



A Priori Model Order Reduction for Transient Neutron Diffusion

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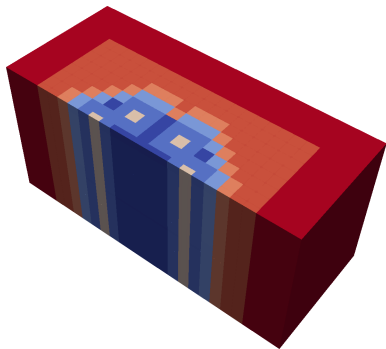
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Outline

1. Motivation
 - Why reduced order modeling?
2. Proper generalized decomposition
3. Research Objectives
4. Results - Transient Neutron Diffusion
 - 1D
 - 2D
5. Conclusions and Future Work

Drawbacks of high fidelity computing

- Current methods (FEM) scale exponentially with the number of dimensions and suffer from “curse of dimensionality”
- Consider a transient 3D transport simulation:
 - 2.7 million dof in space
 - 26 energy groups
 - S_8 quadrature in angle
 - 1000 points in time



Leads to $2.7E6 \times 26 \times 80 \times 1000 = 5.616E12$ dof!



Need for reduced order models

Intractability increasingly apparent for:

- a) multiscale/multiphysics problems
- b) repeated evaluations (e.g. optimization and uncertainty quantification)

Development of accurate, lower order methods is needed.

Reduced Order Modeling

Main idea - develop efficient, low order models that accurately represent high fidelity, large-scale simulations.

Parametric model reduction:

- generation of a reduced order model (ROM) that approximates the original full-order system with high fidelity over a range of parameters
- Projection methods allow for retainment of underlying physics of original full-scale model

Projection Based Methods

Consider the following first order ODE:

$$\frac{dZ}{dt} = \mathbf{A} \cdot Z \quad (1)$$

We can define Z as the product of a *projection matrix*, ρ and the *reduced solution vector*, Z_r :

$$Z = \rho \cdot Z_r \quad (2)$$

Plugging Equation 2 into Equation 1:

$$\frac{d}{dt} (\rho Z_r) = \mathbf{A} \cdot (\rho Z_r)$$

We can arrive at our reduced order system:

$$\rightarrow \frac{dZ_r}{dt} = \rho^{-1} \mathbf{A} \cdot \rho Z_r$$



Projection matrix creation

- POD basis vectors are computed *a posteriori* through the “method of snapshots”
- Assume a set of Q solutions from a series of snapshots are known and defined as:

$$\mathbf{X} = [z_i, z_{i+1}, \dots, z_Q]$$

We can find a solution by constructing a correlation matrix and finding it's eigenvalues and eigenvectors:

$$R = \sum_{i=1}^Q z_i(z_i^T) \quad \rho = [v_1, v_2, \dots, v_j]$$

The eigenvectors, v_1, v_2, \dots, v_j , correspond to the largest eigenvalues $\sigma_j > \sigma_1 \times \epsilon$, where $\epsilon = 10^{-8}$

Drawbacks of POD

- Quality of ROM is *highly* sensitive to snapshot set.
 - What data/solutions are appropriate/useful? Potentially requires ad-hoc/expert knowledge of problem on hand.
- *A posteriori* methods require an online solution of the full-order system.
 - POD ROM cannot be used without a data set - either experimental or simulation. For many problems, this can be difficult or impractical.

A Priori Model Reduction

Ideally, one would want to be able to:

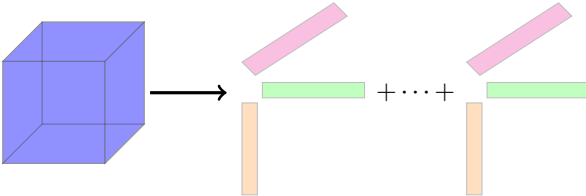
1. Create a ROM *a priori*
 - i.e. without having to rely on previous simulation/experimental data or any previous knowledge of the problem
2. Assess the accuracy of the ROM on-the-fly and improve accuracy if need be.

Proper Generalized Decomposition (PGD)

PGD seeks a solution that is a series expansion whose components are products of separable functions in each dimension of interest:

Full 3D Solution

Finite sum of tensor products of individual dimensions


$$u(x_1, x_2, \dots, x_D) = \sum_{i=1}^n \prod_{k=1}^D x_{i,k}(x_k)$$

“Curse of dimensionality” is overcome by linear relationship!

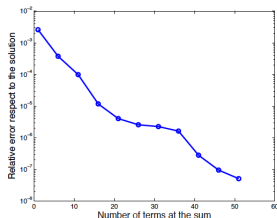
F. Chinesta, et al. *The Proper Generalized Decomposition for Advanced Numerical Simulations: A Primer*. Springer 2014.



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Select Applications of PGD

1. A. Ammar et. al. applied PGD to multi-bead-spring molecular models of polymer solutions in complex fluids
 - Order reduction from 2.56E6 dof (standard) to 3200 dof (PGD)
2. González-Pintor et. al. applied PGD to calculate the dominant mode eigenvalue of a nuclear reactor



3. In nearly all works to date, only a few terms have been required in PGD expansions.

1. A. Ammar, et. al. A new family of solvers for some classes of multidimensional partial differential equations encountered in kinetic theory modeling of complex fluids. Journal of Non-Newtonian Fluid Mechanics, 139:153-176, 2006.
2. S. González-Pintor, et. al.. Using proper generalized decomposition to compute the dominant mode of a nuclear reactor. Mathematical and Computer Modelling 57:1807-1815, 2013.



Potential of PGD in Radiation Transport

Revisiting our 3D transport problem, we can separate the solution into a series of products of 7 1D basis functions:

$$\psi(\mathbf{r}, \boldsymbol{\Omega}, E, t) = \sum_{i=1}^n R(x, y, z) \xi(\theta, \varphi) E(\epsilon) T(t)$$

where:

$$R(x, y, z) = X(x)Y(y)Z(z), \text{ and } \xi(\omega) = A(\theta)P(\varphi)$$

“Curse of dimensionality” overcome by linear relationship!

$$n(140 + 140 + 140 + 26 + 80 + 1000) \ll 5.616\text{E}12$$

Research Objectives

Using the diffusion approximation:

1. Assess the relationship between model reduction and accuracy of an a priori ROM for two-dimensional, energy dependent transient flux calculations.
 - Theoretically possible to include energy as a “dimension” in the PGD approximation and obtain a continuous energy flux distribution.
2. Extend the energy dependent transient flux ROM to include coupled sets of ODEs
 - E.g. reactor kinetics and/or depletion
 - Purpose is to investigate the applicability of a priori ROMs for a select multiscale problem in reactor physics.

Results so far...

1. 1D Transient Heat Transfer (FDM) ✓
2. 1D Transient Neutron Diffusion ✓
 - a) Assume constant cross sections, discretize each independent variable with FDM.
 - b) Expand into spatially dependent cross sections, discretize with FEM.
 - i. Dirichlet BC's, MMS.
 - ii. Reflecting BCs, "real" problem with heterogeneity, reference CFEM solver with backward euler in time.
3. 2D Transient Neutron Diffusion
 - Dirichlet BC's, MMS 1/2



Mechanics of PGD - Preliminaries

Consider 1D transient neutron diffusion:

$$\frac{1}{v} \frac{\partial \phi}{\partial t} - \frac{\partial}{\partial x} \cdot D \frac{\partial}{\partial x} \phi + \Sigma_a(x) \phi(x, t) = S \quad (4)$$

Assume a solution in space and time:

$$\phi(x, t) \approx \sum_{j=1}^n X_j(x) T_j(t) \quad (5)$$

where the:

- a) number of enrichment steps, n and
- b) basis functions, $X_j(x)$ and $T_j(t)$ are unknown a-priori.

Mechanics of PGD - Enriching the Solution

Separated representation is built progressively by “enriching”.

- At enrichment step $n + 1$, assume we know the previous n terms.

$$\begin{aligned}\phi_{n+1}(x, t) &= \phi_n(x, t) + X_{n+1}(x)T_{n+1}(t) \\ &= \sum_{j=1}^n X_j(x)T_j(t) + X(x)\mathcal{T}(t)\end{aligned}\tag{6}$$

Mechanics of PGD - Alternating Direction Algorithm

1. Solve for $\mathcal{X}(x)$ assuming $\mathcal{T}(t)$
2. Solve for $\mathcal{T}(t)$ with obtained $\mathcal{X}(x)$
3. Check convergence of $\mathcal{X}(x)\mathcal{T}(t)$
4. Check convergence of ROM

Alternating Direction Algorithm - Step 1

Starting with weighted residual form of the 1D transient neutron diffusion equation

$$\int_{\Omega_x \times \Omega_t} \phi^* \left(\frac{1}{v} \frac{\partial \phi}{\partial t} - \nabla \cdot D \nabla \phi + \Sigma_a(x) \phi(x, t) - S \right) dx dt = 0 \quad (7)$$

where the test function, ϕ^* , defined as:

$$\phi^*(x, t) = u(x) \mathcal{T}(t) \quad (8)$$

- $\mathcal{T}(t)$ is assumed known

Plugging our test function into the weighted residual form, we can obtain a BVP that is solved via CFEM

$$\begin{aligned}
 & \int_{\Omega_x} u(x) \left[\left(\frac{1}{v} t_2 + t_1 \Sigma_a(x) \right) X(x) - t_1 \frac{d}{dx} \cdot D(x) \frac{dX(x)}{dx} \right] dx \\
 &= - \sum_{j=1}^n \int_{\Omega_x} u(x) \left[\left(\frac{1}{v} t_{4,i} + t_{3,i} \Sigma_a(x) \right) X_i(x) dx - t_{3,i} \frac{d}{dx} \cdot D(x) \frac{dX_i(x)}{dx} dx \right] \\
 & \quad + \int_{\Omega_x} \int_{\Omega_t} u(x) S(x, t) \quad (9)
 \end{aligned}$$

Alternating Direction Algorithm - Step 2

Revisiting our weighted residual form:

$$\int_{\Omega_x \times \Omega_t} \phi^* \cdot \left(\frac{1}{v} \frac{\partial \phi}{\partial t} - \nabla \cdot D \nabla \phi + \Sigma_a(x) \phi(x, t) - S \right) dx dt = 0 \quad (10)$$

This time, with a new test function, ϕ^* , defined as:

$$\phi^*(x, t) = \mathcal{X}(x)w(t) \quad (11)$$

- $\mathcal{X}(x)$ is known from previous step

- Plugging our test function into the weighted residual form, we can obtain an IVP that is solved via DFEM

$$\begin{aligned}
& \frac{1}{v} x_1 \left(w(t) \mathcal{T}(t) \Big|_{surf} - \int_{\Omega_t} \mathcal{T}(t) \frac{dw}{dt} dt \right) + (x_2 - x_3) \int_{\Omega_t} w(t) \mathcal{T}(t) dt \\
&= - \sum_{i=1}^n \left[\frac{1}{v} x_{4,i} \left(w(t) T_i(t) \Big|_{surf} - T_i \frac{dw}{dt} dt \right) + (x_{6,i} - x_{5,i}) \int_{\Omega_t} w(t) T_i(t) dt \right] \\
&+ \int_{\Omega_t} \int_{\Omega_x} w(t) S(x, t)
\end{aligned} \tag{12}$$

- Closure obtained by upwinding on surface terms.
- Initial condition in all tests = 0.0.

Alternating Direction Algorithm - Steps 3 & 4

- Solving for $\mathcal{X}(x)$ and $\mathcal{T}(t)$ involves a nonlinear iteration.
- Convergence criteria, $\nu = 1 \times 10^{-6}$

$$\nu = \sqrt{(\|\mathcal{X}^p\| \|\mathcal{T}^p\| - \|\mathcal{X}^{p-1}\| \|\mathcal{T}^{p-1}\|)^2}$$

note, $\|\cdot\| = \|\cdot\|_{L_2}^2$

- ROM convergence criteria, $\epsilon = 1 \times 10^{-6}$

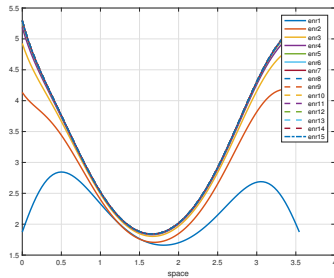
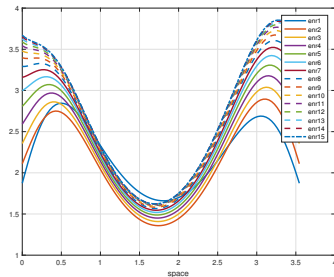
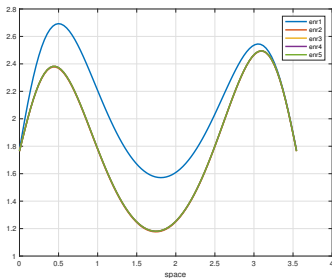
$$\begin{aligned}\epsilon &= \|\phi_{n+1} - \phi_n\| \\ &= \left\| \left(\sum_{i=1}^n X_i T_i + X_{n+1} T_{n+1} \right) - \sum_{i=1}^n X_i T_i \right\| \\ &\leq \|X_{n+1}\| \|T_{n+1}\|\end{aligned}$$

Alternating Direction Algorithm - Review

```
for  $m=1$  to  $m_{max}$   
  define  $X^{(0)}, T^{(0)}$  (initialization)  
    for  $k=1$  to  $k_{max}$   
      compute  $X^{(k)} = F_m(T^{(k-1)})$   
      compute  $T^{(k)} = G_m(X^{(k)})$   
      normalize, s.t.  $\|T^{(k)}\|_{L2}^2 = 1$   
      check convergence,  $\nu < X^{(k)} T^{(k)}$   
    end  
  normalize  $X^{(k)}$  and  $T^{(k)}$   
  set  $X^{(k)} = X_m$  and  $T^{(k)} = T_m$   
  check convergence,  $\epsilon < \|X_m\| \|T_m\|$   
end
```

Importance of Normalizing in Non-linear Iterations

- Not commonly observed in literature
- Crucial to quality and convergence behavior of enrichment steps
- Normalization of time domain enhances convergence behavior and improves solution quality.



Test Problem 1

Using MMS with assumed solution of $\phi_{ref}(x, t) = t \sin(x)$:

Assume $\nu = 1.5$, $D = \Sigma_a = x + 1$

$\Omega_x = [0, \pi]$; CFEM; 250 elements

$\Omega_t = [0, 1]$; DFEM; 60 elements

Both are discretized via 1st order linear polynomials

dof = $n(251 + 120)$

Error quantification is defined by the following:

$$\text{error}_i = \sqrt{\int_{\Omega_t} \int_{\Omega_x} \left(\phi_{ref}(x, t) - \sum_{j=1}^i \phi_{pgd,j}(x, t) \right)^2 dx dt}$$

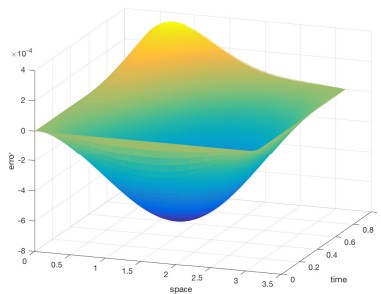
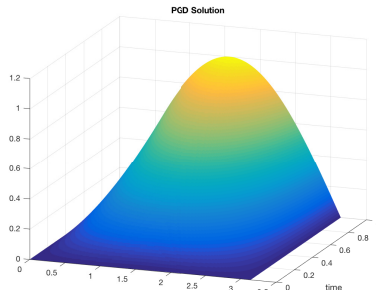
where, i , is the enrichment step of interest



Test Problem 1 - Results

- PGD solution captures reference solution within first enrichment step.
- Higher enrichment steps have negligible effects.

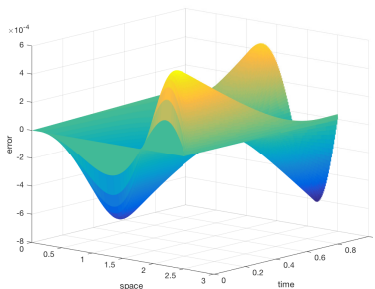
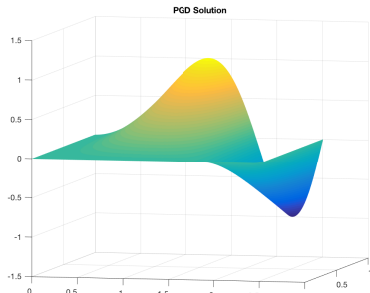
<i>Enr.Step</i>	$\ Ref - PGD\ _{L2}$
1	3.516E-3
2	4.325E-3
3	3.686E-3
4	3.679E-3
5	3.715E-3



Test Problem 2

- $\phi_{ref} = t \sin(x^2)$
- $\Omega_x \in [0, \sqrt{2} \sqrt{\pi}]$; CFEM; 250 elements.
- $\Omega_t = [0, 1]$; DFEM; 60 elements
- Both are discretized via 1st order linear polynomials
- dofs = n(201+120)
- Again, PGD solution captures reference solution within first enrichment step.

<i>Enr.Step</i>	$\ Ref - PGD\ _{L2}$
1	2.5661E-3
2	2.5693E-3
3	2.5694E-3

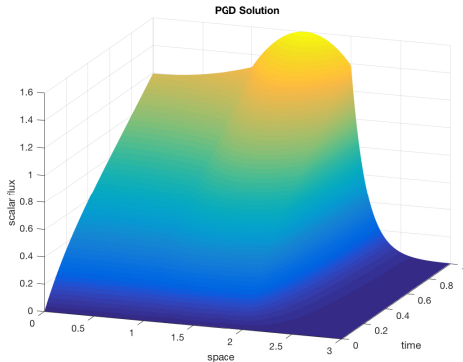


Test Problem 3 - A “real” problem

- Define 3 region heterogeneous problem ($v = 1.5$):

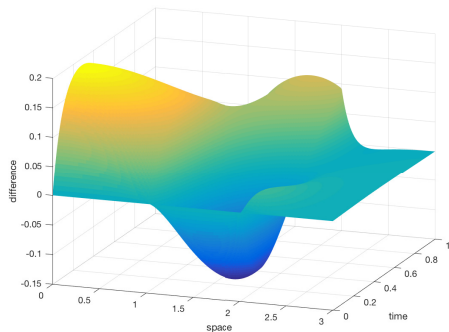
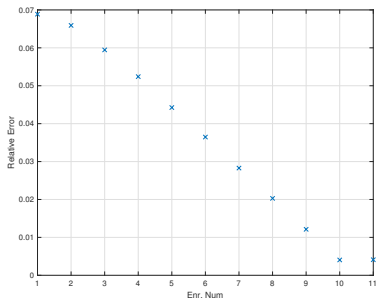
Region	D	Σ_a	Source
1	5.0	0.001	0.0
2	1.0	0.5	3.0
3	0.1	3.5	0.0

- $\Omega_x = [0, 3]$; CFEM; 300 elements
- $\Omega_t = [0, 1]$; DFEM; 100 elements
- 1st order linear polynomials.
- $\text{dofs} = n(301 + 200)$



Test Problem 3 - Error Analysis

- Reference solution generated from solver with CFEM in space and Backward Euler in time
- Reference solution has $256 \times 256 = 65,536$ dof.
- PGD with 10 enrichment steps has $10(301 + 200) = 5,010$ dof.



Test Problem 4 - 2D Transient

- $\phi_{ref} = t \sin(x) \sin(y)$

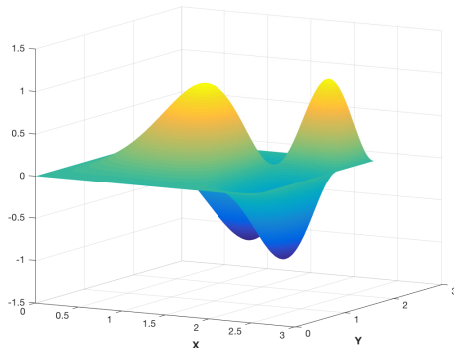
$\Omega_x = \Omega_y \in [0, \sqrt{2} \sqrt{\pi}]$; CFEM; 100 elements.

$\Omega_t = [0, 1]$; DFEM; 100 elements.

$$D = (xy) + 1.0$$

$$\Sigma_t = ((x_r - x)(y_r - y)) + 1.0$$

Enr.Step	$\ Ref - PGD\ _{L2} / \ Ref\ $
1	0.0287
2	0.0221
3	0.3395
4	0.2772
5	0.3184



- 1st order linear polynomials.

- dofs = $n(100+100+100)$

Conclusions

- “Curse of dimensionality” is apparent in reactor physics calculations
- More well developed, data driven methods are potentially impractical
- Proper generalized decomposition provides an avenue for a priori model reduction
- 1D Transient results show promise that PGD is a potentially viable solution to dimensionality issues

Moving Forward

1. 1D Transient problem
 - Mesh refinement studies.
2. 2D Transient problem
 - Improve understanding of normalization process in enrichment process.
 - Non-separable problems.
3. Expand to energy dependence
 - 1D transient formulation under construction now
 - Include energy as PGD dimension - *continuous* in energy
4. Couple energy dependent PGD ROM to ODEs
 - Reactor kinetics; precursor equations and delayed neutrons

Along the way...

- Spatial discontinuities
- Increasingly real problems (fission source, etc)

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Questions?