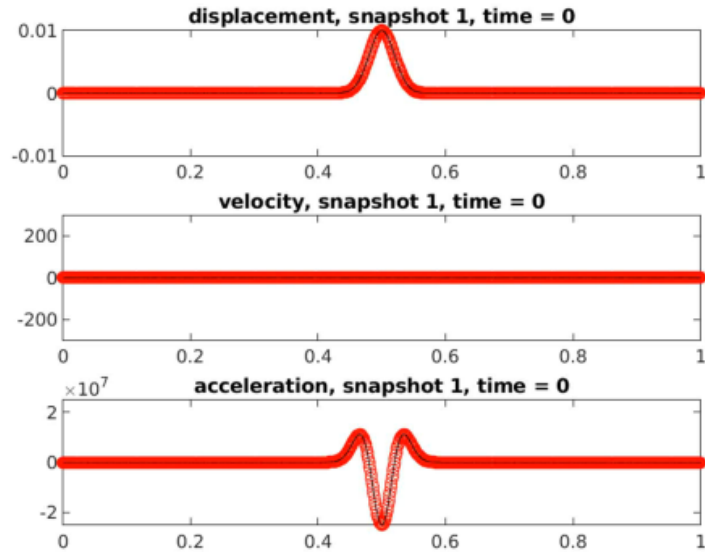
Above: 3D rendering of clamped beam with Gaussian initial condition.
Right: Initial condition (blue) and final solution (red). Wave profile is negative of initial profile at time $T = 1.0e-3$.



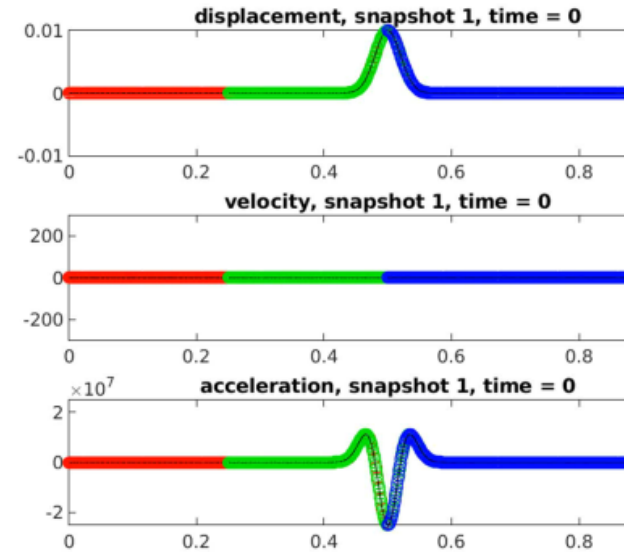
Linear Elastic Wave Propagation Problem: FOM-ROM and ROM-ROM Couplings



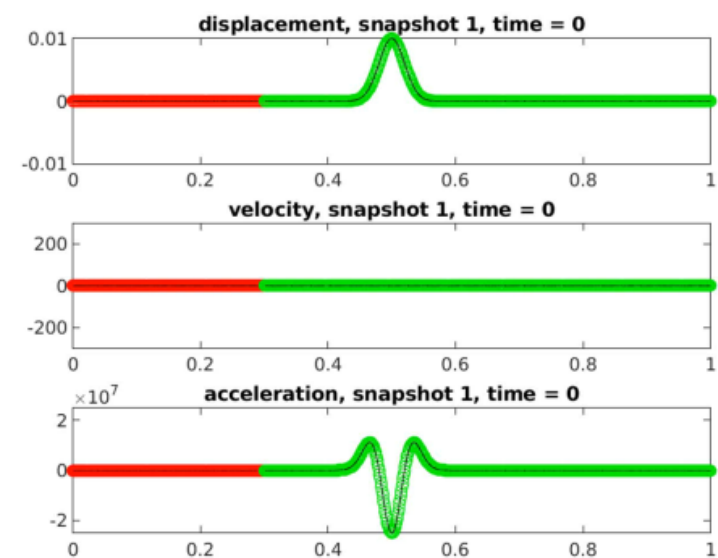
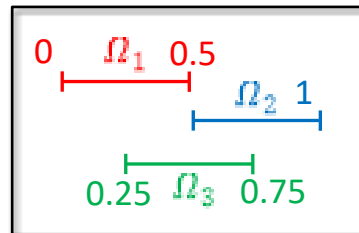
Coupling delivers accurate solution if each subdomain model is reasonably accurate, can couple different discretizations with different Δx , Δt and basis sizes.



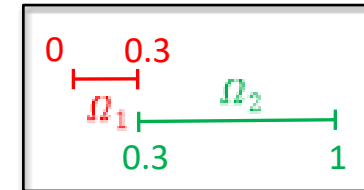
Single Domain FOM



3 overlapping subdomain
ROM¹-FOM²-ROM³



2 non-overlapping subdomain
FOM⁴-ROM⁵ ($\theta = 1$)



¹Implicit 40 mode POD ROM, $\Delta t=1e-6$, $\Delta x=1.25e-3$

²Implicit FOM, $\Delta t=1e-6$, $\Delta x=8.33e-4$

³Explicit 50 mode POD ROM, $\Delta t=1e-7$, $\Delta x=1e-3$

⁵Implicit FOM, $\Delta t=2.25e-7$, $\Delta x=1e-6$

⁴Explicit 50 mode POD ROM, $\Delta t=2.25e-7$, $\Delta x=1e-6$

Linear Elastic Wave Propagation Problem: FOM-ROM and ROM-ROM Couplings



Coupled models are reasonably accurate w.r.t. FOM-FOM coupled analogs and convergence with respect to basis refinement for FOM-ROM and ROM-ROM coupling is observed.

	disp MSE ⁶	velo MSE	acce MSE
Overlapping ROM ¹ -FOM ² -ROM ³	1.05e-4	1.40e-3	2.32e-2
Non-overlapping FOM ⁴ -ROM ⁵	2.78e-5	2.20e-4	3.30e-3

¹Implicit 40 mode POD ROM, $\Delta t = 1e-6$, $\Delta x = 1.25e-3$

²Implicit FOM, $\Delta t = 1e-6$, $\Delta x = 8.33e-4$

³Explicit 50 mode POD ROM, $\Delta t = 1e-7$, $\Delta x = 1e-3$

⁴Implicit FOM, $\Delta t = 2.25e-7$, $\Delta x = 1e-6$

⁵Explicit 50 mode POD ROM, $\Delta t = 2.25e-7$, $\Delta x = 1e-6$

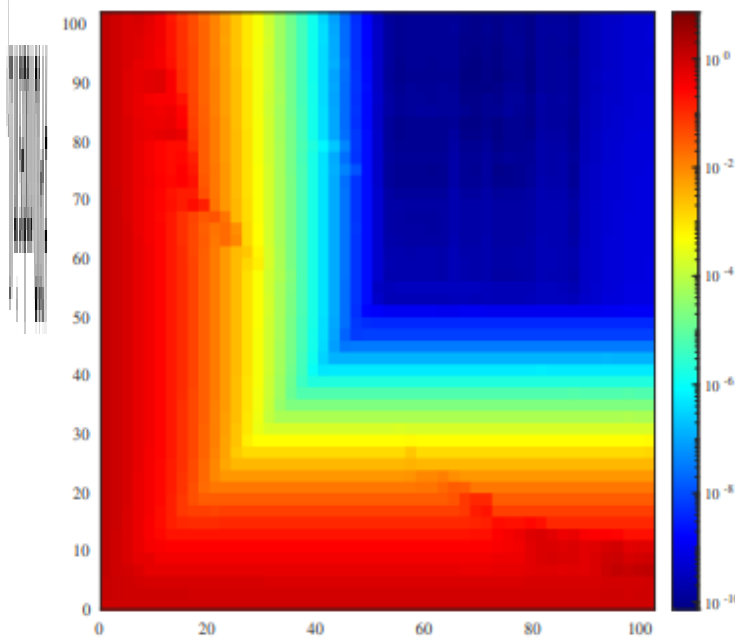
$$^6\text{MSE} = \text{mean squared error} = \sqrt{\sum_{n=1}^{N_t} \|\tilde{\mathbf{u}}^n(\boldsymbol{\mu}) - \mathbf{u}^n(\boldsymbol{\mu})\|_2^2} / \sqrt{\sum_{n=1}^{N_t} \|\mathbf{u}^n(\boldsymbol{\mu})\|_2^2}.$$

Linear Elastic Wave Propagation Problem: ROM-ROM Couplings



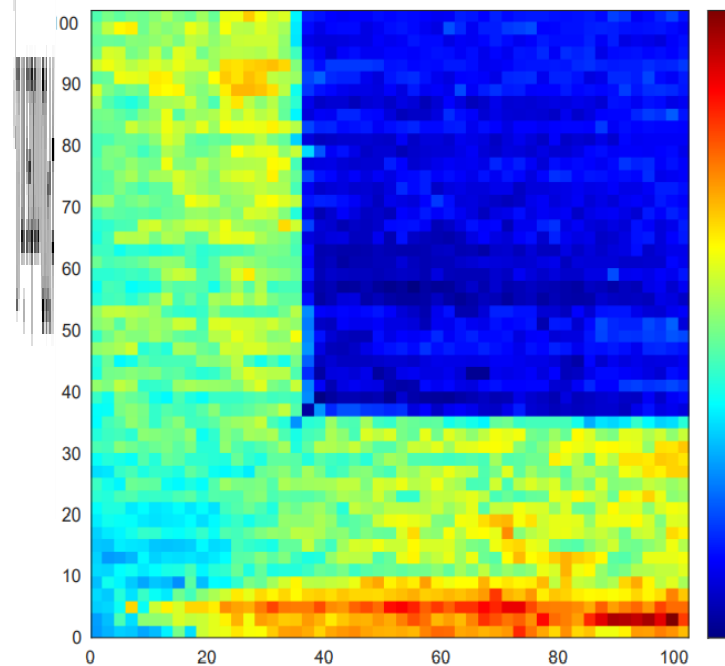
ROM-ROM coupling gives errors $< 0(1e-6)$ & speedups over FOM-FOM coupling for basis sizes > 40 .

MSE in displacement for 2 subdomain ROM-ROM coupling



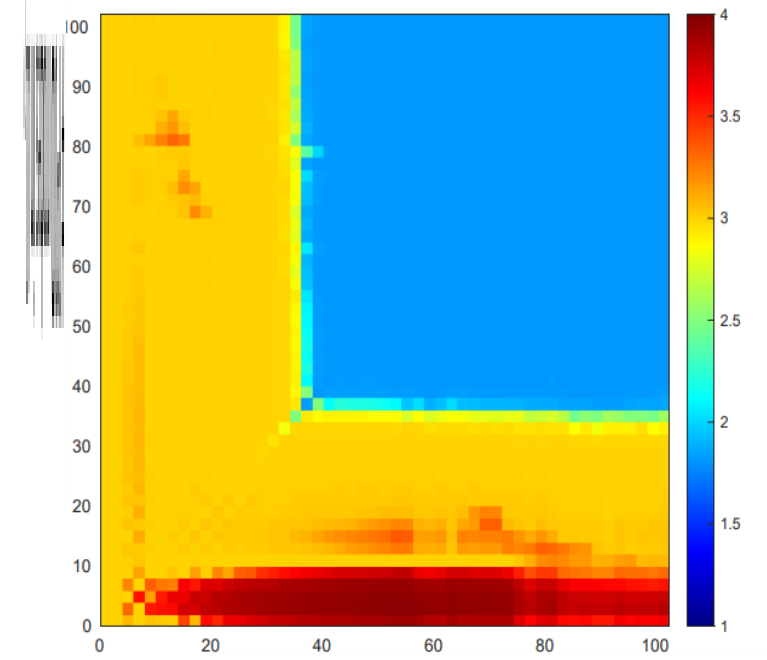
POD modes in Ω_1

CPU times for 2 subdomain ROM-ROM coupling normalized by FOM-FOM CPU time



POD modes in Ω_1

Average # Schwarz iterations for 2 subdomain ROM-ROM coupling



POD modes in Ω_1

- **Smaller ROMs are not the fastest:** less accurate & require more Schwarz iterations to converge.
- All couplings converge in ≤ 4 Schwarz iterations on average (FOM-FOM coupling requires average of 2.4 Schwarz iterations).

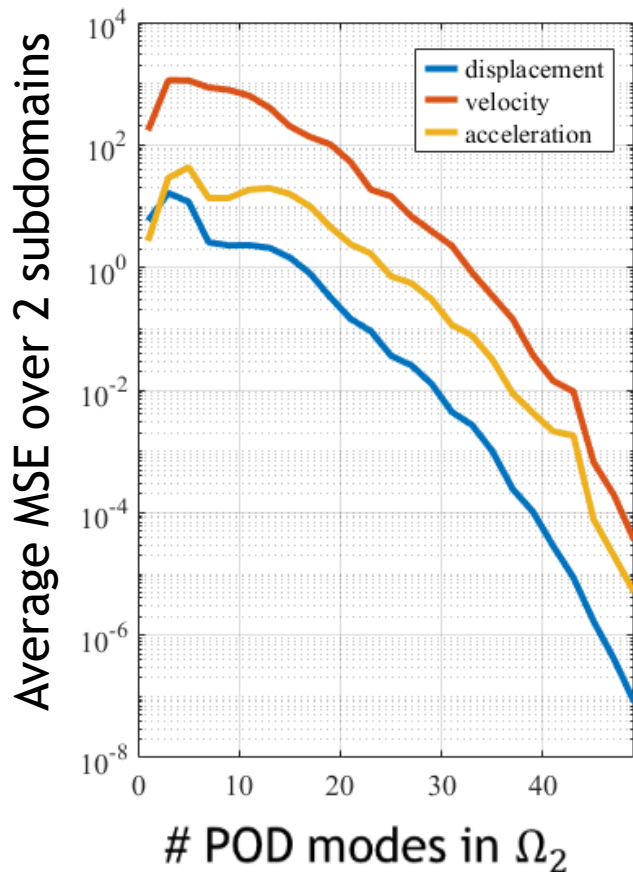
Overlapping implicit-implicit coupling
with $\Omega_1 = [0, 0.75]$, $\Omega_2 = [0.25, 1]$

Linear Elastic Wave Propagation Problem: FOM-ROM

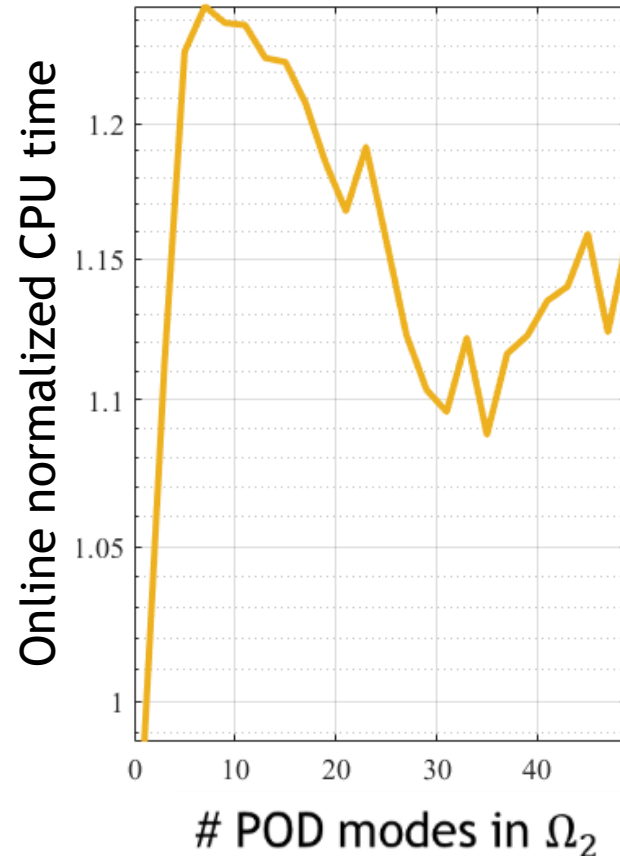
Couplings

FOM-ROM coupling shows convergence with basis refinement. FOM-ROM couplings are 10-15% slower than comparable FOM-FOM coupling due to increased # Schwarz iterations.

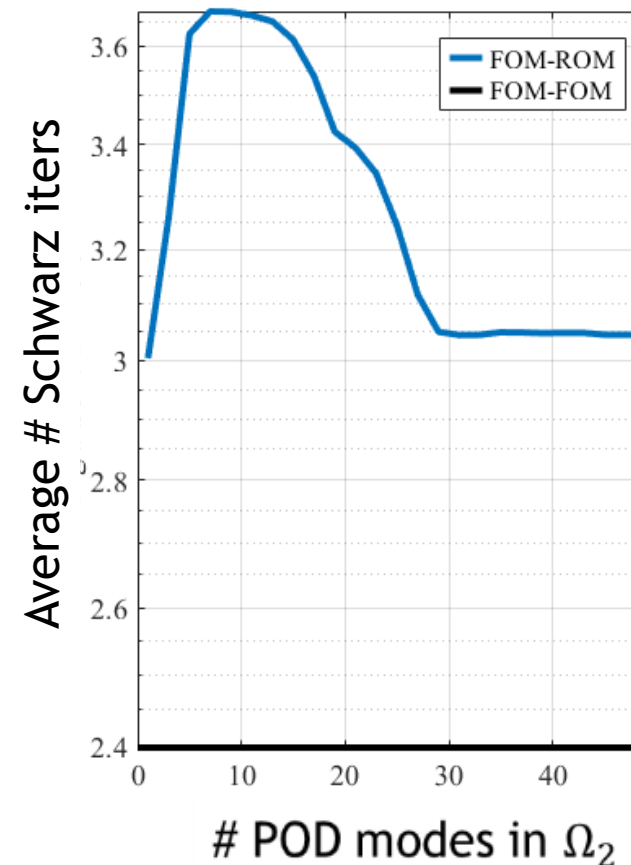
MSE for 2 subdomain
FOM-ROM coupling



CPU times for 2 subdomain
FOM-ROM coupling normalized
by FOM-FOM CPU time



Average # Schwarz iterations for 2
subdomain couplings



WIP:
understanding &
improving FOM-
ROM coupling
performance.

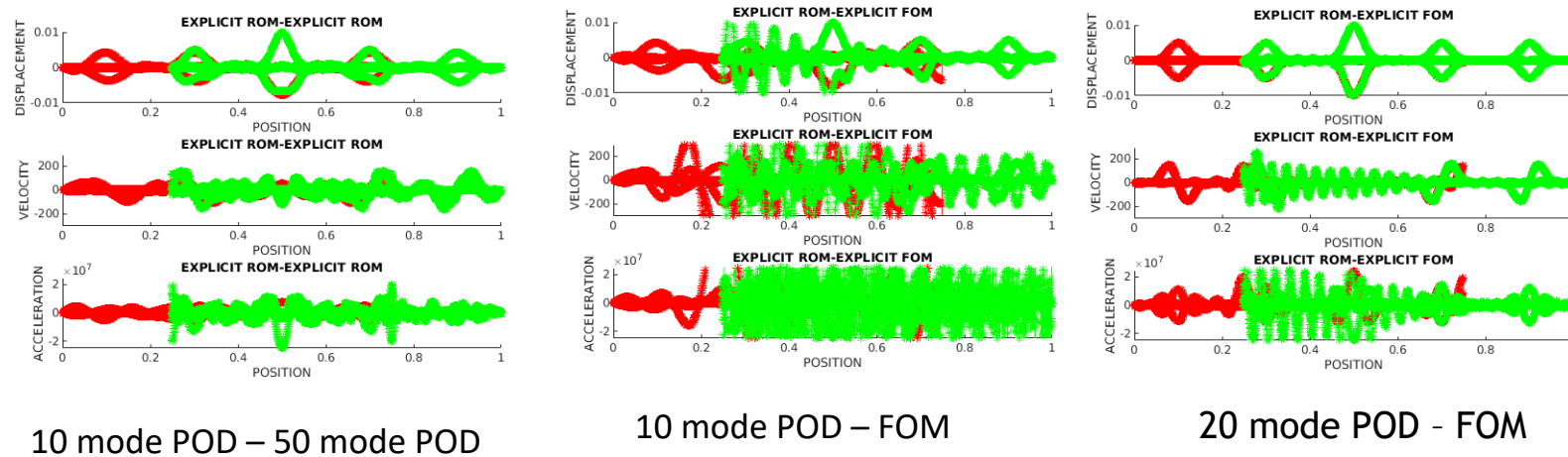
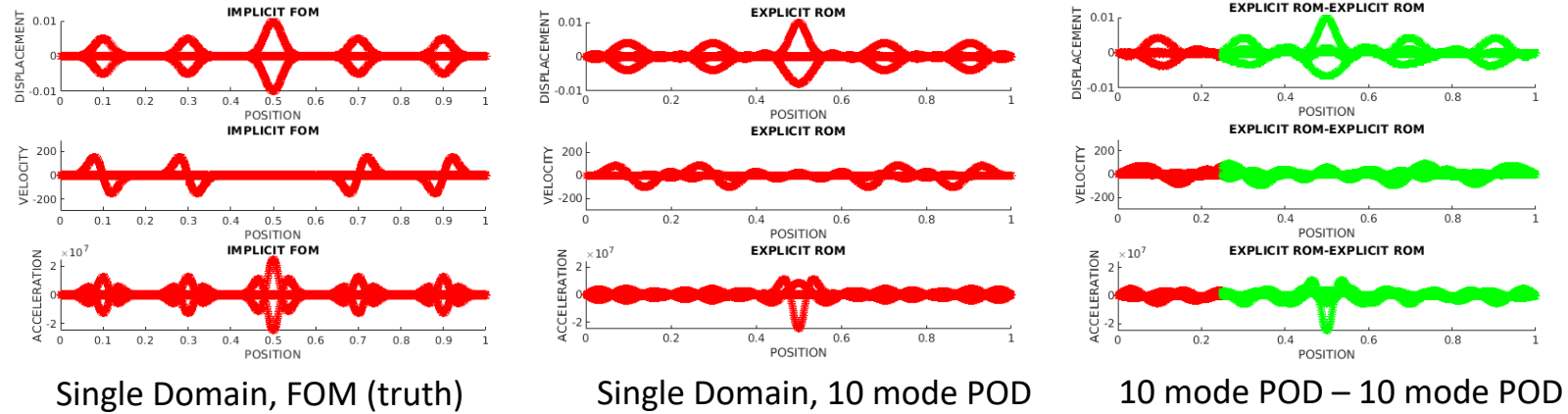
Overlapping
implicit-
implicit
coupling with
 $\Omega_1 = [0, 0.75]$,
 $\Omega_2 = [0.25, 1]$

Linear Elastic Wave Propagation Problem: FOM-ROM and ROM-ROM Couplings



Inaccurate model + accurate model \neq accurate model.

Accuracy can be improved by “gluing” several smaller, spatially-local models



Figures above: $\Omega_1 = [0, 0.75]$, $\Omega_2 = [0.25, 1]$

Observation suggests need for “smart” domain decomposition.

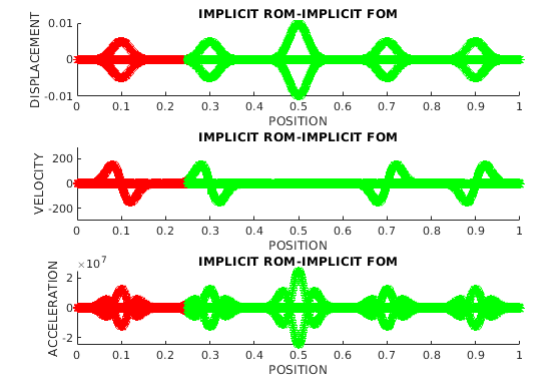
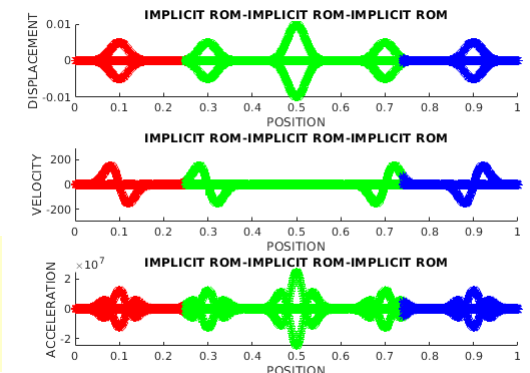


Figure above: $\Omega_1 = [0, 0.3]$, $\Omega_2 = [0.25, 1]$, 20 mode POD - FOM

Figure below: $\Omega_1 = [0, 0.26]$, $\Omega_2 = [0.25, 0.75]$, $\Omega_3 = [0.74, 1]$, 15 mode POD - 30 mode POD - 15 mode POD



Roadmap

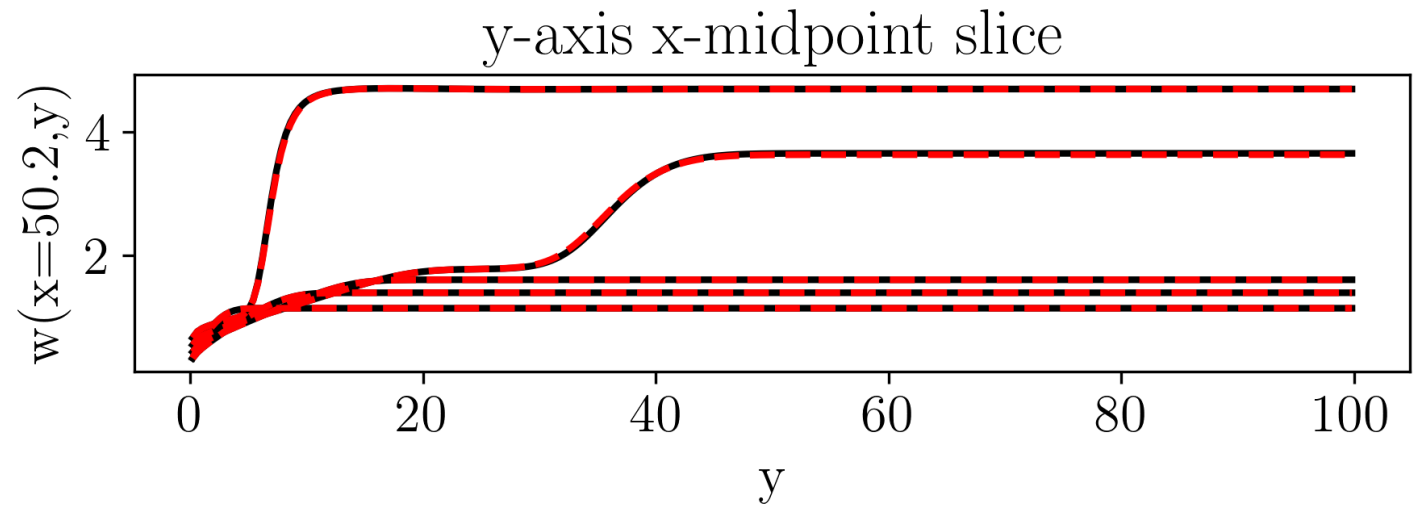
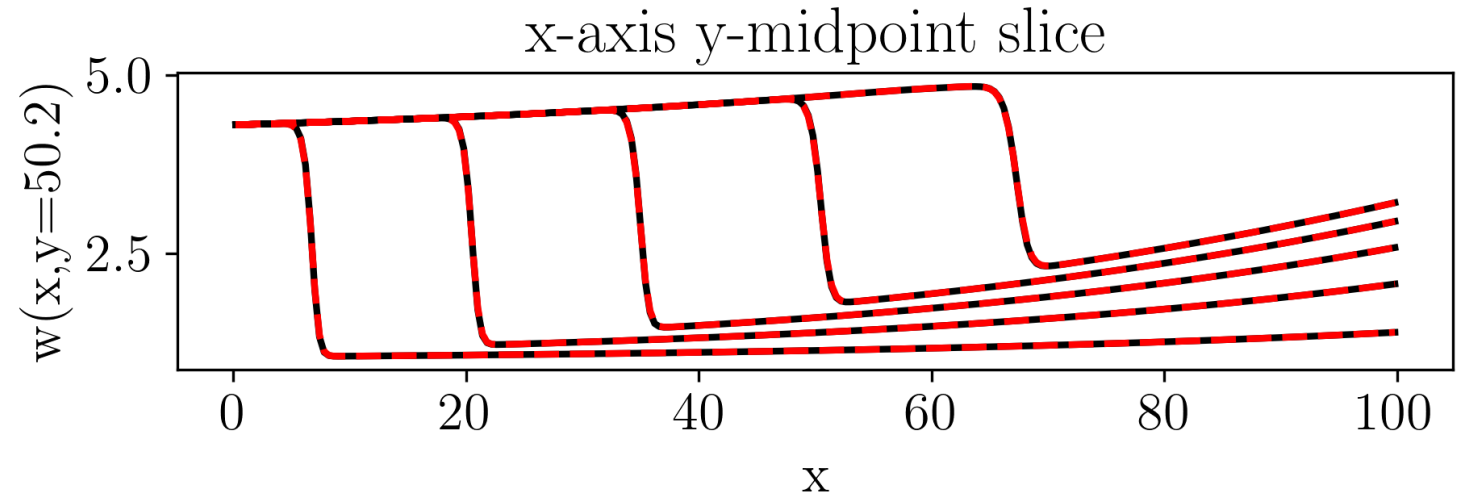


- Demonstrate FOM-FOM coupling with varying time-steps, domain resolutions, and time-stepping schemes
 - Try out splitting domain into four sections
- Develop FOM-ROM, ROM-ROM, HROM-HROM coupling
- Time permitting
 - Adaptive time-stepping based on local CFL number in given domain
 - OR adaptively switch to implicit time stepping after shock has left domain
 - Nonlinear approximation manifolds

2D Burgers: Verifying Implicit Implementation



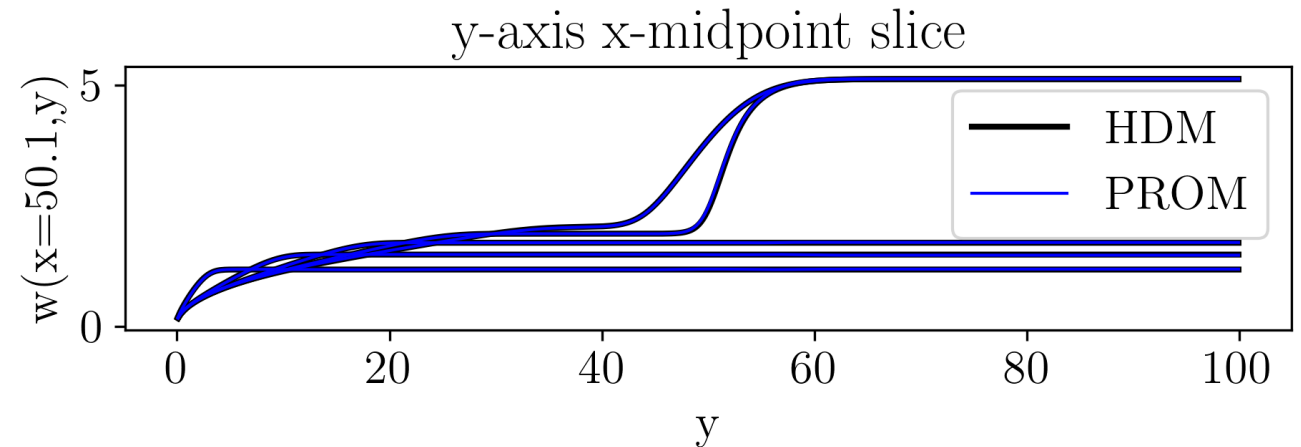
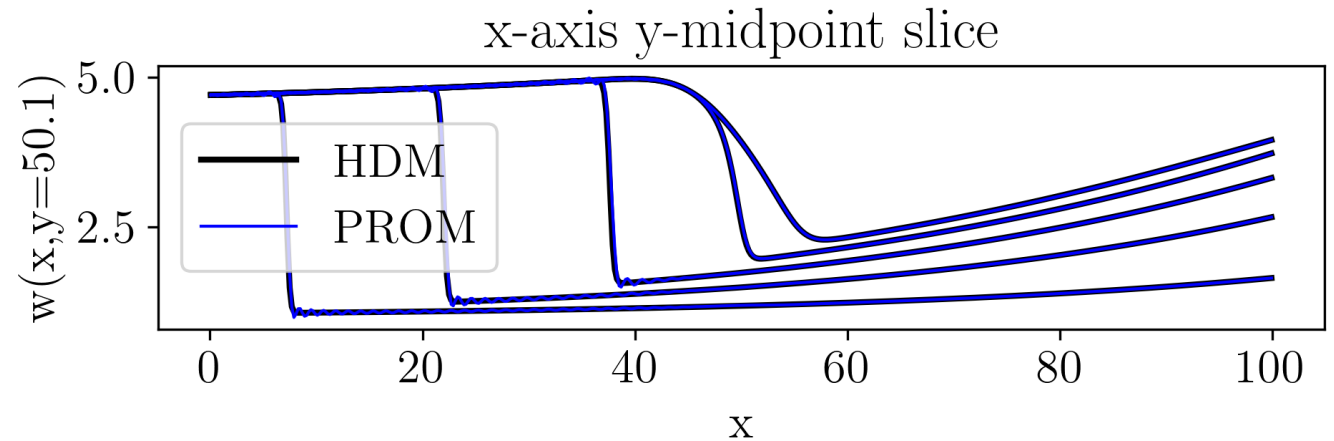
- The plot to the right shows the solution of the u component at various times along **mid-axis slices of the 2D domain**
- FOM and ROM solutions are the **same**



2D Burgers: LSPG PROM



- **Predictive case** where $\mu = [4.7, 0.026]$
- Train bases using **9 total runs** of the FOM with all combinations of $\mu_1 = [(4.25), (4.875), (5.5)]$ with $\mu_2 = [(0.015), (0.0225), (0.03)]$
- Using 113 POD modes
- Relative error of 0.61%
- 321 s wall clock time



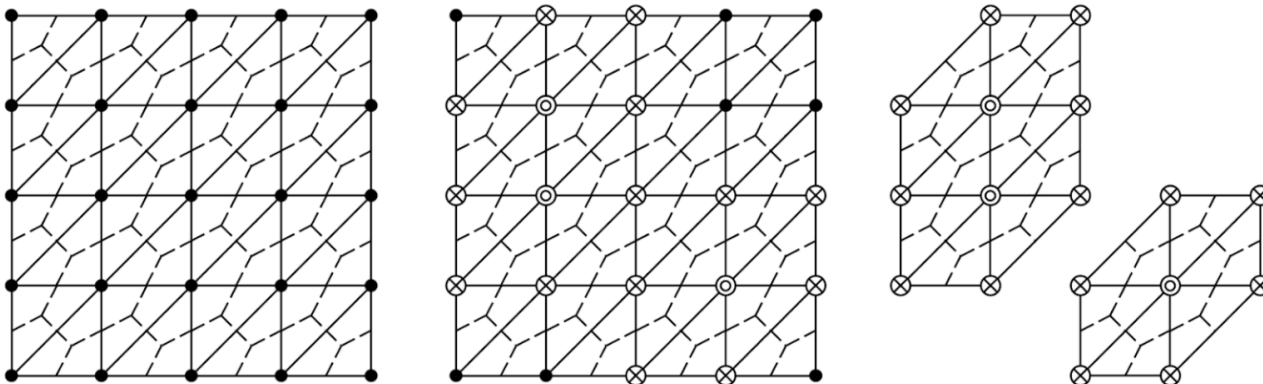
Energy-Conserving Sampling and Weighting (ECSW)



- **Project-then-approximate** paradigm (as opposed to approximate-then-project)

$$\begin{aligned} r_k(q_k, t) &= W^T r(\tilde{u}, t) \\ &= \sum_{e \in \mathcal{E}} W^T L_e^T r_e(L_{e+} \tilde{u}, t) \end{aligned}$$

- $L_e \in \{0,1\}^{d_e \times N}$ where d_e is the **number of degrees of freedom** associated with each mesh element (this is in the context of meshes used in first-order hyperbolic problems where there are N_e mesh elements)
- $L_{e+} \in \{0,1\}^{d_e \times N}$ selects degrees of freedom necessary for **flux reconstruction**
- Equality can be **relaxed**



Augmented reduced mesh: \odot represents a selected node attached to a selected element; and \otimes represents an added node to enable the full representation of the computational stencil at the selected node/element

ECSW: Generating the Reduced Mesh and Weights



- Using a subset of the same snapshots $u_i, i \in 1, \dots, n_h$ used to generate the **state basis** V , we can train the reduced mesh
- Snapshots are first **projected** onto their associated basis and then **reconstructed**

$$c_{se} = W^T L_e^T r_e \left(L_e + \left(u_{ref} + V V^T (u_s - u_{ref}) \right), t \right) \in \mathbb{R}^n$$

$$d_s = r_k(\tilde{u}, t) \in \mathbb{R}^n, \quad s = 1, \dots, n_h$$

- We can then form the **system**

$$\mathbf{C} = \begin{pmatrix} c_{11} & \dots & c_{1N_e} \\ \vdots & \ddots & \vdots \\ c_{n_h 1} & \dots & c_{n_h N_e} \end{pmatrix}, \quad \mathbf{d} = \begin{pmatrix} d_1 \\ \vdots \\ d_{n_h} \end{pmatrix}$$

- Where $\mathbf{C}\xi = \mathbf{d}, \xi \in \mathbb{R}^{N_e}, \xi = \mathbf{1}$ must be the solution
- Further relax the equality to yield **non-negative least-squares problem**:

$$\xi = \arg \min_{x \in \mathbb{R}^n} \|\mathbf{C}x - \mathbf{d}\|_2 \text{ subject to } x \geq 0$$

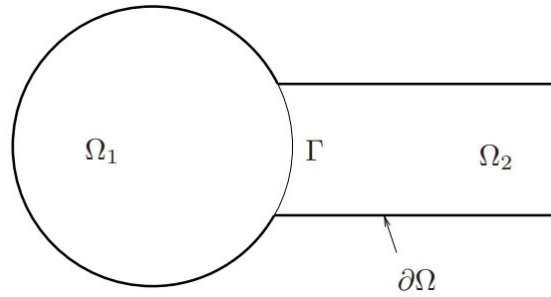
- Solve the above optimization problem using a **non-negative least squares solver** with an **early termination condition** to **promote sparsity** of the vector ξ

Numerical Example: 1D Dynamic Wave Propagation Problem

- Alternating **Dirichlet-Neumann** Schwarz BCs with **no relaxation** ($\theta = 1$) on Schwarz boundary Γ

$$\begin{cases} \text{Div } \mathbf{P}_1^{(n+1)} + \rho \mathbf{B}(t_i) = \mathbf{0}, & \text{in } \Omega_1 \\ \boldsymbol{\varphi}_1^{(n+1)} = \boldsymbol{\chi}, & \text{on } \partial\Omega_1 \setminus \Gamma \\ \boldsymbol{\varphi}_1^{(n+1)} = \boldsymbol{\lambda}_{n+1} & \text{on } \Gamma \end{cases}$$

$$\begin{cases} \text{Div } \mathbf{P}_2^{(n+1)} + \rho \mathbf{B}(t_i) = \mathbf{0}, & \text{in } \Omega_2 \\ \boldsymbol{\varphi}_2^{(n+1)} = \boldsymbol{\chi}, & \text{on } \partial\Omega_2 \setminus \Gamma \\ \mathbf{P}_2^{(n+1)} \mathbf{n} = \mathbf{P}_1^{(n+1)} \mathbf{n}, & \text{on } \Gamma \end{cases}$$



$$\boldsymbol{\lambda}_{n+1} = \theta \boldsymbol{\varphi}_2^{(n)} + (1 - \theta) \boldsymbol{\lambda}_n, \text{ on } \Gamma, \text{ for } n \geq 1$$

θ	Min # Schwarz Iters	Max # Schwarz Iters	Total # Schwarz Iters
1.10	3	9	59,258
1.00	1	4	24,630
0.99	1	5	35,384
0.95	3	6	45,302
0.90	3	8	56,114

➤ A **parameter sweep study** revealed $\theta = 0$ gave best performance (min # Schwarz iterations)

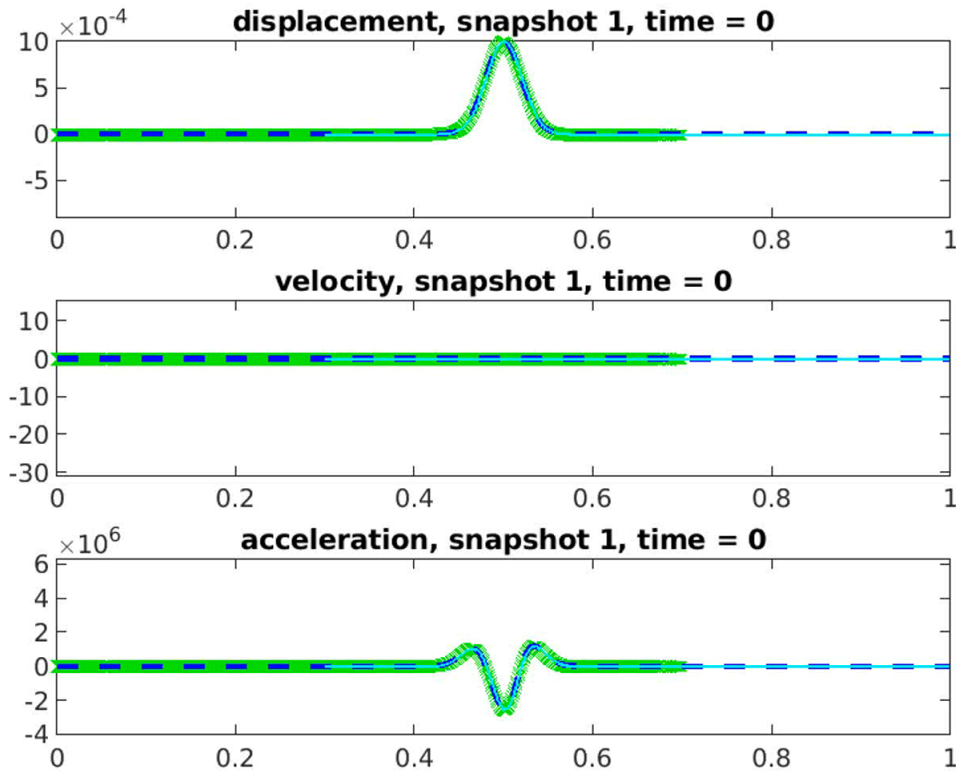
- All couplings were **implicit-implicit** with $\Delta t_1 = \Delta t_2 = \Delta T = 10^{-7}$ and $\Delta x_1 = \Delta x_2 = 10^{-3}$
 - Time-step and spatial resolution chosen to be small enough to resolve the propagating wave
- All reproductive cases run on the **same RHEL8 machine** and all predictive cases run on the **same RHEL7 machine**, in MATLAB
- Model **accuracy** evaluated w.r.t. analogous FOM-FOM coupling using **mean square error (MSE)**:

$$\varepsilon_{MSE}(\tilde{\mathbf{u}}_i) := \frac{\sqrt{\sum_{n=1}^S \|\tilde{\mathbf{u}}_i^n - \mathbf{u}_i^n\|_2^2}}{\sqrt{\sum_{n=1}^S \|\mathbf{u}_i^n\|_2^2}}$$

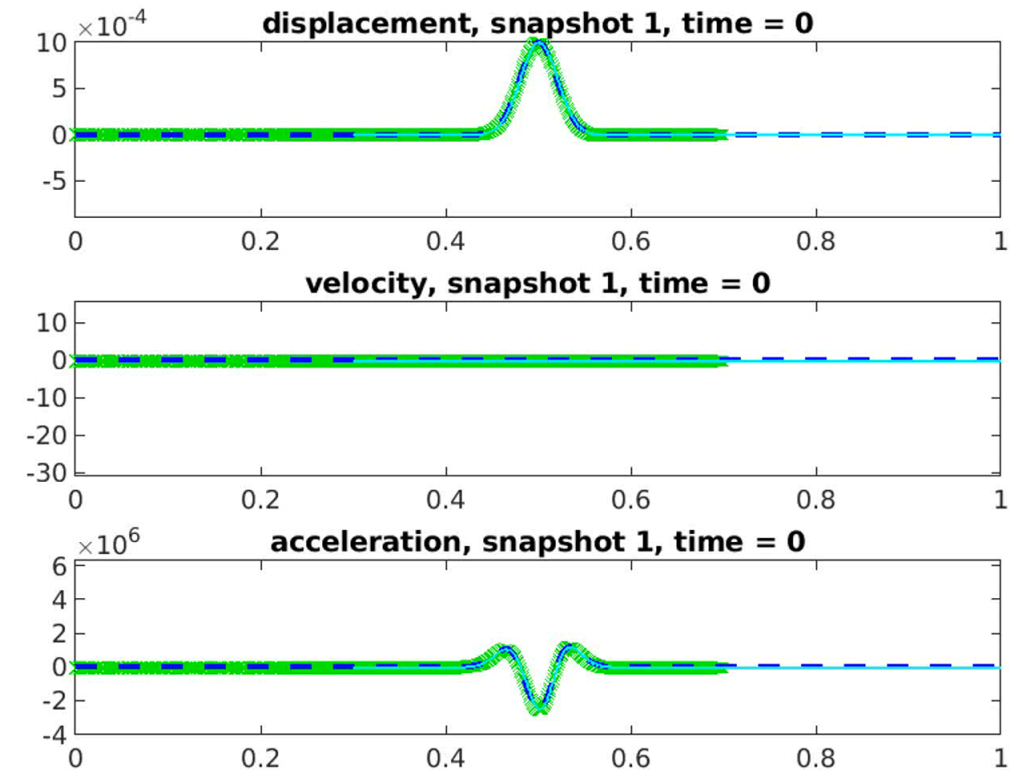
Overlapping Coupling, Nonlinear Henky MM, 2 Subdomains



- $\Omega = [0, 0.7] \cup [0.3, 1]$, implicit-implicit FOM-FOM coupling, $dt = 1e-7$, $dx = 1e-3$.

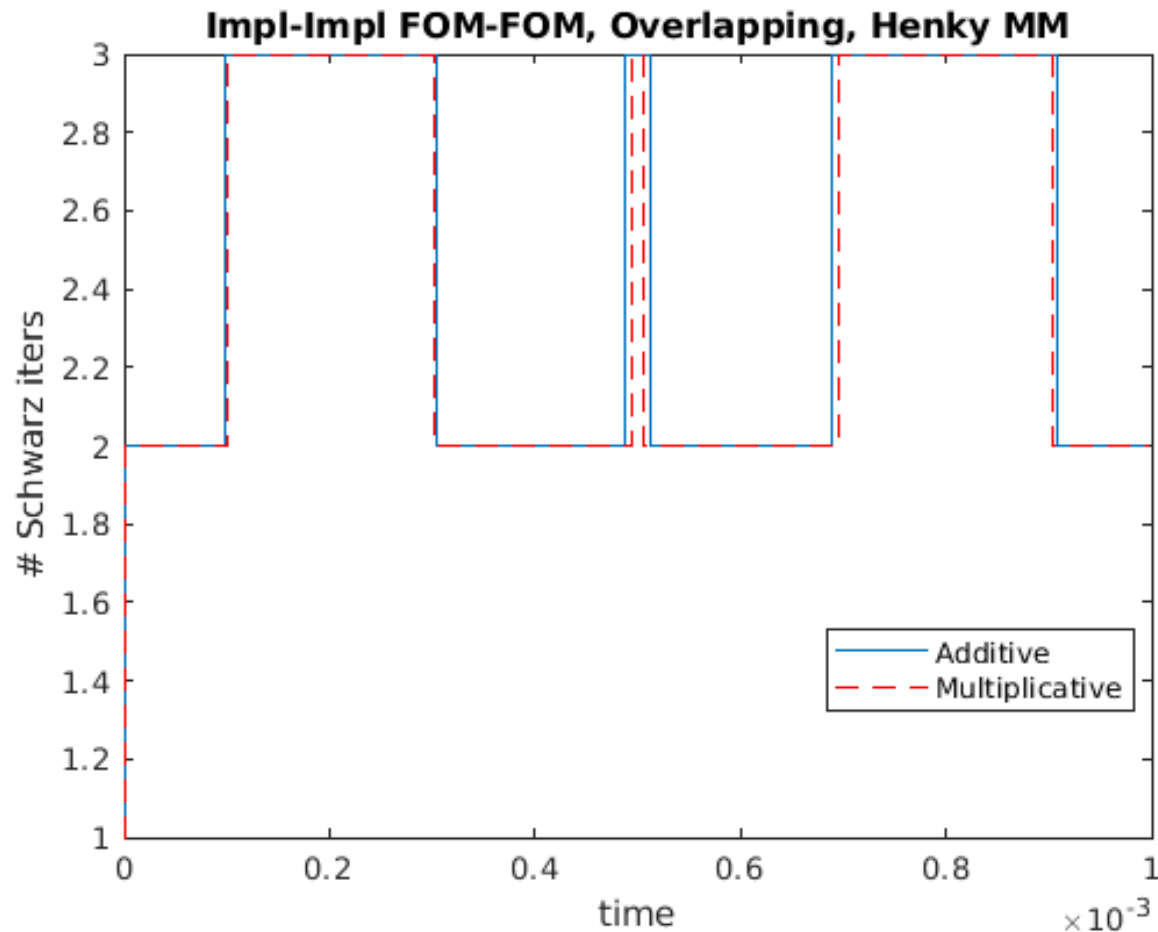


Multiplicative Schwarz



Additive Schwarz

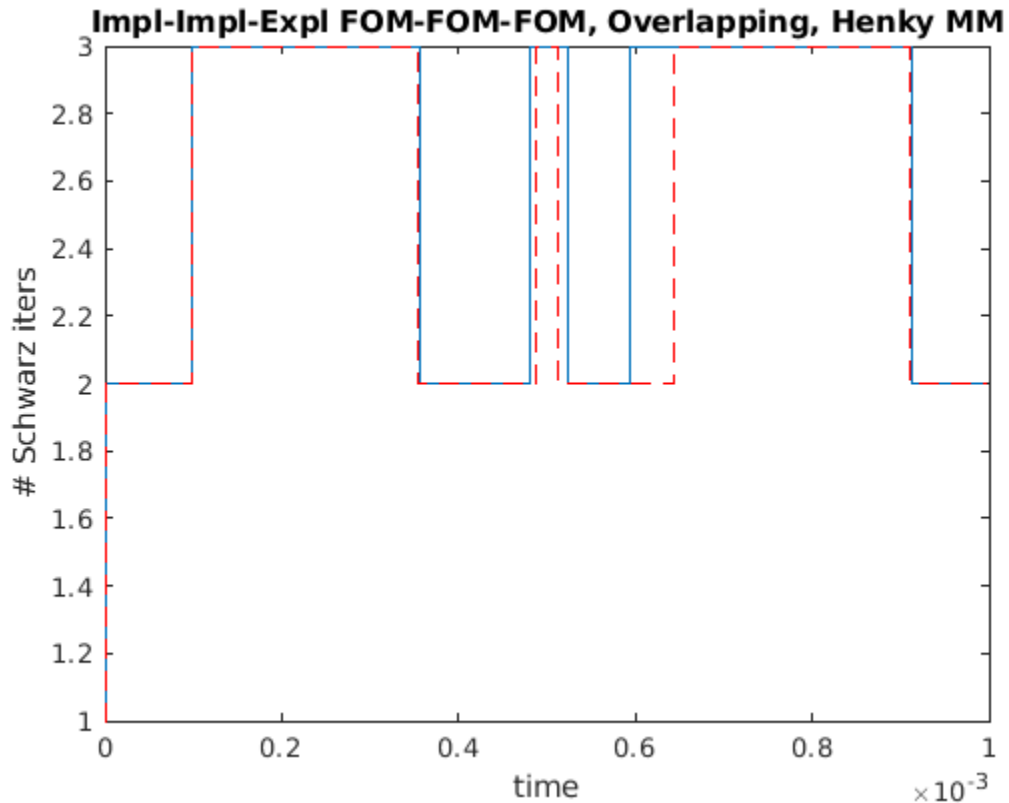
Overlapping Coupling, Nonlinear Henky MM, 2 Subdomains



- $\Omega = [0, 0.7] \cup [0.3, 1]$, implicit-implicit FOM-FOM coupling, $dt = 1e-7$, $dx=1e-3$.
- Additive Schwarz requires slightly more Schwarz iterations but is actually faster.
- Solutions agree effectively to machine precision in mean square (MS) sense.

	Additive	Multiplicative
Total # Schwarz iters	24495	24211
CPU time	2.03e3s	2.16e3
MS difference in disp	6.34e-13/6.12e-13	
MS difference in velo	1.35e-11/1.86e-11	
MS difference in acce	5.92e-10/1.07e-9	

Overlapping Coupling, Nonlinear Henky MM, 3 Subdomains

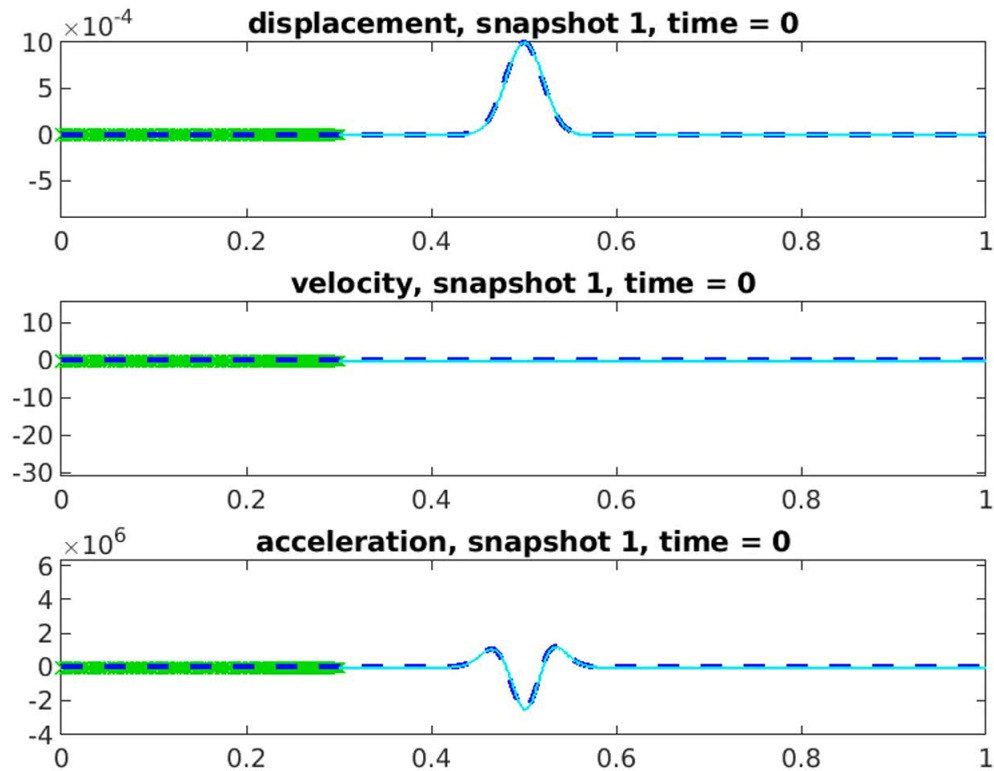


- $\Omega = [0, 0.3] \cup [0.25, 0.75] \cup [0.7, 1]$, implicit-implicit-explicit FOM-FOM-FOM coupling, $dt = 1e-7$, $dx = 0.001$.
- Solutions agree effectively to machine precision in mean square (MS) sense.
- Additive Schwarz has slightly more Schwarz iterations but is slightly faster than multiplicative.

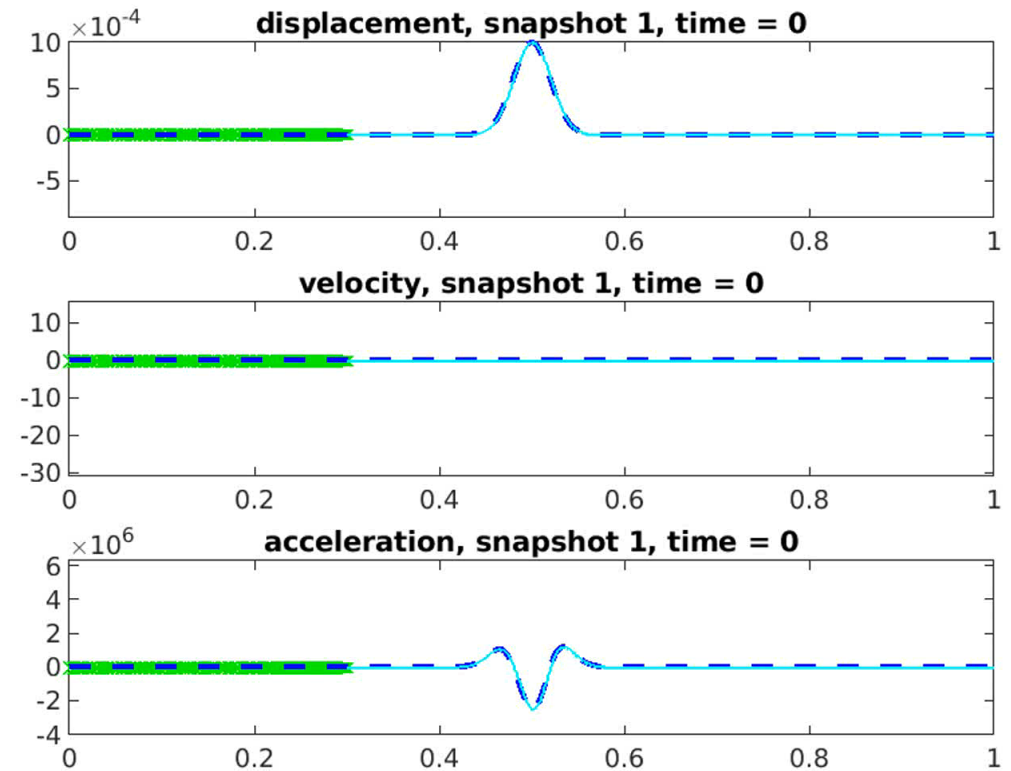
	Additive	Multiplicative
Total # Schwarz iters	26231	25459
CPU time	1.89e3s	2.05e3s
MS difference in disp	5.3052e-13/9.3724e-13/6.1911e-13	
MS difference in velo	7.2166e-12/2.2937e-11/2.4975e-11	
MS difference in acce	2.8962e-10/1.1042e-09/1.6994e-09	

Non-overlapping Coupling, Nonlinear Henky MM, 2 Subdomains

- $\Omega = [0, 0.3] \cup [0.3, 1]$, implicit-implicit FOM-FOM coupling, $dt = 1e-7$, $dx = 1e-3$.

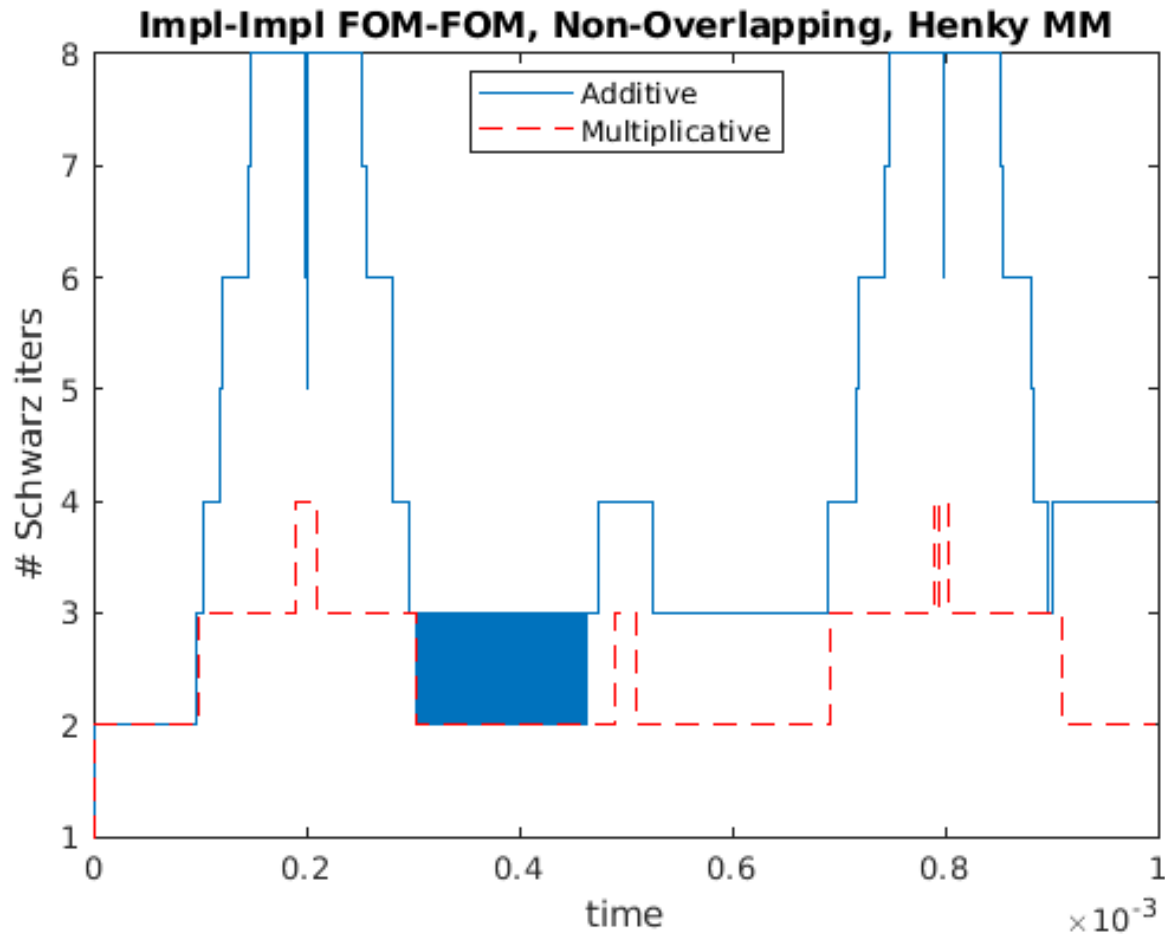


Multiplicative Schwarz



Additive Schwarz

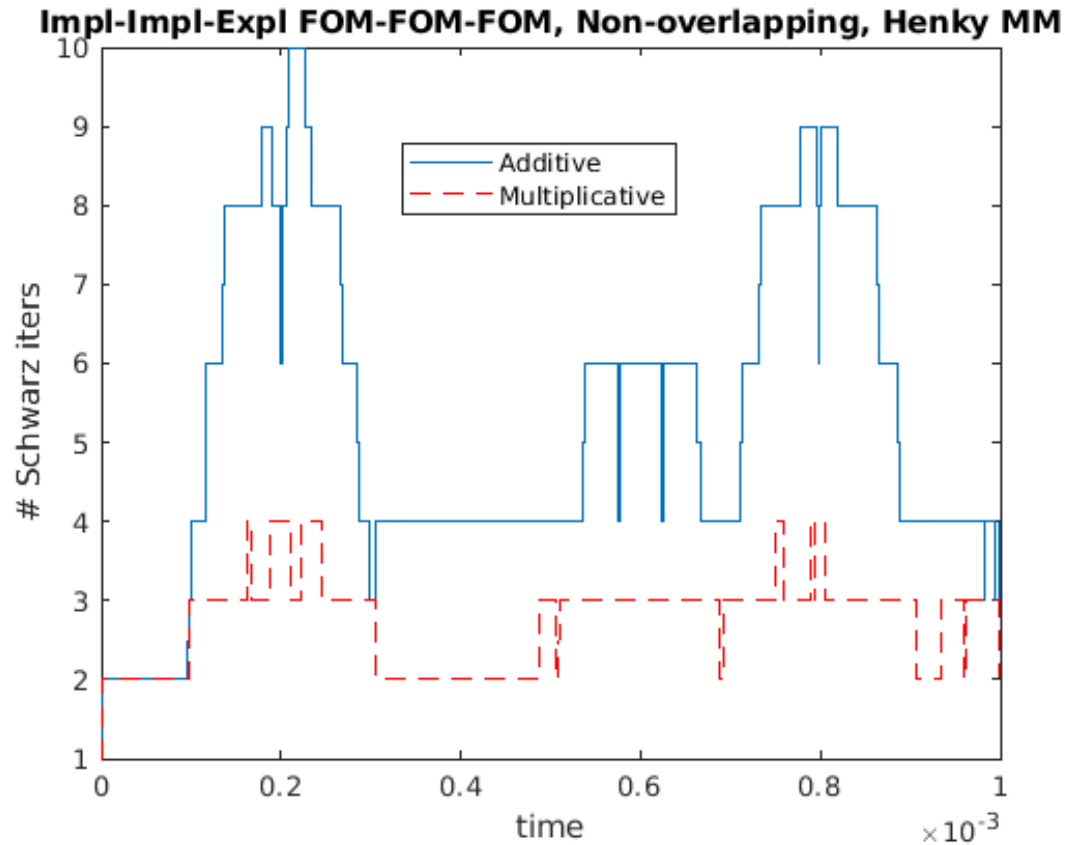
Non-overlapping Coupling, Nonlinear Henry MM, 2 Subdomains



- $\Omega = [0, 0.3] \cup [0.3, 1]$, implicit-implicit FOM-FOM coupling, $dt = 1e-7$, $dx = 1e-3$.
- Additive Schwarz requires 1.81x Schwarz iterations (and 1.9x CPU time) to converge. CPU time could be reduced through added parallelism of additive Schwarz.
 - Note blue square for additive Schwarz...
- Additive and multiplicative solutions differ in mean square (MS) sense by $O(1e-5)$.

	Additive	Multiplicative
Total # Schwarz iters	44895	24744
CPU time	1.87e3s	982.5s
MS difference in disp	4.26e-5/2.74e-5	
MS difference in velo	1.02e-5/5.91e-6	
MS difference in acce	5.84e-5/1.21e-5	

Non-overlapping Coupling, Nonlinear Henry MM, 3 Subdomains



- $\Omega = [0, 0.3] \cup [0.3, 0.7] \cup [0.7, 1]$, implicit-implicit-explicit FOM-FOM-FOM coupling, $dt = 1e-7$, $dx = 0.001$.
- Additive Schwarz has about 1.94x number Schwarz iterations and is about 2.06x slower - similar to 2 subdomain variant of this problem. No “blue square”.
 - Results suggest you could win with additive Schwarz if you parallelize and use enough domains.
- Additive/multiplicative solutions differ by $O(1e-5)$, like for 2 subdomain variant of this problem.

	Additive	Multiplicative
Total # Schwarz iters	53413	27509
CPU time	5.91e3s	2.87e3s
MS difference in disp	2.8036e-05/3.1142e-05/ 8.8395e-06	
MS difference in velo	1.4077e-05/1.2104e-05/6.5771e-06	
MS difference in acce	8.7885e-05/3.2707e-05/1.3778e-05	