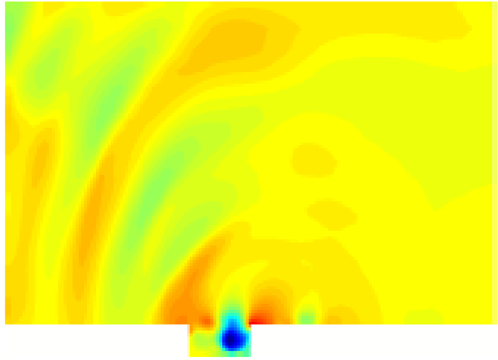
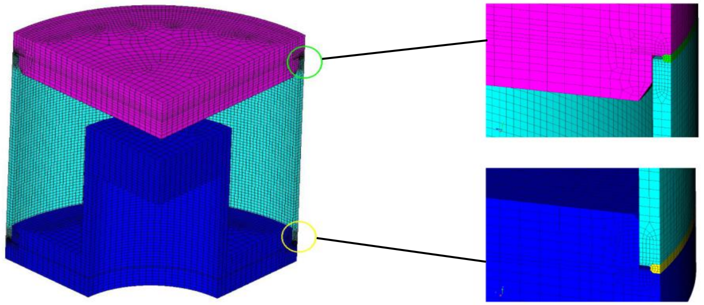
SAND2021-11141C

Sandia National Laboratories

Preconditioned Least-Squares Petrov-Galerkin Reduced Order Models for Fluid and Solid Mechanics Problems





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MMLDT-CSET2021

Wednesday, September 28, 2021

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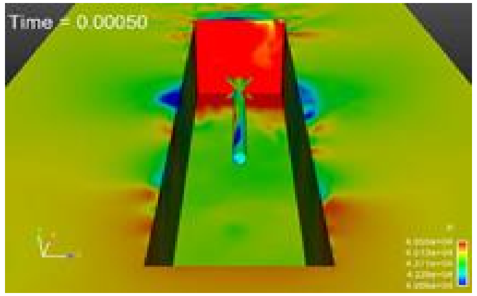
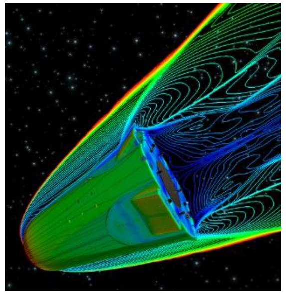
Motivation

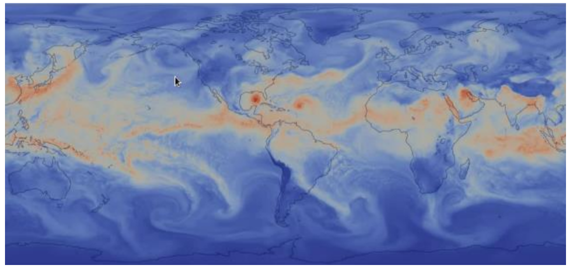
Despite improved algorithms and powerful supercomputers, **“high-fidelity” models** are often too expensive for use in a design or analysis setting.

Sandia application areas in which this situation arises:



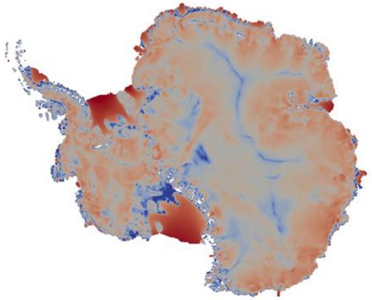


- **Captive-carry** and **re-entry environments:** Large Eddy Simulations (LES) runs require very fine meshes and can take on the order of *weeks*.



- **Fastener failure modeling:** modeling fastener behavior in a full system presents meshing and computational challenges, which limits the number of configurations that can be studied.

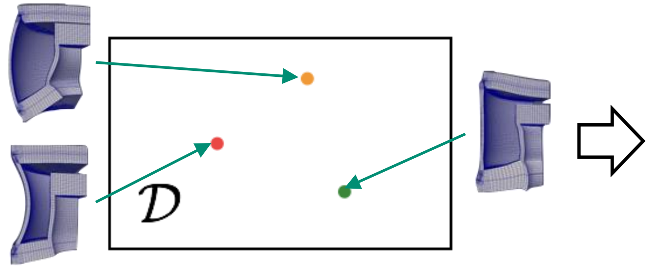
- **Climate modeling** (e.g., land-ice, atmosphere): high-fidelity simulations too costly for uncertainty quantification (UQ); Bayesian inference of high-dimensional parameter fields is intractable.



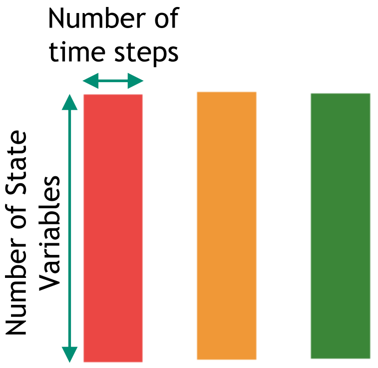
POD/LSPG* Approach to Model Reduction

Full Order Model (FOM) = Ordinary Differential Equation (ODE): $\frac{d\mathbf{x}}{dt} = \mathbf{f}(\mathbf{x}; t, \boldsymbol{\mu})$

1. Acquisition



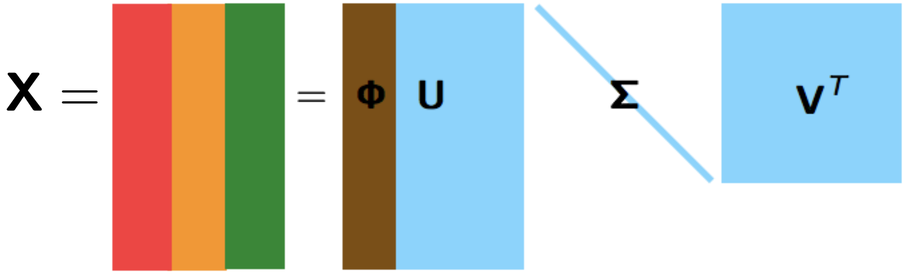
Solve ODE at different design points



Save solution data

2. Learning

Proper Orthogonal Decomposition (POD):



3. Reduction

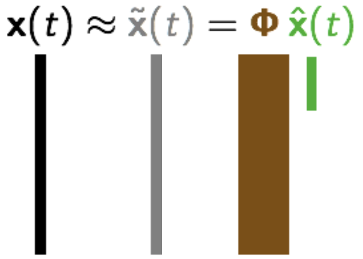
Choose ODE Temporal Discretization

$$\frac{d\mathbf{x}}{dt} = \mathbf{f}(\mathbf{x}; t, \boldsymbol{\mu})$$

$$\Downarrow$$

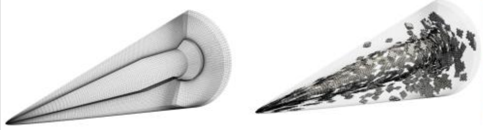
$$\mathbf{r}^n(\mathbf{x}^n; \boldsymbol{\mu}) = \mathbf{0}, \quad n = 1, \dots, T$$

Reduce the number of unknowns

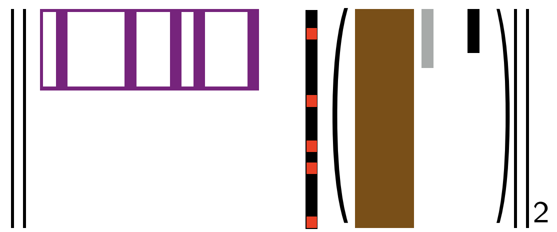


Minimize the Residual

$\underset{\hat{\mathbf{v}}}{\text{minimize}} \| \mathbf{A}\, \mathbf{r}^n(\boldsymbol{\Phi}\, \hat{\mathbf{v}}; \boldsymbol{\mu}) \|_2$



Hyper-reduction/sample mesh



*Least-Squares Petrov-Galerkin Projection [K. Carlberg *et al.*, 2011; K. Carlberg *et al.*, 2017]

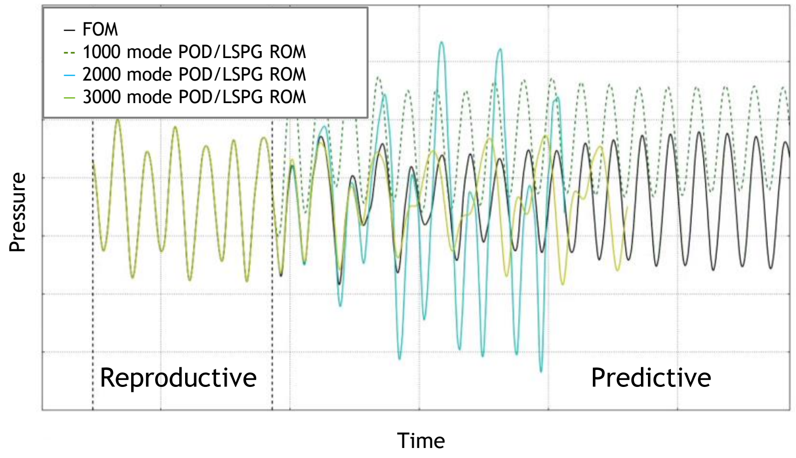
POD/LSPG Approach to Model Reduction

Advantages of POD/LSPG projection:

- Computes a solution that **minimizes the l_2-norm** of the time-discrete residual arising in each Δt
  - Ensures that adding basis vectors yields a **monotonic decrease** in the least-squares objective function defining the underlying minimization problem [Carlberg *et al.*, 2011]
- Possesses **better stability and accuracy** than POD/Galerkin for certain classes of problems (e.g., compressible flow) [Carlberg *et al.*, 2013, Carlberg *et al.*, 2017, Tezaur *et al.*, 2018].

Room for improvement for realistic predictive applications:

- Accuracy for **time-predictive problems** can be inadequate
- Method may **fail to converge** for some realistic problems run in the predictive regime
- Method may struggle when applied to **multi-physics problems** with disparate scales [Washabaugh, 2016]



Solution: introduction of preconditioning into LSPG/ROM formulation.

Preconditioned LSPG ROMs

LSPG Formulation:

$$\hat{\boldsymbol{x}} = \underset{\boldsymbol{y}\in\mathbb{R}^M}{\operatorname{argmin}} ||\boldsymbol{r}(\boldsymbol{\Phi}\boldsymbol{y})||_2^2$$

Optimization problem

$$\delta\hat{\boldsymbol{x}}_{\mathrm{PG}}^{(k)} = \underset{\boldsymbol{y}\in\mathbb{R}^M}{\operatorname{argmin}} ||\boldsymbol{J}^{(k)}\boldsymbol{\Phi}\boldsymbol{y} + \boldsymbol{r}^{(k)}||_2^2$$
$$\hat{\boldsymbol{x}}_{\mathrm{PG}}^{(k)} = \hat{\boldsymbol{x}}_{\mathrm{PG}}^{(k-1)} + \alpha_k \delta\hat{\boldsymbol{x}}_{\mathrm{PG}}^{(k)}$$
$$\tilde{\boldsymbol{x}}_{\mathrm{PG}}^{(k)} = \boldsymbol{\Phi}\hat{\boldsymbol{x}}_{\mathrm{PG}}^{(k)}$$

Gauss-Newton iteration

Normal equations

$$\boldsymbol{J}_{\mathrm{PG}}^{(k)}\delta\hat{\boldsymbol{x}}_{\mathrm{PG}}^{(k)} = -\boldsymbol{r}_{\mathrm{PG}}^{(k)}$$
$$\boldsymbol{J}_{\mathrm{PG}}^{(k)} := \boldsymbol{\Phi}^T\boldsymbol{J}^{(k)T}\,\boldsymbol{J}^{(k)}\boldsymbol{\Phi}$$
$$\boldsymbol{r}_{\mathrm{PG}}^{(k)} := \boldsymbol{\Phi}^T\boldsymbol{J}^{(k)T}\boldsymbol{r}^{(k)}$$

Preconditioned LSPG Formulation:

$$\hat{\boldsymbol{x}} = \underset{\boldsymbol{y}\in\mathbb{R}^M}{\operatorname{argmin}} ||\boldsymbol{M}\boldsymbol{r}(\boldsymbol{\Phi}\boldsymbol{y})||_2^2$$

Optimization problem

$$\delta\hat{\boldsymbol{x}}_{\mathrm{PPG}}^{(k)} = \underset{\boldsymbol{y}\in\mathbb{R}^M}{\operatorname{argmin}} ||\boldsymbol{M}^{(k)}(\boldsymbol{J}^{(k)}\boldsymbol{\Phi}\boldsymbol{y} + \boldsymbol{r}^{(k)})||_2^2$$
$$\hat{\boldsymbol{x}}_{\mathrm{PPG}}^{(k)} = \hat{\boldsymbol{x}}_{\mathrm{PPG}}^{(k-1)} + \alpha_k \delta\hat{\boldsymbol{x}}_{\mathrm{PPG}}^{(k)}$$
$$\tilde{\boldsymbol{x}}_{\mathrm{PPG}}^{(k)} = \boldsymbol{\Phi}\hat{\boldsymbol{x}}_{\mathrm{PPG}}^{(k)}$$

Gauss-Newton iteration

Normal equations

$$\boldsymbol{J}_{\mathrm{PPG}}^{(k)}\delta\hat{\boldsymbol{x}}_{\mathrm{PG}}^{(k)} = -\boldsymbol{r}_{\mathrm{PG}}^{(k)}$$
$$\boldsymbol{J}_{\mathrm{PPG}}^{(k)} := \boldsymbol{\Phi}^T\boldsymbol{J}^{(k)T}\,\boldsymbol{M}^{(k)T}\,\boldsymbol{M}^{(k)}\boldsymbol{J}^{(k)}\boldsymbol{\Phi}$$
$$\boldsymbol{r}_{\mathrm{PPG}}^{(k)} := \boldsymbol{\Phi}^T\boldsymbol{J}^{(k)T}\boldsymbol{M}^{(k)T}\boldsymbol{M}^{(k)}\boldsymbol{r}^{(k)}$$

Preconditioned LSPG ROMs

Adding preconditioning to the POD/LSPG formulation can **improve** not only ROM efficiency but also **ROM accuracy**.

Ideal preconditioned ROM emulates projection of FOM solution increment onto POD basis.

- Upper limit on ROM accuracy is obtained by taking **solution increment** computed by FOM, $\delta \boldsymbol{x}^{(k)}$, at each time step k and **projecting it** onto the **POD basis**:

$$\delta \widetilde{\boldsymbol{x}}^{(k)} = \boldsymbol{\Phi}(\boldsymbol{\Phi}^T \boldsymbol{\Phi})^{-1} \boldsymbol{\Phi}^T \delta \boldsymbol{x}^{(k)} \quad (1)$$

- **Ideal preconditioned** ROM ($\boldsymbol{M}^{(k)} = (\boldsymbol{J}^{(k)})^{-1}$) gives rise to "projected solution increment" solution (1)
- As quality of preconditioner is improved ($\boldsymbol{M}^{(k)} \rightarrow (\boldsymbol{J}^{(k)})^{-1}$), the ROM solution **approaches** the most accurate ROM solution possible for a given basis $\boldsymbol{\Phi}$.

Preconditioning ensures all residual components are on approximately the same scale.

- Minimizing the raw (unweighted) residual $\boldsymbol{r}$ can be problematic for systems of PDEs where different variables have **drastically different magnitudes** (e.g., dimensional PDEs, multi-physics) [Washabaugh, 2016].
- Adding a preconditioner amounts to **scaling** the ROM residual to get all the equations to be roughly the same order.

Numerical Examples: Albany and SPARC codes

Albany multi-physics finite element code

- Open-source[1], parallel, C++ code
- Component-based design for rapid development
- Contains a wide variety of constitutive models for mechanical/thermo-mechanical problems.
- Makes extensive use of libraries from the open-source Trilinos project[2], including preconditioners from the Ifpack library

Problems tested: quasi-static mechanical and **thermo-mechanical** with prediction across **material parameter space**.

[1]https://github.com/SNLComputation/Albany/releases/tag/MOR_support_end
[2]https://github.com/trilinos/trilinos

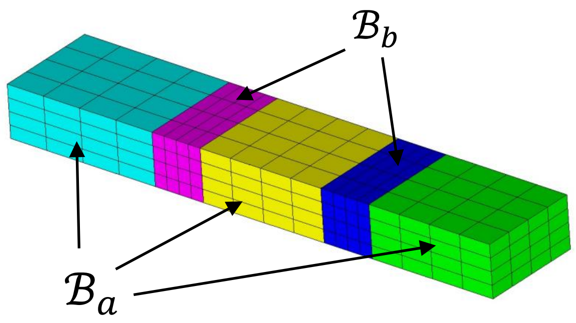
SPARC[3] Flow Solver

- Next-generation transonic and hypersonic C++ CFD code developed at Sandia
- Simulates compressible flow
- Used for analyses involving captive carry and reentry vehicles
- Primary discretization is cell-centered finite volume method
- Leverages libraries from the Trilinos project[2]

Problems tested: transient **compressible laminar flow** over an open cavity with **prediction in time**

[3]Sandia Parallel Aerodynamics and Reentry Code

Thermo-Mechanical Beam (Albany)



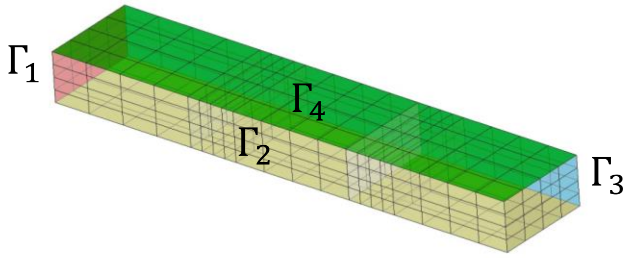
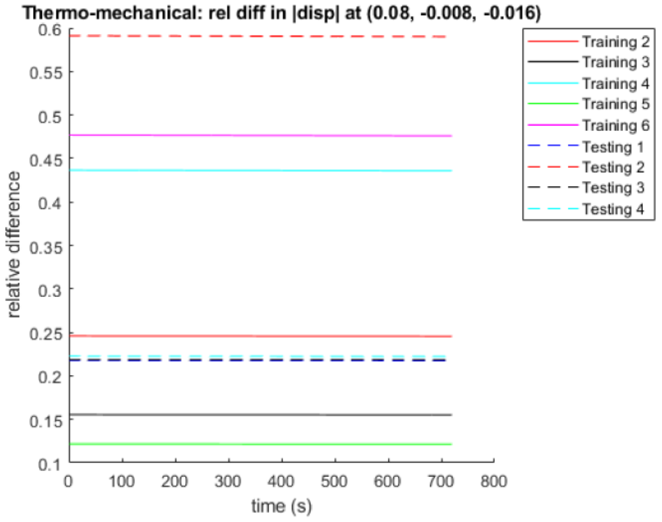


Table 1. Parameters in block $\mathcal{B}_b$ for thermo-mechanical beam problem.

Regime	Case	$E_b(\times 10^9)$ [Pa]	ν_b	$\rho_b(\times 10^{-5})$ [kg/m^3]	$T_{b,\text{ref}}$ [K]
training	1	2.01313	0.285907	7.94827	273.657
	2	1.71637	0.332083	6.93965	318.406
	3	1.96881	0.3478	9.37181	301.406
	4	1.28954	0.29427	9.14636	365.378
	5	1.61326	0.262464	6.32164	223.434
	6	1.54724	0.374118	7.31561	245.778
testing	1	1.52473	0.27925	8.80694	266.674
	2	1.31153	0.345538	7.58234	333.462
	3	1.37015	0.246513	7.73303	345.942
	4	1.703	0.32	7.92	293

- Coupled **thermo-mechanical** problem involving **Neohookean** material
- 2 sets of **material blocks**, $\mathcal{B}_a$ and $\mathcal{B}_b$, each having set of material parameters
  - Material parameters in block $\mathcal{B}_a$ are fixed
  - Material parameters in block $\mathcal{B}_b$ are varied (see Table 1)
- Linearly varying **time-dependent pressure** and **temperature** BC is prescribed on Γ_2; other boundaries are fixed
- Problem is run **quasi-statically** to pseudo-time t =7200s with 2100 dofs
- **Training** is performed for 6 sets of parameters; **testing/prediction** is performed for 4 sets of parameters (see Table 1)
  - **Significant variations** in displacement (up to 60%) are observed with the parameter variations considered (right figure)



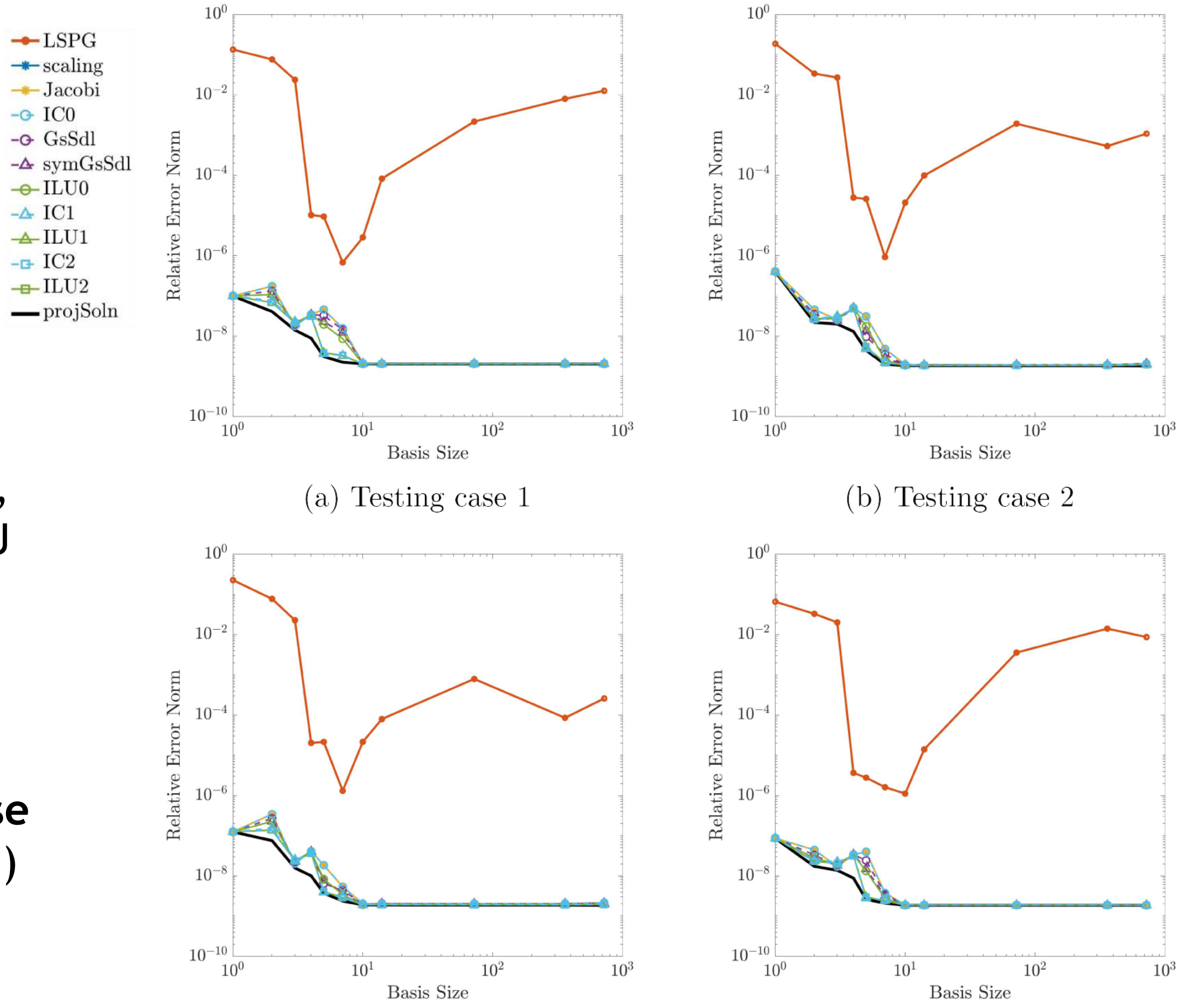
[Lindsay *et al.*, in prep.]

Thermo-Mechanical Beam (Albany)

- Figure plots **global relative error** in approximate ROM solutions:

$$\epsilon := \frac{\sum_{i=0}^{P} \|x_i - \tilde{x}_i\|_2}{\sum_{i=0}^{P} \|x_i\|_2}$$

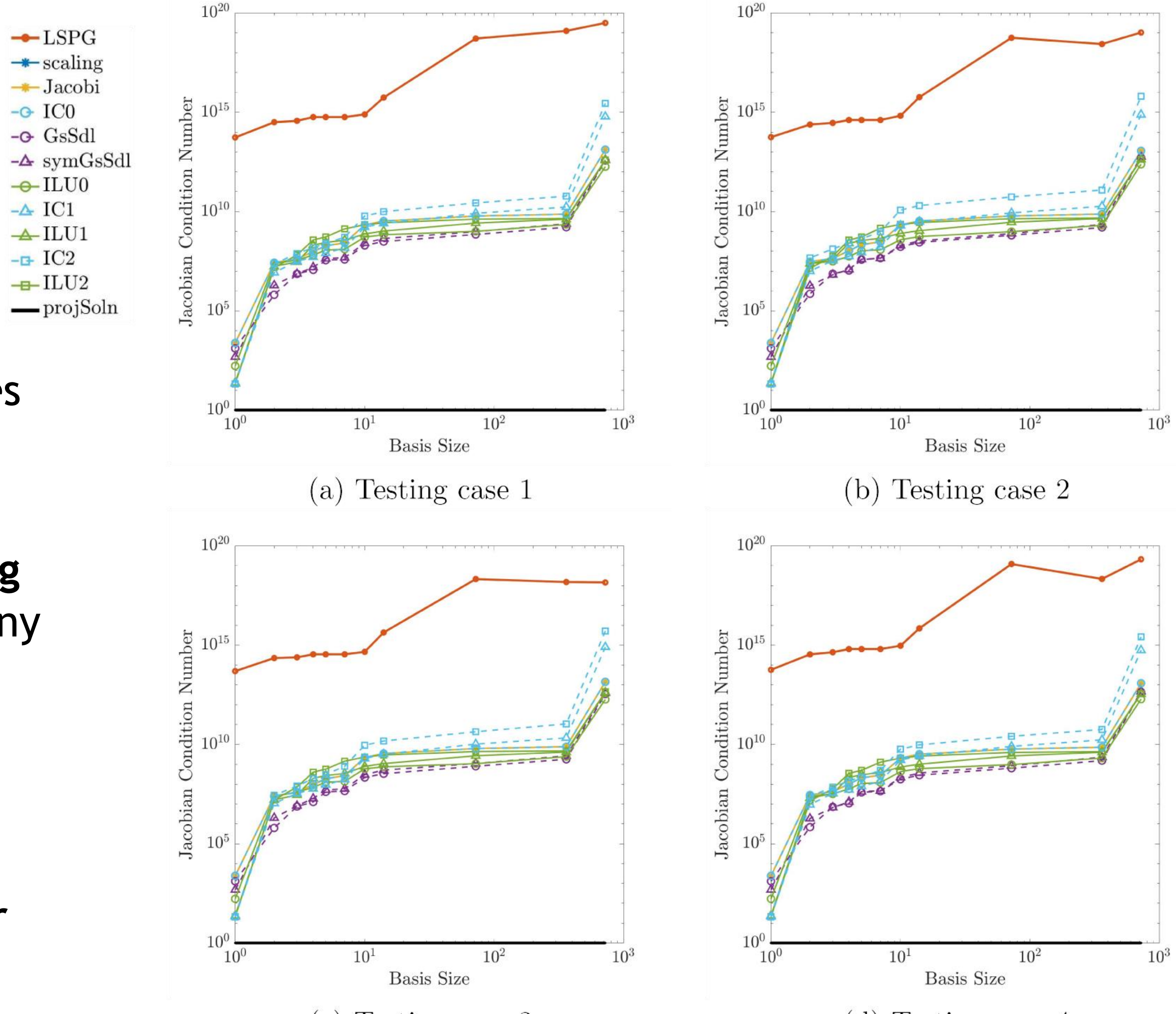
- **Preconditioners evaluated**: Jacobi, Gauss-Seidel, Symmetric Gauss-Seidel, Incomplete Cholesky, ILU and $(\boldsymbol{J}^{(k)})^{-1}$ (denoted by projSoln)
- By introducing preconditioning, it is possible to reduce ϵ by **2-6 orders of magnitude**
- All preconditioned LSPG ROMs achieve **errors close to** (less than one order of magnitude greater than) the error obtained by the **projected solution increment** model



(a) Testing case 1 (b) Testing case 2
(c) Testing case 3 (d) Testing case 4

Thermo-Mechanical Beam (Albany)

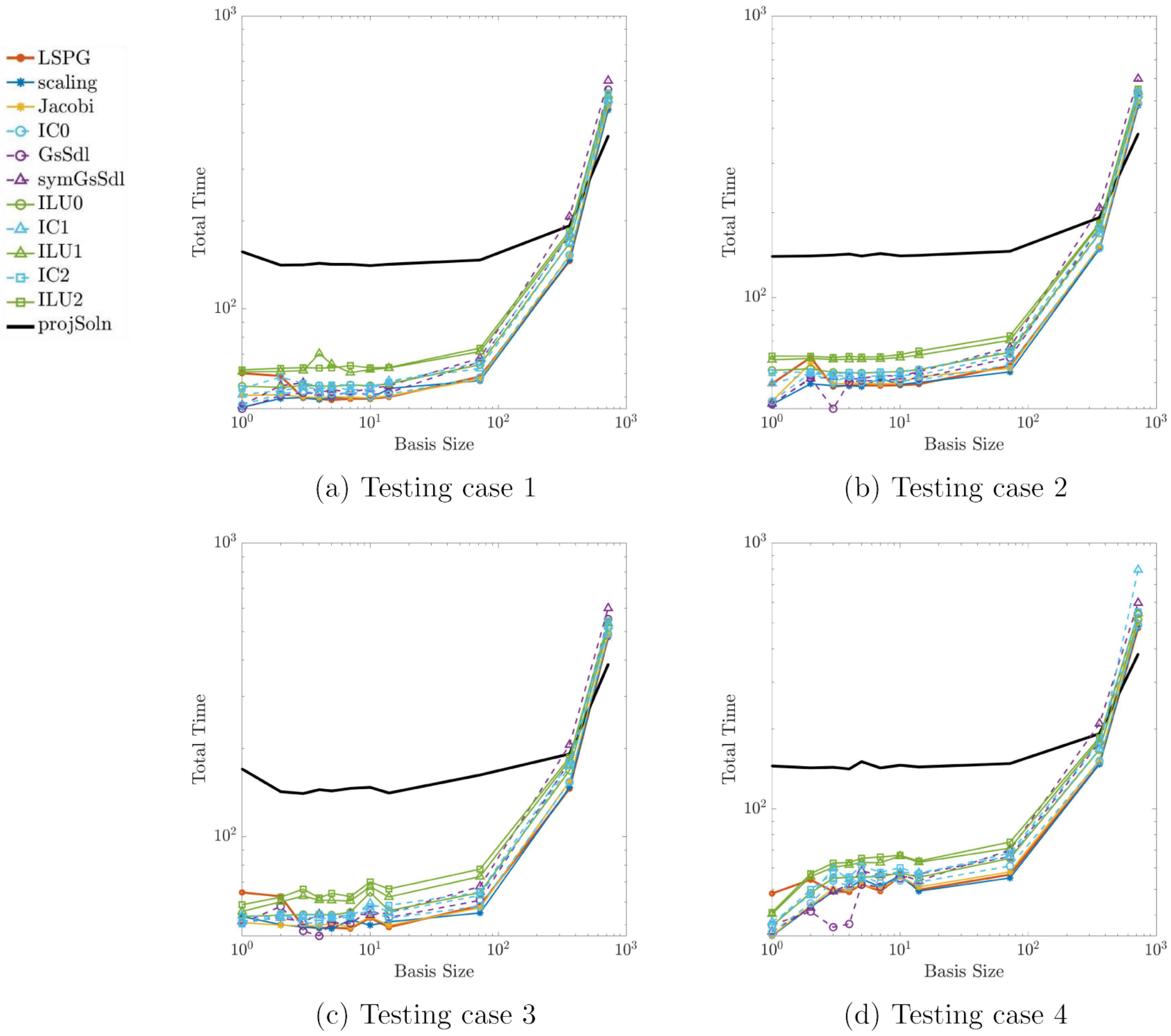
- Figure plots **condition numbers** of reduced Jacobian ($\boldsymbol{J}_{\mathrm{PPG}}^{(k)}$ or $\boldsymbol{J}_{\mathrm{PG}}^{(k)}$) for each ROM.
- Reduced Jacobians for regular LSPG ROM are **very ill-conditioned** ($O(10^{14}) - O(10^{16})$)
  - ➢ Ill-conditioning is due to extreme differences in scale b/w displacement and temperature solutions (9 orders of magnitude)
- Results demonstrate that **simple preconditioning** strategy can reduce condition numbers by as many as **10 orders of magnitude**
  - ➢ **Gauss-Seidel** preconditioners produce the **lowest condition number**
- As expected, projected solution increment reduced Jacobian has **perfect condition number**



(a) Testing case 1 (b) Testing case 2 (c) Testing case 3 (d) Testing case 4

Thermo-Mechanical Beam (Albany)

- Figures shows **CPU-times** for all ROMs considered
- **Preconditioned LSPG ROMs** achieve CPU-times that are **comparable** or **marginally larger** than unpreconditioned LSPG ROM
- Since preconditioned ROMs are substantially more accurate than vanilla LSPG, there is a **significant computational advantage** in applying preconditioning
- **Gauss-Seidel** preconditioners give rise to **lowest CPU-times** of preconditioned ROMs
- As expected, the **projected solution increment** is the **most expensive** to compute



Thermo-Mechanical Pressure Vessel (Albany)

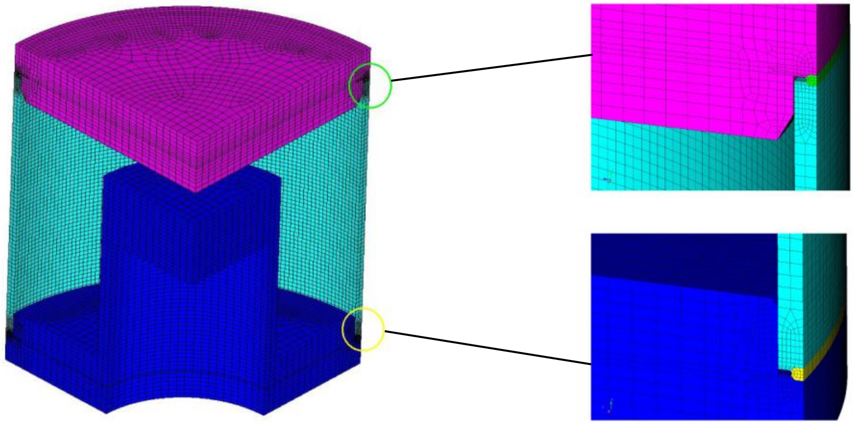


Table 2. Parameters in block $\mathcal{B}_b$ for thermo-mechanical pressure vessel problem.

Regime	Case	$E_b(\times 10^9)$ [Pa]	ν_b	$\rho_b(\times 10^{-3})$ [kg/m^3]	$T_{b,\mathrm{ref}}$ [K]
training	1	1.64424	0.39524	8.33058	311.094
	2	1.77118	0.300065	9.67843	267.396
	3	1.9893	0.32161	7.17625	223.746
	4	1.45551	0.266385	6.67746	331.116
testing	1	2.06416	0.391368	7.79804	252.102
	2	1.703	0.32	7.92	293

- Coupled **thermo-mechanical** problem involving **Neohookean** material
- 2 sets of **material blocks**, $\mathcal{B}_a$ and $\mathcal{B}_b$, each having set of material parameters
  - Material parameters in block $\mathcal{B}_a$ (magenta, cyan) are fixed
  - Material parameters in block $\mathcal{B}_b$ (green, yellow, blue) are varied (see Table 2)
- Pressure vessel is **heated** and **pressurized** from the lateral side
- Problem is run **quasi-statically** to pseudo-time t =720s with 370K dofs
- **Training** is performed for 4 sets of parameters; **testing/prediction** is performed for 2 sets of parameters (see Table 2)

[Lindsay *et al.*, in prep.]

Thermo-Mechanical Pressure Vessel (Albany)

Table 3. Errors ϵ for thermo-mechanical pressure vessel problem

Testing case	Method	Basis size M: 8	79	790
1	LSPG	2.6×10^{-1}	–	–
	GsSdl Preconditioned LSPG	1.4×10^{-5}	1.9×10^{-6}	1.7×10^{-6}
2	LSPG	1.8×10^{-2}	–	–
	GsSdl Preconditioned LSPG	1.1×10^{-5}	2.2×10^{-6}	2.0×10^{-6}

Table 4. CPU-times for thermo-mechanical pressure vessel problem

Testing case	Method	Basis size M: 8	79	790
1	LSPG	19,490	–	–
	GsSdl Preconditioned LSPG	5449	6903	44,400
2	LSPG	9785	–	–
	GsSdl Preconditioned LSPG	4670	5057	14,620

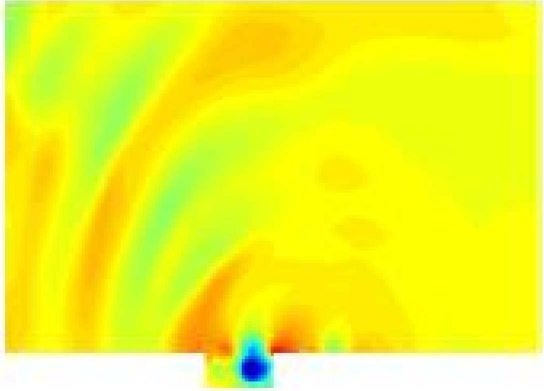
Table 5. Number nonlinear iterations for thermo-mechanical pressure vessel problem

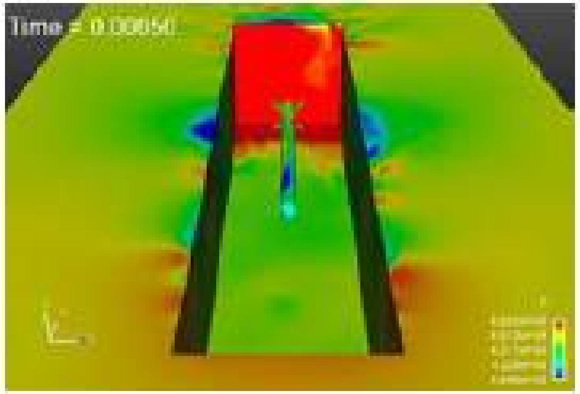
Testing case	Method	Basis size M: 8	79	790
1	LSPG	7849	–	–
	GsSdl Preconditioned LSPG	2104	1963	1971
2	LSPG	4963	–	–
	GsSdl Preconditioned LSPG	1628	1700	1717

- **Three basis sizes considered**: $M = 8, 79, 790$ modes
- One preconditioner considered: **Gauss-Seidel**

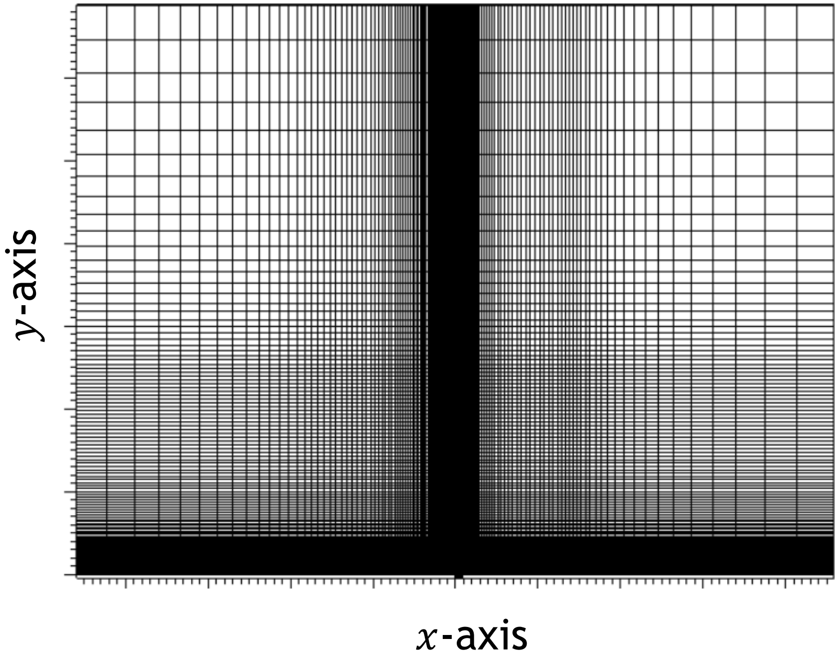
- Vanilla **LSPG ROM** results are **unsatisfactory**
  - LSPG ROM did not converge for larger basis sizes ($M = 79$ and $M = 790$)
  - For smaller basis size ($M = 8$), the LSPG ROM was only able to achieve a global error of $O(10^{-1}) - O(10^{-2})$
- **Preconditioned** LSPG ROM **converges** for all basis sizes and **achieves errors** of $O(10^{-5}) - O(10^{-6})$
- For $M = 8$ case, the preconditioned LSPG ROM achieved a **speedup of up to 3.6x** over LSPG ROM
- Preconditioned LSPG ROM reduces the total number of **nonlinear iterations** by a **factor of 3-4x**

Compressible Cavity Flow (SPARC)



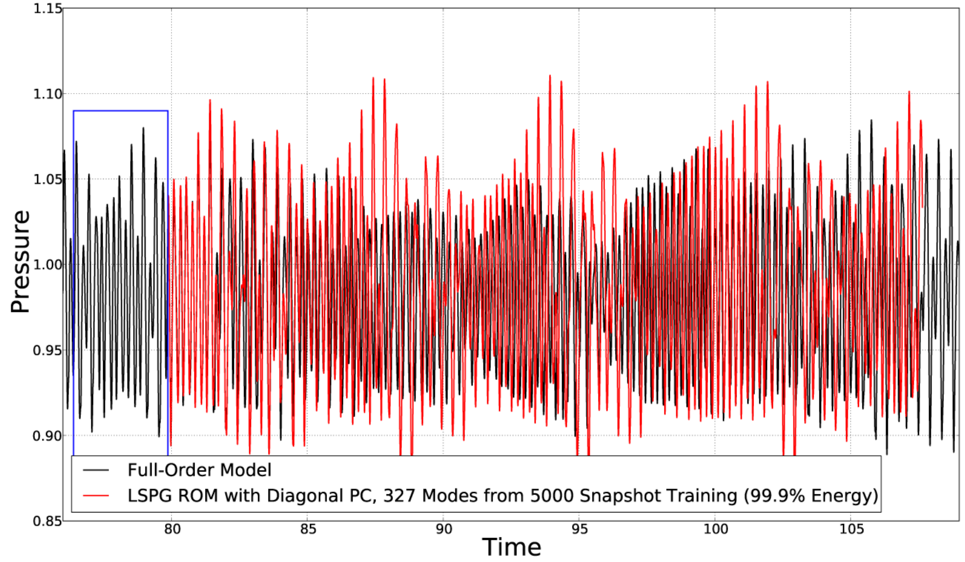


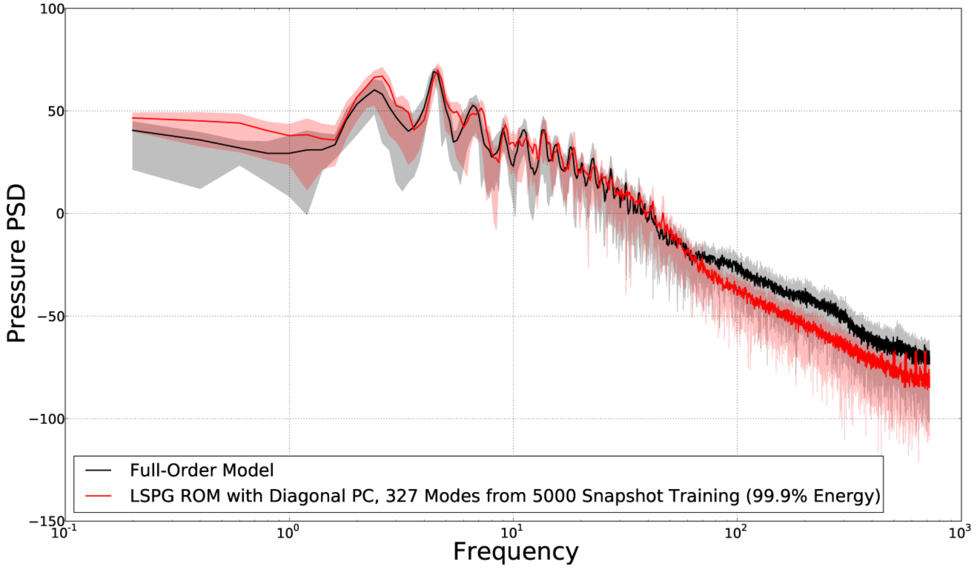
- 2D **viscous laminar flow** around an **open cavity** geometry
  - ➢ Simple model for the **captive carry scenario**
- Mach number = 0.6, Reynolds number ≈ 3000
- Problem is run **non-dimensionally**
- Domain is discretized using 104,500 hexahedral cells (right)
- Of primary interest are **long-time predictive simulations**
  - ➢ ROM is run at **same parameters** as FOM but **much longer in time**
  - ➢ **Relevant QOIs:** statistics of the flow (e.g., pressure power spectral densities or PSDs)



[Tezaur *et al*. 2017, Fike *et al*. 2018]

Compressible Cavity Flow (SPARC)





- **Figure top left:** pressure time history for a point halfway up the downstream wall of the cavity for an LSPG ROM having 327 modes with a Jacobi preconditioner (PC)
- **Figure bottom left:** pressure PSD for the signal in the top left figure (solid line is mean PSD, shaded regions indicate range of values used to construct the mean)
- **Preconditioned LSPG ROM** captures well the **pressure PSD**, including its peaks (Rossiter modes) and the **RMS OASPL**[1]
- Vanilla LSPG ROM **did not run successfully**

Method	RMS OASPL[1] in dB	% Difference from FOM in dB
FOM	66.176	–
projSoln	67.552	2.08%
LSPG	N/A	N/A
LSPG + Jacobi PC	68.033	2.80%

[1]Overall sound pressure level

Summary & Future Work

Summary:

- Adding **preconditioning** to the LSPG formulation gives rise to ROMs with **improved accuracy** and **stability**, especially in the predictive regime
  - ➢ Preconditioning attempts to **emulate projection of FOM solution increment onto POD basis** (the ROM "best-case scenario" for a given basis)
  - ➢ Preconditioning **ensures all components of residual** being minimized are of the **same magnitude**
  - ➢ Results on **predictive (across parameter space) thermo-mechanical** and **predictive (in time) compressible flow** problems are **compelling**

Ongoing/future work:

- **Two manuscripts** on this work are in preparation
  - ➢ P. Lindsay, J. Fike, K. Carlberg, I. Tezaur. "Preconditioned LSPG Reduced Order Models", *in prep*.
  - ➢ J. Fike, P. Lindsay, K. Carlberg, I. Tezaur. "Preconditioned Least-Squares Petrov-Galerkin Reduced Order Models for Compressible Flows", *in prep*.
- **Application** of preconditioned LSPG approach to **more sophisticated problems** relevant to Sandia's mission spaces
  - ➢ Preconditioning LSPG ROMs has been helpful for **hypersonic aero**, **thermal/ablation** and **reacting hypersonic flow** problems

Outline

1. Motivation
2. POD/LSPG Approach to Model Reduction
3. Preconditioned LSPG ROMs
4. Numerical Results
    - Thermo-Mechanical Beam
    - Themo-Mechanical Pressure Vessel
    - Compressible Cavity Flow
5. Summary & Future Work