## SP<sub>N</sub> Update

Stuart R. Slattery Engineering Physics Department University of Wisconsin - Madison

March 20, 2013



### Neutron Transport Solution Methods



$$\hat{\Omega} \cdot \vec{\nabla} \psi(\vec{r}, \hat{\Omega}, E) + \sigma(\vec{r}, E) \psi(\vec{r}, \hat{\Omega}, E) = 
\int \int \sigma_{s}(\vec{r}, E' \to E, \hat{\Omega}' \to \hat{\Omega}) \psi(\vec{r}, \hat{\Omega}', E') d\Omega' dE' + q(\vec{r}, \hat{\Omega}, E) \quad (1)$$

- $S_N$  transport is expensive
  - Difficult to parallelize: sweeps in space, pipelining in angle, energy decoupling
  - · Large storage requirements
  - Ray effects
- P<sub>N</sub> equations still expensive
  - Complicated system:  $(N+1)^2$  equations in 3D
  - Coupling of equations through both angular moments and spatial derivatives

## SP<sub>N</sub> Approximation



- Ad-hoc generalization of planar  $P_N$  equations by Gelbard in the 1960's
- Rigorous formulation through asymptotic and variational analysis in 1990's and 2000's
- Simpler system (N+1)/2 equations in 3D
- Yields elliptic, diffusion-like equations
- Applicable when diffusion theory is applicable: reasonable flux gradients, full-core transport
- ullet Typically does not converge to transport solution as  $N o\infty$
- Can build the full linear operator
- Parallelism through the linear solver

# SP<sub>N</sub> Approximation



#### SP<sub>N</sub> Equations

$$-\nabla \cdot \left[ \frac{n}{2n+1} \frac{1}{\Sigma_{n-1}} \nabla \left( \frac{n-1}{2n-1} \phi_{n-2} + \frac{n}{2n-1} \phi_n \right) + \frac{n+1}{2n+1} \frac{1}{\Sigma_{n+1}} \nabla \left( \frac{n+1}{2n+3} \phi_n + \frac{n+2}{2n+3} \phi_{n+2} \right) \right] + \Sigma_n \phi_n = q \delta_{n0} \qquad n = 0, 2, 4, \dots, N, \quad (2)$$

# SP<sub>N</sub> Numerical Spectral Analysis



- Monte Carlo methods for have strong restrictions on the eigenvalues of the operator for convergence
- MCSA has the same restrictions on the outer stationary iteration
- We need to compute these eigenvalues for various forms of the  $SP_N$  equations to verify convergence of these methods.

We need eigenvalues for A, H<sub>J</sub>, and H<sub>GS</sub> with:

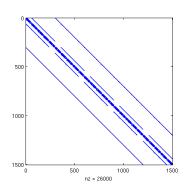
$$\mathbf{H}_{\mathsf{J}} = \mathbf{I} - \mathbf{D}^{-1} \mathbf{A} \tag{3}$$

where  $\mathbf{D} = diag(\mathbf{A})$  and

$$\mathbf{H}_{\mathsf{GS}} = (\mathbf{L} + \mathbf{D})^{-1} \mathbf{U} \tag{4}$$

# $SP_7$ , $P_3$ , 3 groups, reflecting boundaries





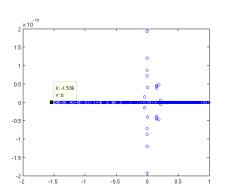
3×10<sup>-15</sup>
2-0
11
12:001529
1-1
-2
0
2
4
6
8
10
12
14

Figure: Linear operator sparsity pattern

Figure: Linear operator eigenvalues

# $SP_7$ , $P_3$ , 3 groups, reflecting boundaries





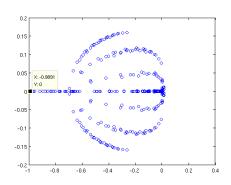


Figure: Jacobi iteration matrix eigenvalues

Figure: Gauss-Seidel iteration matrix eigenvalues

### Oh No!



 The Jacobi method won't converge - all that stuff I said in my prelim won't work

### Solution



- Bug fix in Denovo  $SP_N$  implementation
- ullet A new kind of preconditioning  $\cdots$

# Multigroup Matrix Pattern



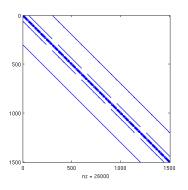


Figure: Linear operator sparsity pattern

# Block Jacobi Preconditioning



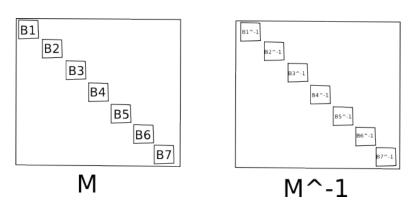


Figure: Block Jacobi Preconditioner

### Point Jacobi Results



### Block Jacobi Results



#### Conclusions



- Block Jacobi preconditioning is a simple and appropriate solution for preconditioning the  $SP_N$  equations
- Implementation is general slides right into ANA framework
- Implementation is scalable local operations only
- Implementation works can move on with research