

Dimensionality reduction for thermal radiative transfer problems using a moment-based approach combined with the proper orthogonal decomposition

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- Fundamental approach and basic ideas
 - Model order reduction for Boltzmann transport problems
 - Thermal radiative transfer (TRT) problems
 - Nonlinear projective approach
- Formulation of data-driven ROMs for nonlinear TRT problems
 - Approximating the Eddington tensor with the POD
 - A POD-Galerkin projection of the Boltzmann transport equation
 - Numerical results for multigroup TRT problems are presented in 2D and 1D Cartesian geometries
- Discussion
- This is a joint work with Dmitriy Anistratov (NCSU)

- Radiative transfer is the physical process of energy transfer via the propagation, emission and absorption of photon radiation in the host medium
- Radiative transfer becomes the dominant mode of energy redistribution in materials at extreme temperatures, and is an essential piece of physics for many phenomena spanning several fields
 - high-energy density physics
 - astrophysics
 - plasma physics
 - atmospheric science
- These phenomena are described by complex multiphysical systems of differential equations (radiation hydrodynamics)
- The particle transport physics is modeled by the Boltzmann transport equation (BTE)

Challenges in Simulation of Particle Transport Problems

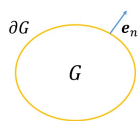
- The numerical simulation of multiphysical particle transport problems faces several challenges
 - High-dimensionality
 - Strong nonlinearity
 - Strong coupling of equations
 - Multi-scale characterization
 - Distinct characteristic behavior in different energy ranges
 - System of equations of different types
 - Integro-differential BTE
- The BTE is especially challenging to solve
 - Hyperbolic differential operator
 - The solution at any point depends on the solution everywhere in phase space due to the integral operator
 - The solution is high-dimensional
- The BTE largely influences the dimensionality of these problems
- Reduced order models (ROMs) for the BTE are commonly employed to reduce the cost of multiphysics simulations involving radiative transfer

- Some ROMs have seen widespread adoption for their usefulness and simplicity
 - Diffusion-based models like flux limited diffusion (FLD)
 - P_1 , $P_{1/3}$, P_3
 - Minerbo models
- However, the accuracy of these models is limited
- The development of *advanced* ROMs for the BTE that can achieve both computational efficiency and high accuracy is an active field of research
- Recently substantial research efforts have been made towards developing *data-driven* ROMs for Boltzmann transport
- Many advanced methods for data-driven model order reduction were originally developed in the fluid dynamics community
- The majority of these ROMs focus on linear particle transport problems
- Many questions remain for nonlinear problems of high energy density physics (radiation hydrodynamics problems)
 - How to preserve and reproduce essential features of fundamental physics
 - Dealing with multiscale behavior

- Nonlinear projective approach
 - interpretation
 - nonlinear method of moments
 - multigrid approach
 - Known to give advantage in multiphysical, multiscale applications
- The BTE is coupled with a hierarchy of low-order moment equations
 - Each moment system is exactly closed through nonlinear functionals of the BTE solution (e.g. the Eddington tensor)
 - Moment equations are conservation equations for integral (low-dimensional) quantities
 - Moment equations account for different scales of the problem
 - Multiphysics equations are coupled to moment equations on the same dimensional scale
- Data-driven methods of approximation to estimate closures for low-order equations
 - proper orthogonal decomposition (POD)
 - dynamic mode decomposition (DMD)
 - neural network estimators

Nonlinear Thermal Radiative Transfer Problem

- Prototypes of these ROMs are designed for the fundamental thermal radiative transfer (TRT) problem
 - Supersonic radiation flow problem neglecting material motion, photon scattering, heat conduction and external sources
- The high-order multigroup Boltzmann transport equation (BTE)

$$\frac{1}{c} \frac{\partial I_g(\mathbf{r}, \boldsymbol{\Omega}, t)}{\partial t} + \boldsymbol{\Omega} \cdot \nabla I_g(\mathbf{r}, \boldsymbol{\Omega}, t) + \kappa_g(T) I_g(\mathbf{r}, \boldsymbol{\Omega}, t) = \kappa_g(T) B_g(T)$$

$$\mathbf{r} \in G, \text{ for all } \boldsymbol{\Omega}, \quad g = 1, \dots, N_g, \quad t \geq t_0,$$
$$I_g|_{\mathbf{r} \in \partial G} = I_g^{in}, \quad \boldsymbol{\Omega} \cdot \mathbf{e}_n < 0, \quad t \geq t_0,$$
$$I_g|_{t=t_0} = I_g^0, \quad \mathbf{r} \in G, \text{ for all } \boldsymbol{\Omega},$$

- \mathbf{r} - spatial position, $\boldsymbol{\Omega}$ - direction of particle motion, g - photon frequency group, t - time, $I_g(\mathbf{r}, \boldsymbol{\Omega}, t)$ - specific intensity of photons in the group g
- The material energy balance (MEB) equation

$$\frac{\partial \varepsilon(T)}{\partial t} = \sum_{g=1}^{N_g} \int_{4\pi} \kappa_g(T) \left(I_g(\mathbf{r}, \boldsymbol{\Omega}, t) - B_g(T) \right) d\boldsymbol{\Omega}, \quad T|_{t=t_0} = T^0(\mathbf{r}), \text{ for } \mathbf{r} \in G.$$

Nonlinear Projective Approach for TRT

- Multilevel quasidiffusion (QD) equations:

$$\begin{aligned} \text{High order BTE: } & \mathcal{L}I = \mathcal{Q}[T] \\ \text{Multigroup QD equations: } & \mathcal{K}[f]\zeta = \mathbf{q}[T], \quad \zeta = \mathcal{P}I \\ \text{Effective grey QD equations: } & \bar{\mathcal{K}}[\varphi]\bar{\zeta} = \bar{\mathbf{q}}[T], \quad \bar{\zeta} = \bar{\mathcal{P}}\zeta \\ \text{Material Energy Balance: } & \mathcal{R}T = \mathcal{H}[I] \end{aligned}$$

- Unknowns in projected space:

$$\begin{aligned} \zeta &= (E_g, \mathbf{F}_g), \quad E_g = \frac{1}{c} \int_{4\pi} I_g d\Omega, \quad \mathbf{F}_g = \int_{4\pi} \Omega I_g d\Omega \\ \bar{\zeta} &= (E, \mathbf{F}), \quad E = \sum_g E_g, \quad \mathbf{F} = \sum_g \mathbf{F}_g \end{aligned}$$

- Closures of equations:

$$f_g[I] = \frac{\int_{4\pi} \Omega \otimes \Omega I_g d\Omega}{\int_{4\pi} I_g d\Omega} = \begin{pmatrix} f_{xx,g} & f_{xy,g} & f_{xz,g} \\ f_{xy,g} & f_{yy,g} & f_{yz,g} \\ f_{xz,g} & f_{yz,g} & f_{zz,g} \end{pmatrix}, \quad \varphi[E_g, \mathbf{F}_g] = \frac{\sum_g \alpha_g \beta_g}{\sum_g \beta_g}, \quad \beta = E_g, \mathbf{F}_g$$

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Approximation of closure: $\tilde{f} = \mathcal{G}[f^*]$, f^* known

Multigroup QD equations: $\mathcal{K}[\tilde{f}]\zeta = \mathbf{q}[T]$, $\zeta = \mathcal{P}I$

Effective grey QD equations: $\bar{\mathcal{K}}[\varphi]\bar{\zeta} = \bar{\mathbf{q}}[T]$, $\bar{\zeta} = \bar{\mathcal{P}}\zeta$

Material Energy Balance: $\mathcal{R}T = \hat{\mathcal{H}}[\bar{\zeta}]$

- Use data-driven methods to define the operator \mathcal{G}
- \mathcal{G} will allow for efficient compression and approximation of data
- Available methods include:
 - Proper orthogonal decomposition
 - Dynamic mode decomposition
 - Neural networks
 - etc.

- Projection, compression of data
 - Given: full-order solution to some TRT problem for N_t time steps, N_g frequency groups, N_x spatial cells
 - Vectors of each Eddington Tensor component at time t^n

$$\mathbf{f}_{\alpha\beta}^n \in \mathbb{R}^{N_x N_g}, \quad \alpha, \beta = x, y, z$$

- Construction of snapshot matrices

$$\mathbf{A}^{\mathbf{f}_{\alpha\beta}} = [\mathbf{f}_{\alpha\beta}^1 \ \mathbf{f}_{\alpha\beta}^2 \ \dots \ \mathbf{f}_{\alpha\beta}^{N_t}] \in \mathbb{R}^{N_x N_g \times N_t}$$

- Define projection operator \mathcal{G}^k that will project a given matrix \mathbf{A} onto a rank- k subspace

$$\mathcal{A}_k^{\mathbf{f}_{\alpha\beta}} = \mathcal{G}^k \mathbf{A}^{\mathbf{f}_{\alpha\beta}}, \quad k \leq \text{rank}(\mathbf{A}^{\mathbf{f}_{\alpha\beta}})$$

- $\mathcal{A}_k^{\mathbf{f}_{\alpha\beta}}$ is constructed of k sets of various vectors and factors
- Approximation of data from rank k representation
 - A map \mathcal{M}^n is defined by the same method used to define \mathcal{G}^k

$$\mathbf{f}_{\alpha\beta}^n \approx \mathcal{M}^n \mathcal{A}_k^{\mathbf{f}_{\alpha\beta}}$$

POD of the Eddington Tensor

- Centered data matrix

$$\hat{\mathbf{A}}^{\mathbf{f}_{\alpha\beta}} = [\hat{\mathbf{f}}_{\alpha\beta}^1, \dots, \hat{\mathbf{f}}_{\alpha\beta}^{N_t}], \quad \hat{\mathbf{f}}_{\alpha\beta}^n = \mathbf{f}_{\alpha\beta}^n - \bar{\mathbf{f}}_{\alpha\beta}, \quad \bar{\mathbf{f}}_{\alpha\beta} = \frac{1}{N_t} \sum_{n=1}^{N_t} \mathbf{f}_{\alpha\beta}^n$$

- A thin singular value decomposition (SVD) represents the matrix in the form

$$\hat{\mathbf{A}}^{\mathbf{f}_{\alpha\beta}} = \mathbf{U}\mathbf{S}\mathbf{V}^T,$$

$\mathbf{U} \in \mathbb{R}^{N_x N_g, d}$ holds the left singular vectors $\{\mathbf{u}_\ell\}_{\ell=1}^d$ in its columns

$\mathbf{V} \in \mathbb{R}^{N_t, d}$ holds the right singular vectors $\{\mathbf{v}_\ell\}_{\ell=1}^d$ in its columns

$\mathbf{S} \in \mathbb{R}^{d, d}$ holds the singular values $\{\sigma_\ell\}_{\ell=1}^d$ along its diagonal in decreasing order,

$$d = \text{rank}(\hat{\mathbf{A}}^{\mathbf{f}_{\alpha\beta}}) = \min(N_x N_g, N_t)$$

- The rank- k POD representation of $\mathbf{f}_{\alpha\beta}$

$$\mathcal{A}_k^{\mathbf{f}_{\alpha\beta}} = \bar{\mathbf{f}}_{\alpha\beta} \cup \{\sigma_\ell, \mathbf{u}_\ell, \mathbf{v}_\ell\}_{\ell=1}^k$$

$$\tilde{\mathbf{f}}_{\alpha\beta}^n \leftarrow \bar{\mathbf{f}}_{\alpha\beta} + \sum_{\ell=1}^k \sigma_\ell (\mathbf{v}_\ell)_n \mathbf{u}_\ell = \mathcal{M}^n \mathcal{A}_k^{\mathbf{f}_{\alpha\beta}}$$

- For each data matrix \mathbf{A} , the rank k must be calculated to store \mathcal{A}_k
- We consider the rank- k truncated SVD

$$\mathbf{A} \approx \mathbf{A}_k = \mathbf{U}_k \mathbf{S}_k \mathbf{V}_k^T$$
$$\mathbf{U}_k = [\mathbf{u}_1 \dots \mathbf{u}_k], \quad \mathbf{S}_k = \text{diag}(\sigma_1, \dots, \sigma_k), \quad \mathbf{V}_k = [\mathbf{v}_1 \dots \mathbf{v}_k]$$

- The error in Frobenius norm

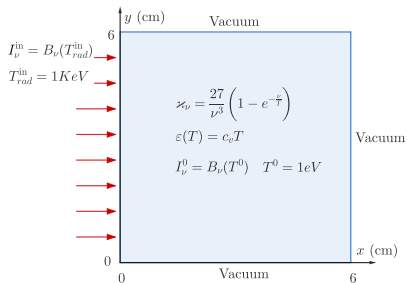
$$\|\mathbf{A} - \mathbf{A}_k\|_F^2 = \sum_{\ell=k+1}^d \sigma_\ell^2$$

- We calculate k by choosing the relative Frobenius norm error ξ

$$\xi^2 = \frac{\sum_{\ell=k+1}^d \sigma_\ell^2}{\sum_{\ell=1}^d \sigma_\ell^2} = \frac{\|\mathbf{A} - \mathbf{A}_k\|_F^2}{\|\mathbf{A}\|_F^2}$$

- k increases as ξ decreases
 - Increasing k increases cost in calculating approximate closures
 - Accuracy is also expected to increase with k

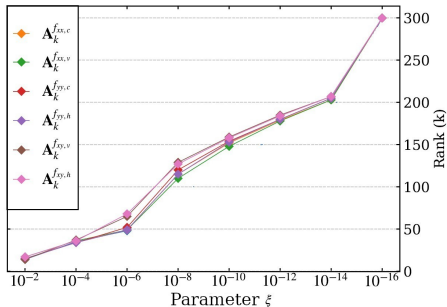
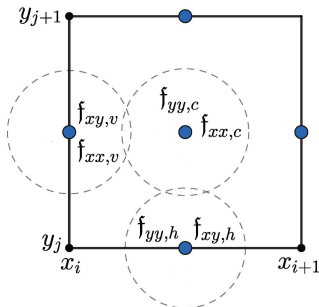
Numerical Test Problem



- We test this method on a 2D extension of the Fleck-Cummings (F-C) test
- Fully-implicit time integration
- BTE discretized with simple corner balance scheme
- All low-order equations discretized with 2nd order finite volumes
- Grid:
 - 20x20 spatial cells, 17 groups, 144 discrete directions
 - 300 time steps $\Delta t = .02\text{ns}$ for $0 \leq t \leq 6\text{ns}$
- Degrees of freedom: 1.175×10^9
- ROM degrees of freedom: 1.728×10^7

Numerical Results (POD)

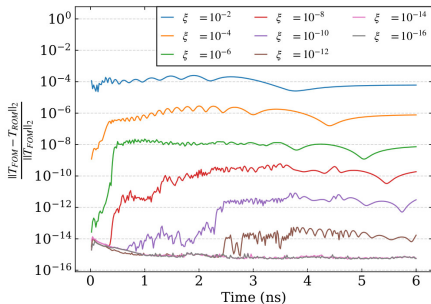
- Databases are formed from the full-order model solution
- Ranks of approximation and memory requirements for the POD with varying ξ



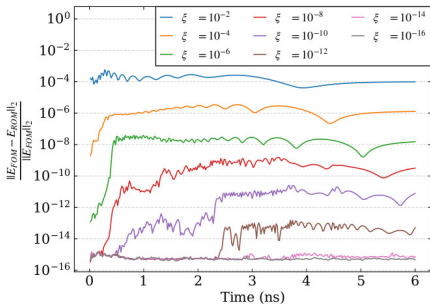
Ranks k vs parameter ξ

Numerical Results (POD)

- Relative errors in the 2-norm using the POD compared to the full-order solution
- Errors plotted vs time, each curve corresponds to a value for ξ



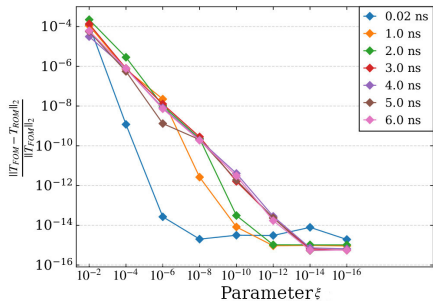
Material Temperature



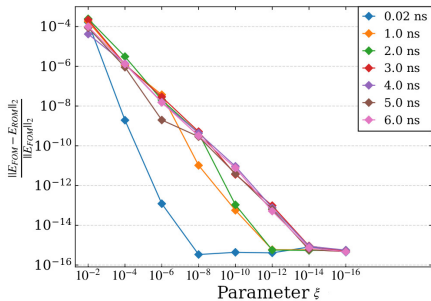
Radiation Energy Density

Convergence of the ROM with Rank (POD)

- Relative errors in the 2-norm using the POD compared to the full-order solution
- Errors plotted vs ξ , each curve corresponds to an instant of time



Material Temperature



Radiation Energy Density

- The ROM that approximates the Eddington tensor with the POD performs well
- The ROM converges to the full-order solution it was trained on
 - uniform convergence in time
 - linear convergence rate vs ξ
- We have also shown this methodology capable of reproducing fundamental radiative transfer physics
 - Accurate predictions of breakout times of radiation
 - Accurate predictions of radiation spectrum
- Next up: projection of the BTE onto proper orthogonal modes that describe known radiation intensities

$$\text{POD-Galerkin Projected BTE: } \hat{\mathcal{L}}[\mathbf{u}]\tilde{\mathbf{I}} = \hat{\mathcal{Q}}[\mathbf{u}, T]$$

$$\text{Multigroup QD equations: } \mathcal{K}[\tilde{\mathbf{I}}]\zeta = \mathbf{q}[T], \quad \zeta = \mathcal{P}I$$

$$\text{Effective grey QD equations: } \bar{\mathcal{K}}[\varphi]\bar{\zeta} = \bar{\mathbf{q}}[T], \quad \bar{\zeta} = \bar{\mathcal{P}}\zeta$$

$$\text{Material Energy Balance: } \mathcal{R}T = \hat{\mathcal{H}}[\bar{\zeta}]$$

- We formulate a POD-Galerkin (POD-G) projection of the BTE
 - A POD basis is calculated based on base-case solutions of the BTE solution
 - Intensities are expanded in the POD basis over the whole phase space
 - The BTE is projected onto the POD basis and solves for coefficients of the expansion
- In this way the POD-G BTE takes the place of the discretized BTE in the multilevel QD hierarchy
 - Large gains in computational efficiency since there are far fewer coefficients than degrees of freedom on the intensities

- The POD-G projection method is formulated in discrete space
- The high-order Boltzmann transport equation

$$\frac{1}{c} \frac{\partial I_g(\mathbf{r}, \boldsymbol{\Omega}, t)}{\partial t} + \boldsymbol{\Omega} \cdot \nabla I_g(\mathbf{r}, \boldsymbol{\Omega}, t) + \kappa_g(T) I_g(\mathbf{r}, \boldsymbol{\Omega}, t) = \kappa_g(T) B_g(T)$$

- Discretize with: Discrete-Ordinates, Backward-Euler, Simple Corner Balance

$$\frac{1}{c \Delta t^n} (\mathbf{I}^n - \mathbf{I}^{n-1}) + \mathcal{L}_h \mathbf{I}^n + \mathcal{K}_h^n(T) \mathbf{I}^n = \mathbf{Q}^n(T), \quad (1)$$

- Discrete operators $\mathcal{L}_h, \mathcal{K}_h^n(T)$ determined by scheme
- N_x spatial degrees of freedom, N_Ω discrete directions, N_t time steps,
- $D = N_x N_\Omega N_g$
- Solution vector: $\mathbf{I}^n = ((\mathbf{I}_1^n)^\top \dots (\mathbf{I}_{N_g}^n)^\top)^\top \in \mathbb{R}^D$
- Construct snapshot matrix

$$\mathbf{A} = [\mathbf{I}^1, \dots, \mathbf{I}^{N_t}] \quad (2)$$

- Goal: expand intensities in basis functions $\{\mathbf{u}_\ell\}_{\ell=1}^r$

$$\mathbf{I}_r^u(t^n) = \sum_{\ell=1}^r \lambda_\ell^n \mathbf{u}_\ell \quad (3)$$

- We formulate the POD basis $\{\mathbf{u}_\ell\}_{\ell=1}^r$, $r \ll D$ using snapshots in \mathbf{A}

$$\min_{\mathbf{u}_1, \dots, \mathbf{u}_r} \sum_{n=1}^{N_t} \Delta t^n \left\| \mathbf{I}^n - \sum_{\ell=1}^r \langle \mathbf{I}^n, \mathbf{u}_\ell \rangle_W \mathbf{u}_\ell \right\|_W^2, \quad (4)$$

- Weighted inner product specific to the discretization: $\langle \mathbf{u}, \mathbf{v} \rangle_W = \mathbf{u}^\top \mathbf{W} \mathbf{v}$

- Standard POD uses the identity matrix $\mathbf{W} = \mathbb{I}$ so that $\langle \mathbf{u}, \mathbf{v} \rangle_{\mathbf{W}} = \langle \mathbf{u}, \mathbf{v} \rangle$
- We seek \mathbf{W} to correspond to the discrete integration over space, angle, frequency
- For the considered discretization schemes we have (in 1D geometry)

$$\int_0^{\infty} \int_{-1}^1 \int_0^{L_x} u(x, \mu, \nu) dx d\mu d\nu \Rightarrow \sum_{g=1}^{N_g} \sum_{m=1}^{N_{\Omega}} w_m \sum_{i=1}^{N_x} \frac{\Delta x_i}{2} (\mathbf{u}_{g,m,i,L} + \mathbf{u}_{g,m,i,R}) \quad (5)$$

- We find the matrix \mathbf{W} as

$$\mathbf{W} = \bigoplus_{g=1}^{N_g} \bigoplus_{m=1}^{N_{\Omega}} w_m \hat{\mathbf{W}}^x, \quad \hat{\mathbf{W}}^x = \bigoplus_{i=1}^{N_x} \begin{pmatrix} \frac{\Delta x_i}{2} & 0 \\ 0 & \frac{\Delta x_i}{2} \end{pmatrix} \quad (6)$$

- Construct snapshot matrix

$$\mathbf{A} = [\mathbf{I}^1, \dots, \mathbf{I}^{N_t}] \quad (7)$$

- Calculate weighted snapshot matrix

$$\hat{\mathbf{A}} = \mathbf{W}^{1/2} \mathbf{A} \mathbf{D}^{1/2}, \quad \mathbf{D} = \text{diag}(\Delta t^1, \dots, \Delta t^{N_t}) \quad (8)$$

- Find singular value decomposition of $\hat{\mathbf{A}}$

$$\hat{\mathbf{A}} = \hat{\mathbf{U}} \hat{\mathbf{S}} \hat{\mathbf{V}}^\top \quad (9)$$

$$\hat{\mathbf{U}} = [\hat{\mathbf{u}}_1, \dots, \hat{\mathbf{u}}_d], \quad \hat{\mathbf{S}} = \text{diag}(\sigma_1, \dots, \sigma_d), \quad \hat{\mathbf{V}} = [\hat{\mathbf{v}}_1, \dots, \hat{\mathbf{v}}_d] \quad (10)$$

- The POD basis is then found as $\mathbf{U} = [\mathbf{u}_1, \dots, \mathbf{u}_d]$ with $d = \text{rank}(\hat{\mathbf{A}})$ using

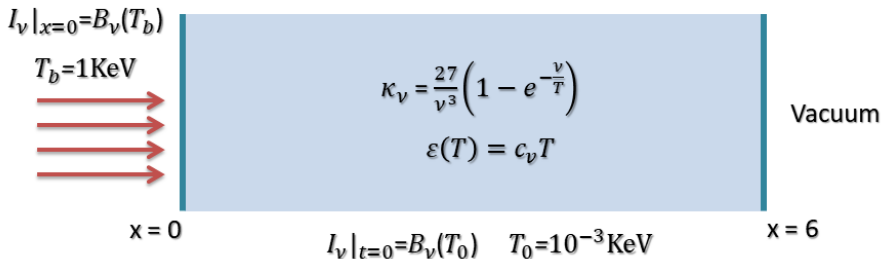
$$\mathbf{U} = \mathbf{W}^{-1/2} \hat{\mathbf{U}} \quad (11)$$

$$\frac{1}{c\Delta t^n} (\mathbf{I}^n - \mathbf{I}^{n-1}) + \mathcal{L}_h \mathbf{I}^n + \mathcal{K}_h^n(T) \mathbf{I}^n = \mathbf{Q}^n(T), \quad \mathbf{I}_r^u(t^n) = \sum_{\ell=1}^r \lambda_\ell^n \mathbf{u}_\ell$$

- POD Galerkin-Projected BTE (apply $\langle \mathbf{u}_\ell, \cdot \rangle_W$)

$$\begin{aligned} \frac{1}{c\Delta t^n} (\lambda_\ell^n - \lambda_\ell^{n-1}) + \sum_{\ell'=1}^r \lambda_{\ell'}^n \langle \mathbf{u}_\ell, \mathcal{L}_h \mathbf{u}_{\ell'} \rangle_W \\ + \sum_{\ell'=1}^r \lambda_{\ell'}^n \langle \mathbf{u}_\ell, \mathcal{K}_h^n(T) \mathbf{u}_{\ell'} \rangle_W = \langle \mathbf{u}_\ell, \mathbf{Q}^n(T) \rangle_W \end{aligned} \quad (12)$$

- Used orthogonality of basis: $\langle \mathbf{u}_{\ell'}, \mathbf{u}_\ell \rangle_W = \delta_{\ell, \ell'}$
- Dense system of equations for $\{\lambda_\ell^n\}$



- Fleck & Cummings, 1971
- 17 frequency (energy) groups
- 60 spatial cells, $\Delta x = 0.1$ cm
- $\Delta t = 2 \times 10^{-2}$ ns
- $0 \leq t \leq 6$ ns, 300 time steps
- DS_4 Gaussian quadrature set
- Finite volume in space & fully implicit scheme for LOQD eqs.

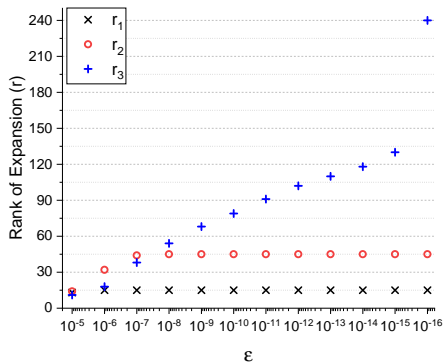
- The F-C test is characterized by three distinct temporal stages
 - Rapid wave formation $t \in [0, 0.3\text{ns}]$
 - Propagation of wave from left to right $t \in (0.3, 1.2\text{ns}]$
 - Slow heating of entire domain towards steady state $t \in (1.2, 6\text{ns}]$
- Finding a POD basis that can represent all three physical regimes is a challenge
- Instead, a separate POD basis can be formulated for each regime

Calculation of Basis

- We calculate a unique POD basis for each distinct stage of the F-C test
- \mathbf{A}_1 , \mathbf{A}_2 , \mathbf{A}_3 with $d_i = \text{rank}(\mathbf{A}_i)$
- ranks $r_i \leq d_i$ are calculated based off singular values of \mathbf{A}_i

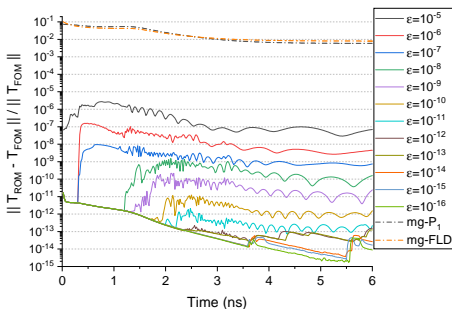
$$\xi^2 = \frac{\sum_{\ell=k+1}^d \sigma_{\ell}^2}{\sum_{\ell=1}^d \sigma_{\ell}^2}$$

- Stage 1 (r_1): full rank = 15
- Stage 2 (r_2): full rank = 45
- Stage 3 (r_3): full rank = 240

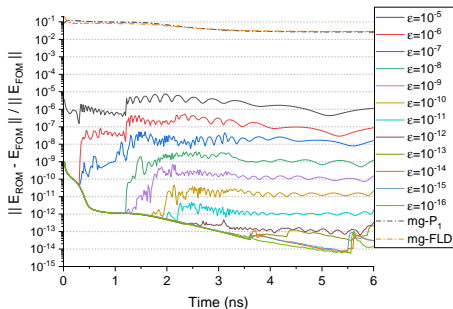


Numerical Results

- Relative errors in 2-norm at each instant of time

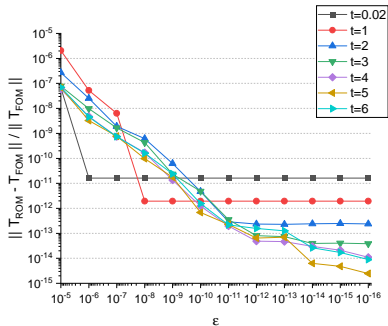


Temperature

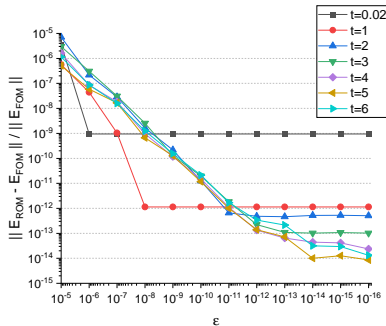


Energy density

- Relative errors in 2-norm plotted vs ξ for certain times



Temperature



Energy density

- Prototype advanced ROMs for TRT have been developed and tested in 1D and 2D geometries
- All models require data on the BTE solution
- Multiphysical equations of interest are coupled moment equations on a low-dimensional scale
- Use of the low-order moment equations enforces conservation of fundamental physics in radiative transfer component
- The proposed methods have been shown to perform well on highly nonlinear thermal radiative transfer problems
- Future research items
 - Optimal sampling techniques for generation of data to inform and train ROMs for TRT
 - Investigation of more complex data-driven methods for approximation
 - Parametrized ROMs for TRT
- Acknowledgement
 - This research project is funded by the Department of Defense, Defense Threat Reduction Agency, grant number HDTRA1-18-1-0042.

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Questions?