# Sandia National Laboratories

M2dt: Multifaceted Mathematics for Predictive Digital Twins **Component-Based Coupling of First-Principles and Data-Driven Models** 



I. Tezaur<sup>1</sup>, P. Bochev<sup>1</sup>, P. Kuberry<sup>1</sup>, C. Wentland<sup>1</sup>, J. Barnett<sup>1,2</sup>, A. de Castro<sup>1,3</sup>, E. Hawkins<sup>1,3</sup>, J. Owen<sup>1</sup>, E. Huynh<sup>1,4</sup>



## **Ongoing and Future Work**

**Other Coupling Approaches** 

Model problem: time-dependent advection-diffusion problem (1) **Compatibility conditions: continuity** of **states** and **flux** from (2)

#### **Optimization-Based Coupling (OBC)**

<u>Key Idea</u>: introduce control as the shared Neumann BC on the interface  $\Gamma$  (Figure 1) satisfying the continuity of flux, and form a loss function that, when minimized, will enforce the continuity of states.

• In each time-step, find  $(u_1^n, u_2^n, g^n) \in X_1^n \times X_2^n \times L^2(\Gamma)$  that **minimizes**  $J_{\delta}(u_1^n, u_2^n, g^n) := \frac{1}{2} ||u_1^n - u_2^n||_{\Gamma}^2 + \frac{1}{2} \delta ||g^n||_{\Gamma}^2$ (6)

The **control**  $q^n$  is common to both subdomains, implicitly enforcing

#### equipped to handle plug-and-play integration of data-driven models (e.g., projection-based reduced order models or ROMs)!

	M2DT: MULTIFACETED MATHEMATICS FOR PREDICTIVE DIGITAL TWINS							
<b>Objective (under RT3.1 of</b>	DRIVING SCIENTIFIC APPLICATIONS AREAS							
M2dt). discover mathematical	Advanced m	nufacturing			lce/ocean systems			
	INTEGRATIVE RESEARCH THRUSTS							
principles guiding assembly of	RT1: Dynamica	RT2: Reduced-order &			RT3: Mathematics of coupling			
standard and data-driven	data assimilation	surrogate modeling			for predictive DTs			
	RESEARCH SUB-THRUSTS							
models in stable, accurate and	dynamic OED a	nd stochastic	nonlinear	structure	geometric	coupled	distributed	optimal
	data causa	l optimal	dimensionality	preserving	deep learning	heterogeneous	optimization	model
physically consistent ways.	assimilation inferen	ce control	reduction	ROMs	surrogates	models	for coupling	mgmt
	EDUCATION, TRAINING & OUTREACH							

Coupling via Generalized Mortar Methods

(1)

#### Approach

**Model problem:** time-dependent **advection-diffusion** problem on  $\Omega = \Omega_1 \cup \Omega_2$  with  $\Omega_1 \cap \Omega_2 = \emptyset$ 

 $\dot{c}_i - \nabla \cdot F_i(c_i) = f_i$ , in  $\Omega_i \times [0, T]$ , i = 1, 2on  $\Gamma_i \times [0, T]$ , i = 1, 2 $c_i = g_i$ ,  $c_i(\mathbf{x}, 0) = c_{i,0}(\mathbf{x}), \text{ in } \Omega_i, i = 1,2$ 

**Compatibility conditions:** on interface  $\Gamma \times [0, T]$  (Figure 1)

 $\mathcal{M}^2 dt$ 

• **Continuity of states**:  $c_1(x, t) - c_2(x, t) = 0$ • Continuity of flux:  $F_1(x,t) \cdot n_{\Gamma} = F_2(x,t) \cdot n_{\Gamma}$  $\Rightarrow$  Imposed weakly using Lagrange multiplier (LM)  $\lambda$ 

Semi-discrete monolithic coupled formulation: obtained by discretizing weak monolithic formulation using FEM in space. *Note the alternative form of the constraint!* 







- Can couple **different mesh resolutions** and **element types**
- Allows the use of **different time-integrators** with **different time-steps** in different subdomains
- **No interface bases** are required in ROM-ROM and ROM-FOM couplings
- Requires sequential subdomain solves in multiplicative Schwarz variant
- Concurrent subdomain solves possible with additive Schwarz variant
- Possesses theoretical convergence properties/guarantees [6-7]

 $\frac{\partial t}{\partial t} \int \rho v$ 

# Ω<sub>3</sub> High-fidelity mesh-free model (Physics 3)

Vision: create a "plug-and-play" *framework* for arbitrary *mixing* and *matching* of *conventional* and *data*driven models following a domain

using **fewer modes** 

subject to

#### continuity of flux

## $\frac{1}{\Lambda t} \left( u_i^n - u_i^{n-1}, v \right) + \left( \sigma_i(u_i^n), \nabla v \right) = (f_i^n, v) + (-1)^i (g^n, v)_{\Gamma}, \forall v \in V_i, \ i = 1, 2$ (7)

• We **relax** the constrained optimization problem with a Lagrange multiplier  $\mu_i$ 

## $\mathcal{L}(u_1^n, u_2^n, g^n, \mu_1, \mu_2) \coloneqq J_{\delta}(u_1^n, u_2^n, g^n) + \sum_{i=1}^2 \left[ \frac{1}{\Delta t} \left( u_i^n - u_i^{n-1}, \mu_i \right) + (\sigma_i(u_i^n), \nabla \mu_i) = (f_i^n, \mu_i) + (-1)^i (g^n, \mu_i)_{\Gamma} \right]$

and solve the optimality conditions with gradient descent and a reduced space algorithm

- This approach was developed in [12] in the setting of coupled linear elliptic PDEs, extended in [13] to **coupled nonlinear parabolic PDEs**, and later to **fluid-structure interaction** in [14]
- Here we further extend this approach to **ROM-ROM** and **ROM-FOM coupling**
- Accurate results for ROM-ROM coupling when using FEM adjoints (Figure 10)
- Linear patch tests pass to the tolerance of the penalty parameter  $\delta$
- Ongoing work investigating alternative snapshot matrices onto which the adjoint equations are projected to enable



#### Figure 10. ROM-ROM coupling at final timestep.

## Flux Surrogates

Key Idea: use data-driven techniques to create efficient surrogates that approximate the dynamics of the **interface flux**. This **eliminates** the more **expensive Schur complement** solves in GMM.



 $M_i$ : mass matrices,  $K_i$ : stiffness matrices,  $G_i$ : constraint matrices

**Decoupling via Schur complement:** equation (2) equivalent to

 $\begin{pmatrix} \boldsymbol{M}_1 & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{M}_2 \end{pmatrix} \begin{pmatrix} \dot{\boldsymbol{c}}_1 \\ \dot{\boldsymbol{c}}_2 \end{pmatrix} = \begin{pmatrix} \boldsymbol{f}_1 - \boldsymbol{K}_1 \boldsymbol{c}_1 - \boldsymbol{G}_1^T \boldsymbol{\lambda} \\ \boldsymbol{f}_2 - \boldsymbol{K}_2 \boldsymbol{c}_2 + \boldsymbol{G}_2^T \boldsymbol{\lambda} \end{pmatrix}$ 

where  $(\boldsymbol{G}_1 \boldsymbol{M}_1^{-1} \boldsymbol{G}_1^T + \boldsymbol{G}_2 \boldsymbol{M}_2^{-1} \boldsymbol{G}_2^T) \boldsymbol{\lambda} = \boldsymbol{G}_1 \boldsymbol{M}_1^{-1} (\boldsymbol{f}_1 - \boldsymbol{G}_1)$  $K_1c_1) - G_2M_2^{-1}(f_2 - K_2c_2)$ 

After solving Schur complement problem (4), the subdomain problems in (3) **decouple**.

 $N_{R,2\Gamma}$ , where  $N_{R,i\Gamma}$  = # POD modes in  $\boldsymbol{\Phi}_{i,\Gamma}$ , and approximate  $\boldsymbol{\lambda} \approx \boldsymbol{\Phi}_{LM} \hat{\boldsymbol{\lambda}}$  where  $\boldsymbol{\Phi}_{\mathrm{LM}} = \boldsymbol{\Phi}_{i,\Gamma}$  for i = 1,2, so that  $N_{R,\Gamma} = N_{R,i\Gamma}.$ 

ROM-ROM coupling with **reduced LM space** guaranteed to have **non-singular dual Schur complement** if underlying FOM-FOM coupling satisfies conditions in [1].

#### **Key Features of GMM-Based Coupling**

(3)

- Based on a **non-overlapping** DD (ideal for transmission/multi-physics problems)
- Effective for coupling conventional models (FOM) and reduced order models (ROM)
- Monolithic formulation (more intrusive to implement but more efficient)
- Allows the use of **different time-integrators** with **different time-steps** [3,4]

## **Numerical Results**

- High Peclet advection-diffusion transmission problem (1) on  $\Omega = (0,1) \times (0,1)$ with cone, cylinder and smooth hump initial condition, Dirichlet BCs, rotating advection field, run for 1 full rotation (Figure 4)
- FOM discretization: finite elements in space  $(h = \frac{1}{64})$ , Crank-Nicholson in time with ( $\Delta t = 6.734 \times 10^{-3}$ )
- **ROM discretization**: POD/Galerkin method
- ROMs evaluated in **predictive regime**, with prediction across  $\kappa_i$ • **Snapshots** collected by running **monolithic FOM** at testing parameters

Reduce LM space to size  $N_{R,\Gamma} < N_{R,1\Gamma} +$ 

RR coupling, rLM
 FR coupling, fLM
 FR coupling, rLM
 FR coupling

RR coupling, fLM
 RR coupling, rLM
 FR coupling, fLM

FR coupling, rLM

 $10^1$   $10^2$   $10^3$ Composite reduced basis size,  $d_{i,C}$ 

Figure 2: relative errors as a function of

the reduced basis size.

- Can couple **different mesh resolutions** and **discretization types**
- > Explicit time-integrators enable concurrent subdomain solves
- Possesses theoretical convergence properties/guarantees [1,2]

#### Numerical Results

Model problem: Riemann problem for the 2D unsteady Euler equations

iemann problem for the **2D unsteady Euler equations**  

$$\int + \frac{\partial}{\partial x} \begin{pmatrix} \rho u \\ \rho u^{2} + p \\ \rho u v \\ (E+p)u \end{pmatrix} + \frac{\partial}{\partial y} \begin{pmatrix} \rho v \\ \rho u v \\ \rho v^{2} + p \\ (E+p)v \end{pmatrix} = \mathbf{0}, \qquad p = (\gamma - 1) \left( \rho E - \frac{1}{2} \rho (u^{2} + v^{2}) \right)$$

- Homogeneous Neumann BCs on system boundaries of  $\Omega \times [0, T] = (0, 1) \times (0, 1) \times [0, 0.8]$ .
- FOM discretization:  $100 \times 100$  Cartesian grid, 1<sup>st</sup> order finite volume scheme, BDF1 time integration,  $\Delta t = 0.005$ .
- **ROM discretization**: POD/Least-Squares Petrov-Galerkin (LSPG) projection [9] with no hyper-reduction
- $\blacktriangleright$  Solution has strong gradients/shocks  $\Rightarrow$  poor linear representation
- > ROMs evaluated in the **predictive regime**
- Snapshots collected by running monolithic FOM at testing parameters
- **Coupling specifications:** 
  - Four subdomain overlapping DD:  $\Omega = \bigcup_{i=1}^{4} \Omega_i$  (Figure 5)
  - > Dirichlet BCs on Schwarz boundaries enforced weakly
  - Fixed parameters:  $\rho_1 = 1.5$ ,  $u_1 = v_1 = 0$ ,  $p_3 = 0.029$
- $\succ$  Varied parameters:  $p_1$ , initial condition from compatibility relations [10]
  - ♦  $p_{1,\text{train}} \in [1.0, 1.25, 1.5, 1.75, 2.0]$ ✤  $p_{1,test} \in [1.125, 1.375, 1.625, 1.875]$





• **Training data** consists of both the flux  $(\lambda_{k-1})$  and patches of the states near the interface • DMD or nODE trained to **learn** the **mapping** from IVR(C) IVR(L) DMD-FS  $\mathbf{y}_{k-1} \coloneqq \left( \boldsymbol{\lambda}_{k-1}, \boldsymbol{u}_{1,k}(\delta_1), \boldsymbol{u}_{2,k}(\delta_2) \right)^{\mathsf{T}}$  to  $\mathbf{y}_k$ • Preliminary results indicate that the **new DMD** approach is more accurate than lumped mass GMM approach and around **20**× times cheaper than a



Figure 11. CPU times (left) and relative errors (right) for GMM method with consistent mass (IVR(C)), lumped mass (IVR(L)) and a DMD surrogate (DMD-FS)

## **Additional Future Work**

arXiv:2003.07798v3, 2021

consistent mass GMM approach (Figure 11)

- Development of error indicator-based or reinforcement learning-based algorithm to determine "optimal" DD and ROM/FOM assignment
- Development of algorithms for on-the-fly ROM-FOM switching to improve predictive capabilities of the resulting hybrid model
- Incorporation of **structure preservation** into couplings
- Development/coupling of "bottom-up" subdomain ROMs that are trained separately
- Extension of coupling approaches to DMD and non-intrusive operator inference ROMs



• New coupling methodologies enable the rigorous integration of data-driven models into modeling & simulation toolchains in a "plug-and-play" fashion for both multi- and mono-physics problems, including M2dt exemplars (land iceocean interaction, self-assembly of block copolymers)

• New DD-based couplings can improve trustworthiness and predictive capabilities of data-driven models by enabling spatial localization of ROMs (via DD) and online integration of high-fidelity information into these models (via FOM coupling).





## Figure 5: four subdomain overlapping DD.

Pressure, K = 60



Main takeaway: provably-stable ROM-ROM GMM method delivers artifact-free solution, maintains Schur complement condition # of O(1) regardless of basis size, and converges with basis refinement!



Figure 4: coupled solutions to the targeted transmission problem at the final time. Naïve ROM-ROM coupling (left), provably-stable ROM-ROM coupling (middle) and FOM-FOM coupling (left).

coupled ROM (right) solutions at initial time. ROM solutions have K = 50 modes

and w/o DD as a function of the basis size K



coupled ROM (right) solutions at final time. ROM solutions have K = 50 modes.

**Main takeaways:** DD and Schwarz coupling of ROMs stabilizes the solution! Coupled ROM has comparable CPU time to monolithic ROM with additive Schwarz. Hyperreduction is needed to achieve true cost savings (WIP).

\* The Pressio demo-apps library is available on github: <a href="https://github.com/Pressio/pressio-demoapps">https://github.com/Pressio/pressio-demoapps</a>

Pressure,  $\mu = 1.875$ ,  $N_o = 4$ -- Monolithic PROM — Multiplicative - Additive --- Additive (theoretical) 0 2 4 6 8 10 12 Runtime (FOM runs) Figure 9: Pareto plots for various ROMs and alternating Schwarz-based couplings.

Suite of test cases (e.g., shallow water equations, compressible flow equations, etc.) available via **Pressio demo-apps** [11] open-source implementation\*!

References [1] K. Peterson, P. Bochev, P. Kuberry, Explicit synchronous partitioned algorithms for interface problems based on Lagrange multipliers, CMAME, 78 459–482, 2019 [2] A. de Castro, P. Bochev, P. Kuberry, I. Tezaur. Explicit synchronous partitioned scheme for coupled reduced order models based on composite reduced bases", special issue celebrating Tom Hughes's 80th birthday *Comput. Meth. Appl. Mech. Engng.*, 2023. [3] J. Connors, K. Sockwell, A Multirate Discontinuous-Galerkin-in-Time Framework for Interface-Coupled Problems, SIAM J. Numer. Anal., 5 (60), 2373-2404, 2022 [4] K.C. Sockwell, P. Bochev, K. Peterson, P. Kuberry. Interface Flux Recovery Framework for Constructing Partitioned Heterogeneous Time-Integration Methods, *NMPDE*, 39(5) 3572-3593, 2023. [5] M. Gunzburger, J. Peterson, J. Shadid. Reduced-order modeling of time-dependent PDEs with multiple parameters in the boundary data. CMAME 196 1030-1047, 2007. [6] A. Mota, I. Tezaur, C. Alleman. The Schwarz Alternating Method in Solid Mechanics, CMAME, 319, 19-51, 2017. [7] A. Mota, I. Tezaur, G. Phlipot. The Schwarz Alternating Method for Dynamic Solid Mechanics, CMAME. 121 (21) (2022) 5036-5071. [8] J. Barnett, I. Tezaur, A. Mota. The Schwarz alternating method for the seamless coupling of nonlinear reduced order models and full order models, in CSRI Proceedings 2022, S.K. Seritan and J.D. Smith, eds., Technical Report SAND2022-10280R, Sandia National Laboratories, 2022, pp. 31-55. [9] K. Carlberg, C. Farhat, J. Cortial, D. Amsallem. The GNAT method for nonlinear model reduction: Effective implementation and application to computational fluid dynamics and turbulent flows, JCP, 242, 623-647, 2013. [10] C. Schulz-Rinne. Classification of the Riemann Problem for Two-Dimensional Gas Dynamics, SINUM 24 (1), 1993. [11] F. Rizzi, P. Blonigan, E. Parish, K. Carlberg. Pressio: Enabling Projection-based Model Reduction for Large-scale Nonlinear Dynamical Systems,

[12] M. Gunzburger, J. Peterson, H. Kwon, An Optimization Based Domain Decomposition Method for Partial Differential Equations, CAMWA, 37, 77-93. 1999. [13] M. Gunzburger, H.K. Lee, An Optimization-Based Domain Decomposition Method for the Navier-Stokes Equations, *SINUM*, 37(5), 1455-1480, 2000. [14] P. Kuberry, H. Lee, A Decoupling Algorithm for Fluid-Structure Interaction Problems Based on Optimization, CMAME, 267, 594-605, 2013.



andia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525

• Sandia National Laboratories. <sup>2</sup> Stanford University. <sup>3</sup> Clemson University. <sup>4</sup>University of Arizona.

SAND2024-150380

