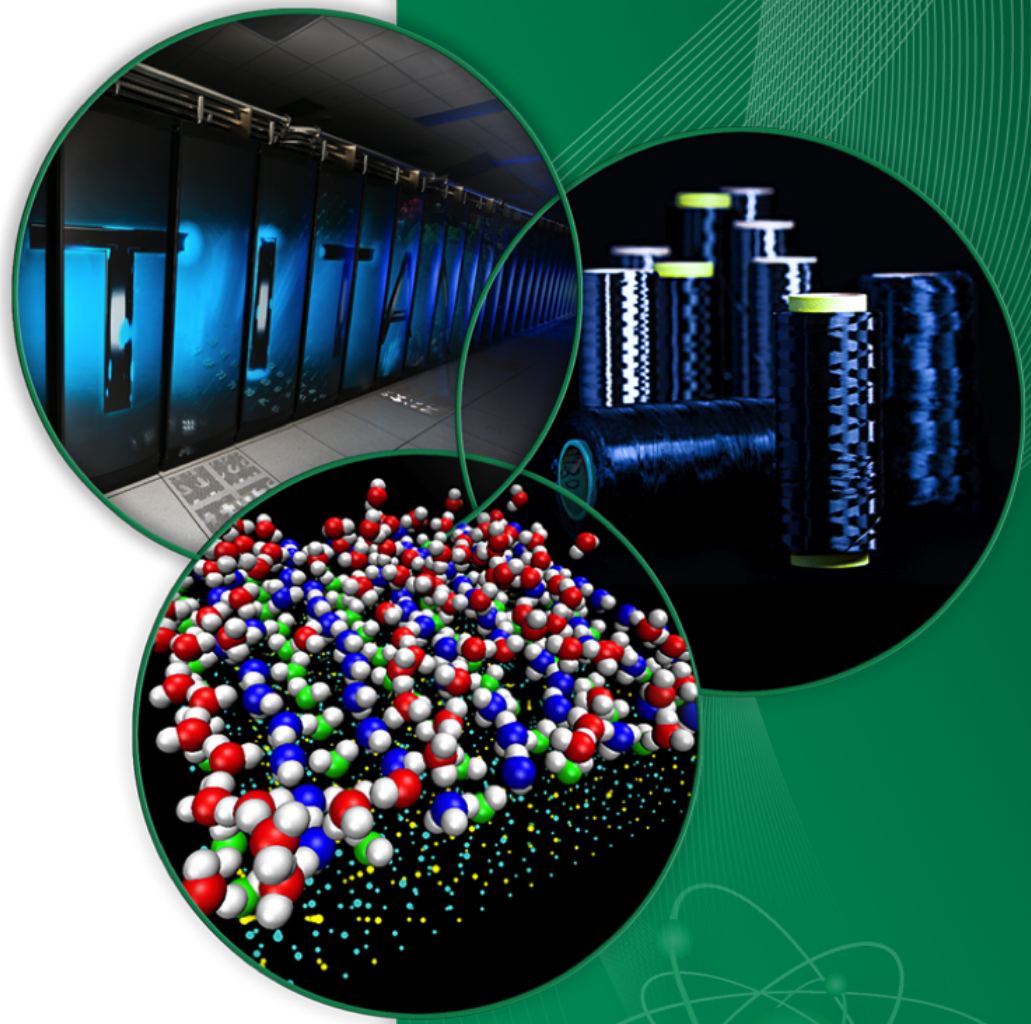
Parallel Algorithms for Monte Carlo Linear Solvers



Stuart Slattery
Steven Hamilton
Tom Evans

Oak Ridge National Laboratory

March 17, 2015

Acknowledgements

This material is based upon work supported by the U.S. Department of Energy, Office of Science, Advanced Scientific Computing Research program.

This research used resources of the Oak Ridge Leadership Computing Facility at the Oak Ridge National Laboratory, which is supported by the Office of Science of the U.S. Department of Energy under Contract No. DE-AC05-00OR22725.

OAK RIDGE National Laboratory

Motivation

- As we move towards exascale computing, the rate of errors is expected to increase dramatically
    - The probability that a compute node will fail during the course of a large scale calculation may be near 1
- Algorithms need to not only have increased concurrency/scalability but have the ability to recover from hardware faults
    - Lightweight machines
    - Heterogeneous machines
    - Both characterized by low power and high concurrency

OAK RIDGE National Laboratory

Towards Exascale Concurrency and Resiliency

- Two basic strategies:

1. State with current "state of the art" methods and make incremental modifications to improve scalability and fault tolerance
   - Many efforts are heading in this direction, attempting to find additional concurrency to exploit

2. Start with methods having natural scalability and resiliency aspects and work at improving performance (e.g. Monte Carlo)
   - Soft failures a component of the tally variance
   - Hard failures potentially mitigated by replication
   - Concurrency enabled by several levels of parallelism

OAK RIDGE National Laboratory

Outline

- Monte Carlo Linear Solvers
- Domain Decomposition and Replication
- Scaling Studies
- Algorithm Variations
- Conclusions and Future Work

OAK RIDGE National Laboratory

Monte Carlo Methods

OAK RIDGE National Laboratory

Monte Carlo for Linear Systems

- Suppose we want to solve $\mathbf{Ax} = \mathbf{b}$
- If $\rho(\mathbf{I} - \mathbf{A}) < 1$, we can write the solution using the Neumann series

$$\mathbf{x} = \sum_{n=0}^{\infty} (\mathbf{I} - \mathbf{A})^n \mathbf{b} = \sum_{n=0}^{\infty} \mathbf{H}^n \mathbf{b}$$

  where $\mathbf{H} \equiv (\mathbf{I} - \mathbf{A})$ is the Richardson iteration matrix

- Build the Neumann series stochastically

$$x_i = \sum_{k=0}^{\infty} \sum_{i_1}^{N} \sum_{i_2}^{N} \cdots \sum_{i_k}^{N} h_{i,i_1} h_{i_1,i_2} \ldots h_{i_{k-1},i_k} b_{i_k}$$

- Define a sequence of state transitions

$$\nu = i \to i_1 \to \cdots \to i_{k-1} \to i_k$$

OAK RIDGE National Laboratory

Forward Monte Carlo

- Choose a row-stochastic matrix $\mathbf{P}$ and weight matrix $\mathbf{W}$ such that $\mathbf{H} = \mathbf{P} \circ \mathbf{W}$
- Typical choice (Monte Carlo Almost-Optimal):

$$\mathbf{P}_{ij} = \frac{|\mathbf{H}_{ij}|}{\sum_{j=1}^{N} |\mathbf{H}_{ij}|}$$

- To compute solution component $\mathbf{x}_i$:
  - Start a history in state i (with initial weight of 1)
  - Transition to new state j based probabilities determined by $\mathbf{P}_i$
  - Modify history weight based on corresponding entry in $\mathbf{W}_{ij}$
  - Add contribution to $\mathbf{x}_i$ based on current history weight and value of $\mathbf{b}_j$
- A given random walk can only contribute to a single component of the solution vector with $\mathbf{x} \approx \mathbf{M_{MC}b}$

OAK RIDGE National Laboratory

Sampling Example (Forward Monte Carlo)

- Suppose

$$\mathbf{A} = \begin{bmatrix} 1.0 & -0.2 & -0.6 \\ -0.4 & 1.0 & -0.4 \\ -0.1 & -0.4 & 1.0 \end{bmatrix} \rightarrow \mathbf{H} \equiv (\mathbf{I} - \mathbf{A}) = \begin{bmatrix} 0.0 & 0.2 & 0.6 \\ 0.4 & 0.0 & 0.4 \\ 0.1 & 0.4 & 0.0 \end{bmatrix}$$

  then

$$\mathbf{P} = \begin{bmatrix} 0.0 & 0.25 & 0.75 \\ 0.5 & 0.0 & 0.5 \\ 0.2 & 0.8 & 0.0 \end{bmatrix}, \quad \mathbf{W} = \begin{bmatrix} 0.0 & 0.8 & 0.8 \\ 0.8 & 0.0 & 0.8 \\ 0.5 & 0.5 & 0.0 \end{bmatrix}$$

- If a history is started in state 3, there is a 20% chance of it transitioning to state 1 and an 80% chance of moving to state 2

OAK RIDGE National Laboratory

Solving the Heat Equation: Forward Method

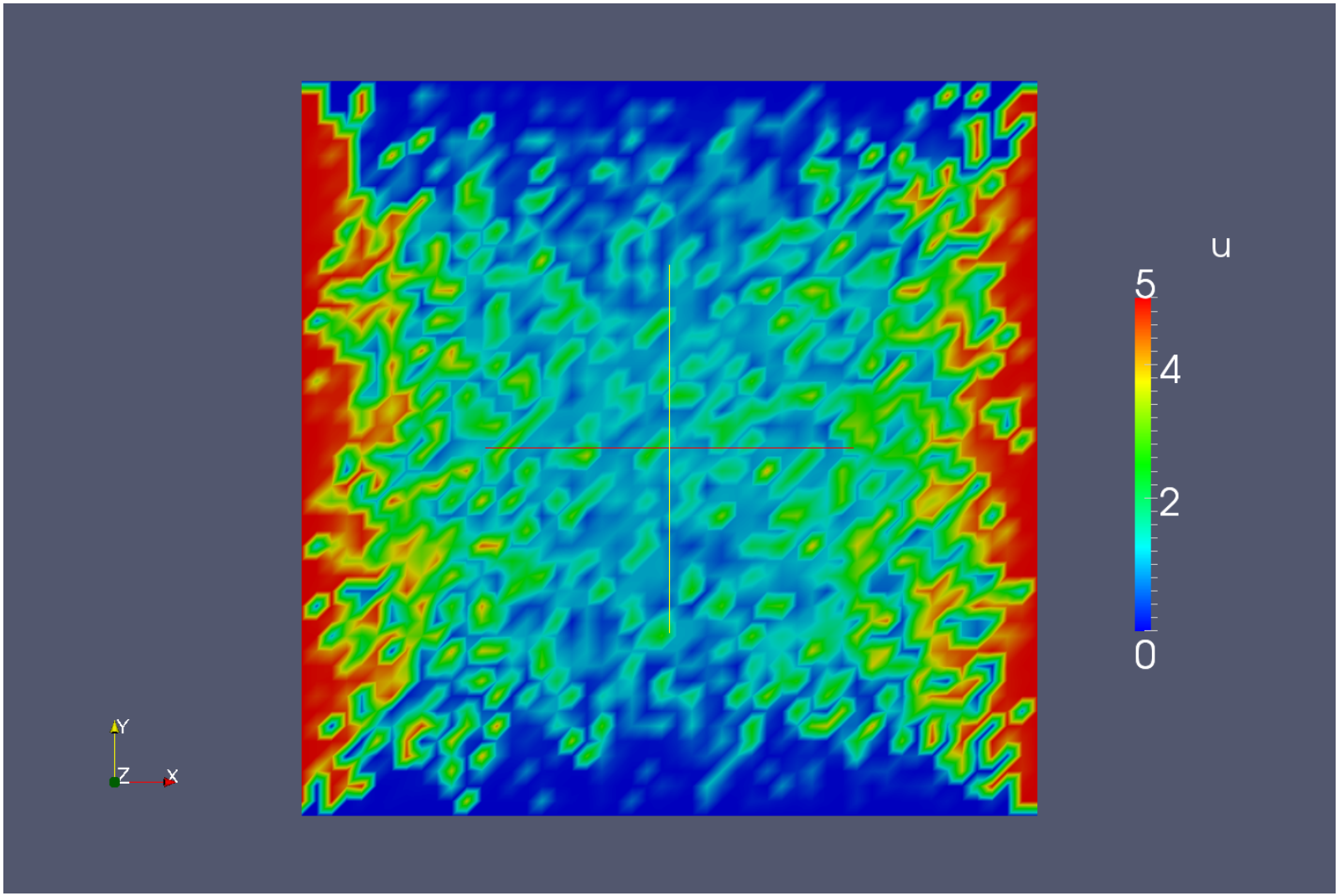


Figure : **Forward solution.** 2.5×10^3 *total histories.*

OAK RIDGE National Laboratory

Solving the Heat Equation: Forward Method

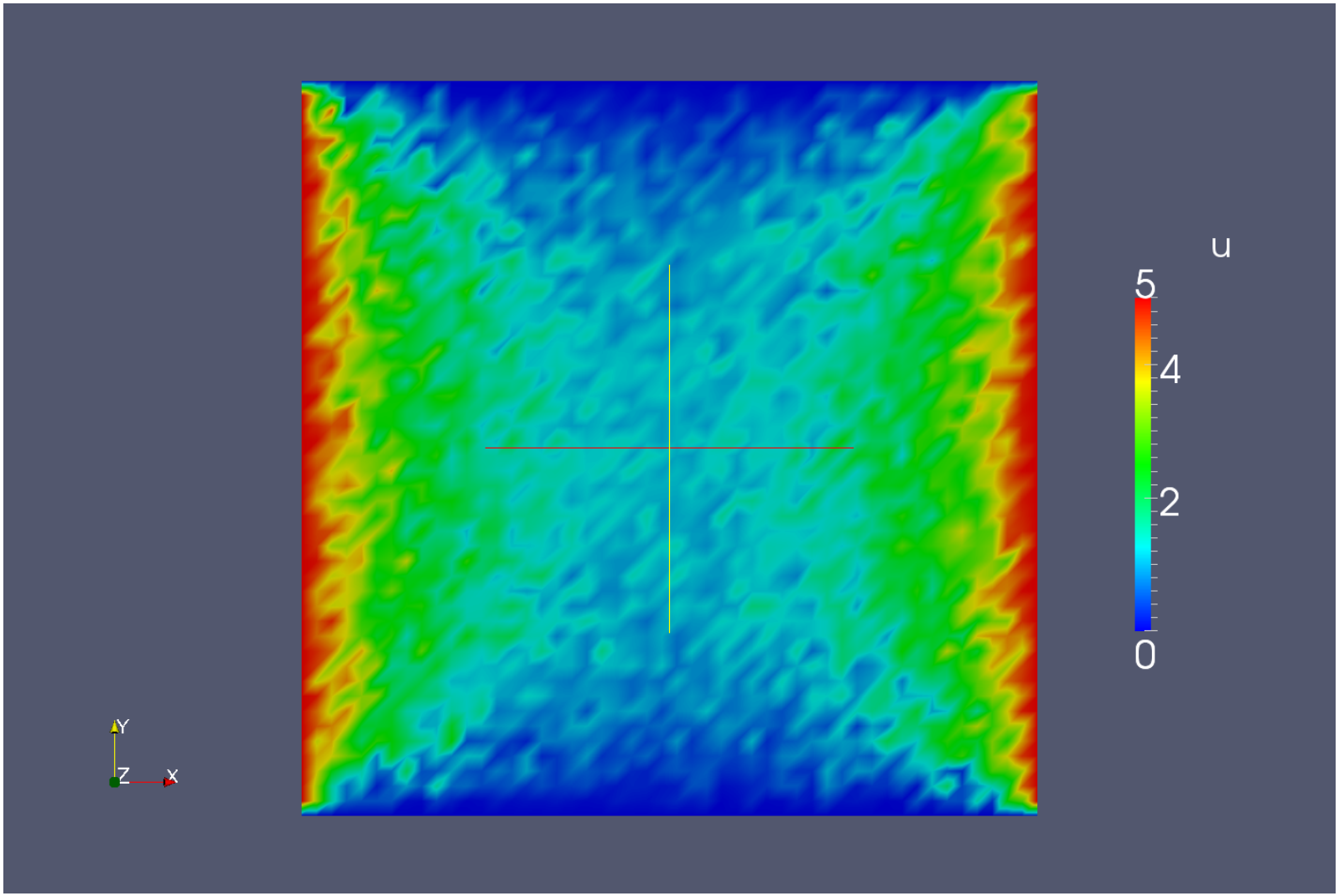


Figure : **Forward solution.** 2.5×10^4 *total histories.*

OAK RIDGE National Laboratory

Solving the Heat Equation: Forward Method

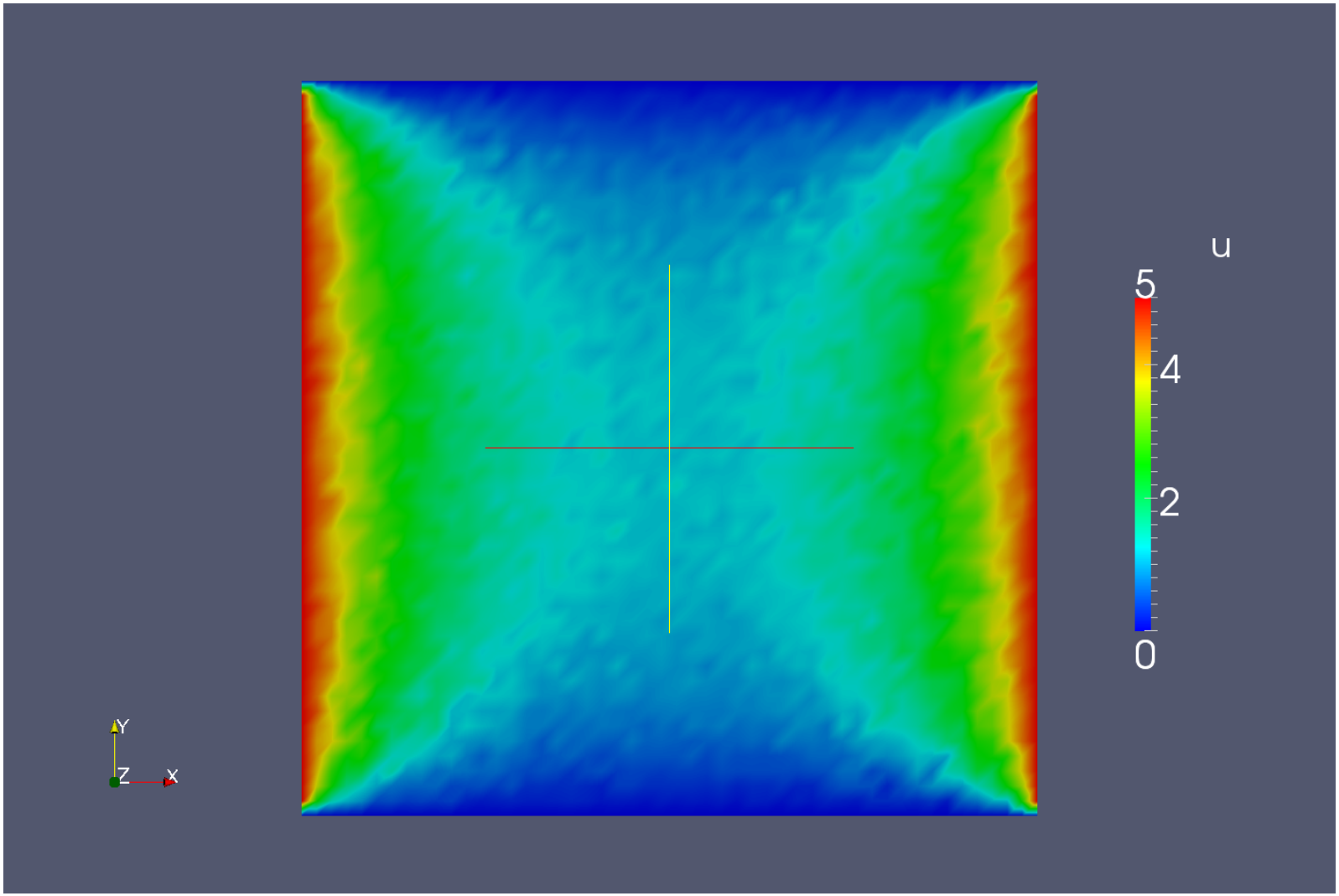


Figure : **Forward solution.** 2.5×10^5 *total histories.*

OAK RIDGE National Laboratory

Solving the Heat Equation: Forward Method

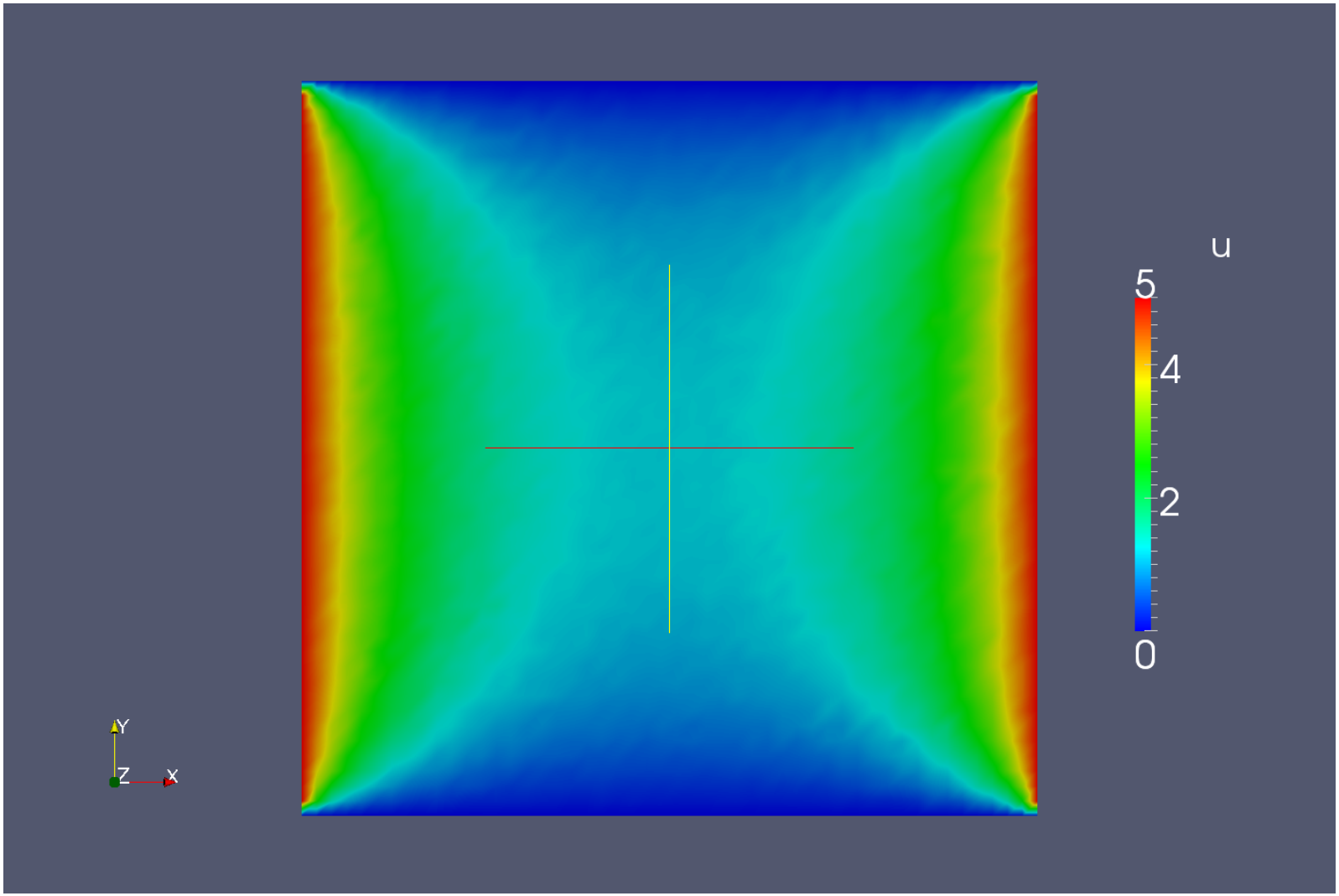


Figure : **Forward solution.** 2.5×10^6 *total histories.*

OAK RIDGE National Laboratory

Domain Decomposition and Replication

Domain Decomposed Monte Carlo

- Each parallel process owns a piece of the domain (linear system)
- Random walks must be transported between adjacent domains through parallel communication
- Domain decomposition determined by the input system
- Load balancing not yet addressed

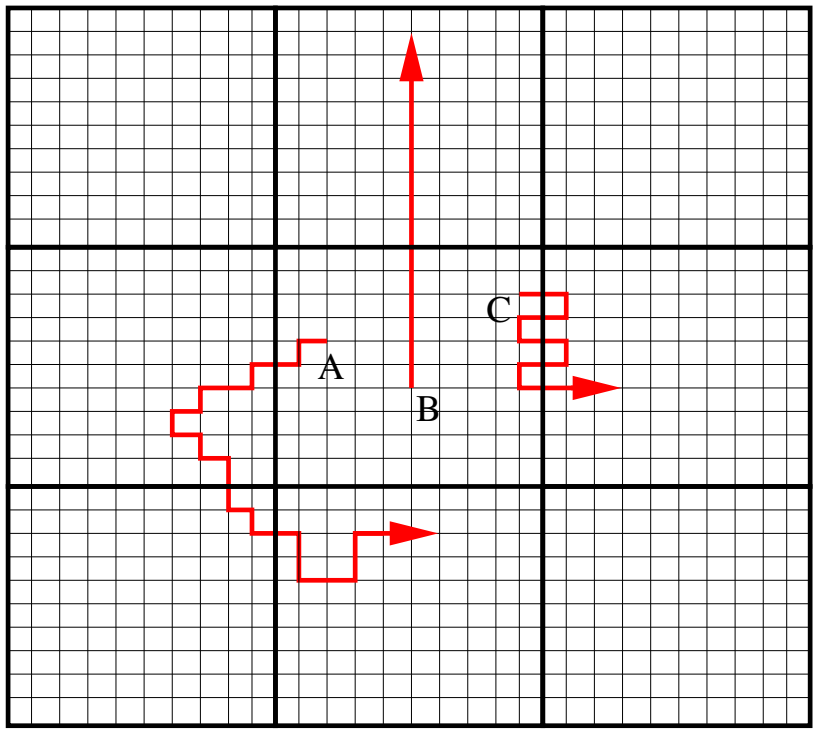
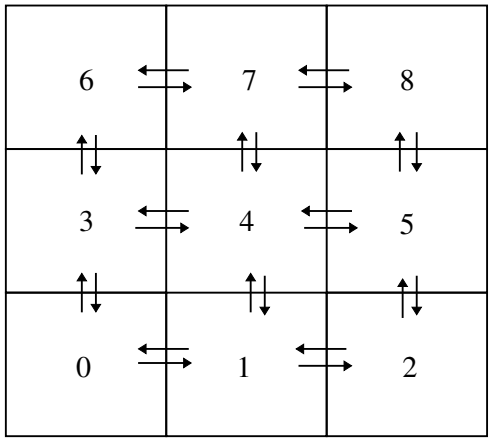


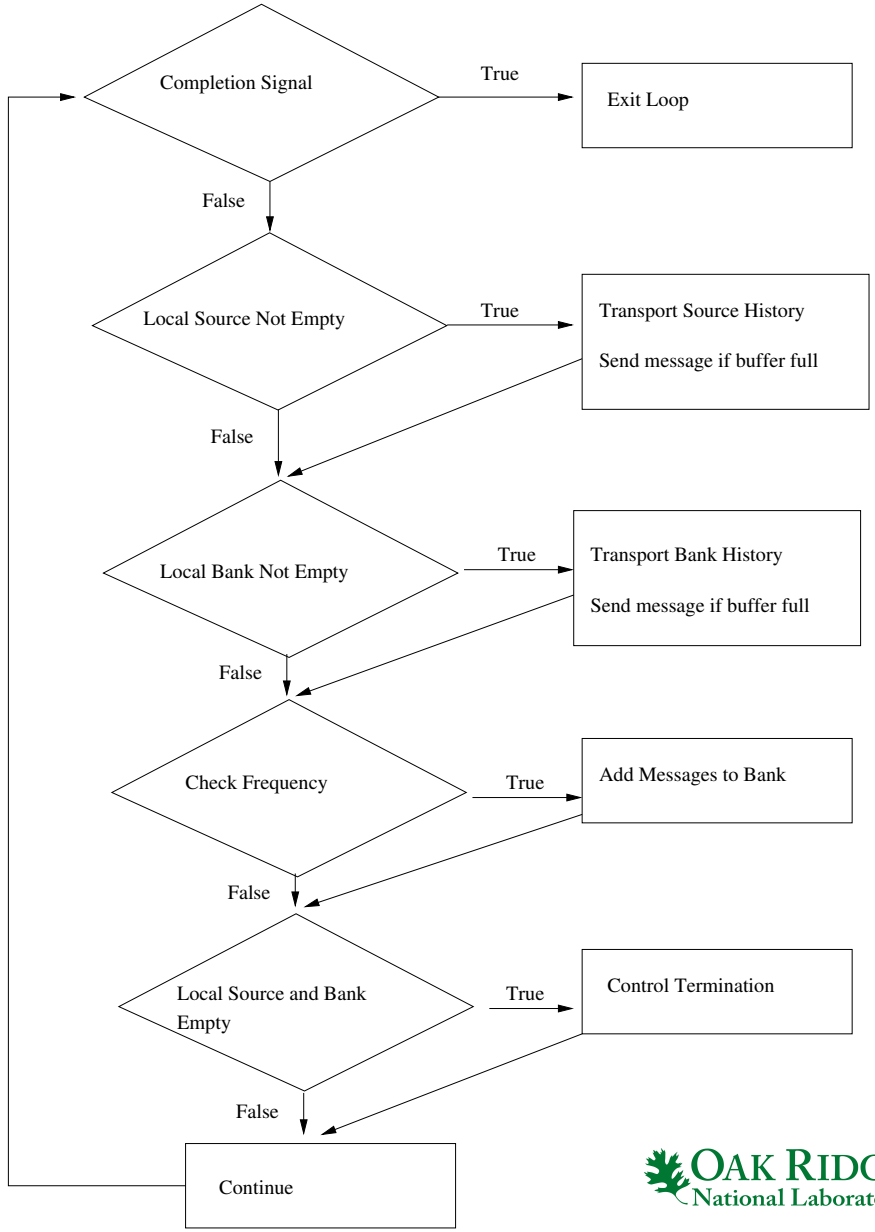
Figure : Domain decomposition example illustrating how domain-to-domain transport creates communication costs.

OAK RIDGE National Laboratory

Asynchronous Monte Carlo Transport Kernel

- General extension of the Milagro algorithm (LANL)
- Asynchronous nearest neighbor communication of histories
- System-tunable communciation parameters of buffer size and check frequency (performance impact)
- Need an asynchronous strategy for exiting the transport loop without a collective (running sum)





OAK RIDGE National Laboratory

Exiting the Transport Loop without Collectives

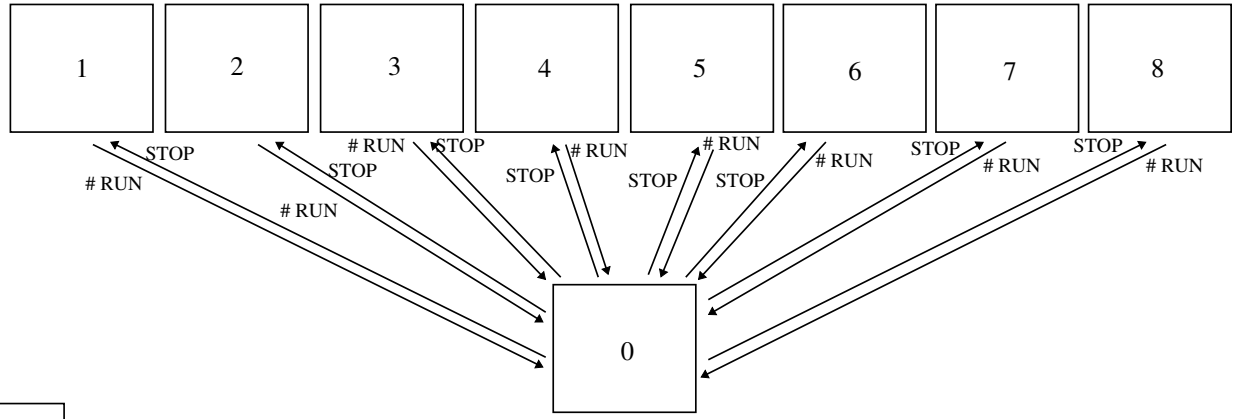


Figure : Master/Slave

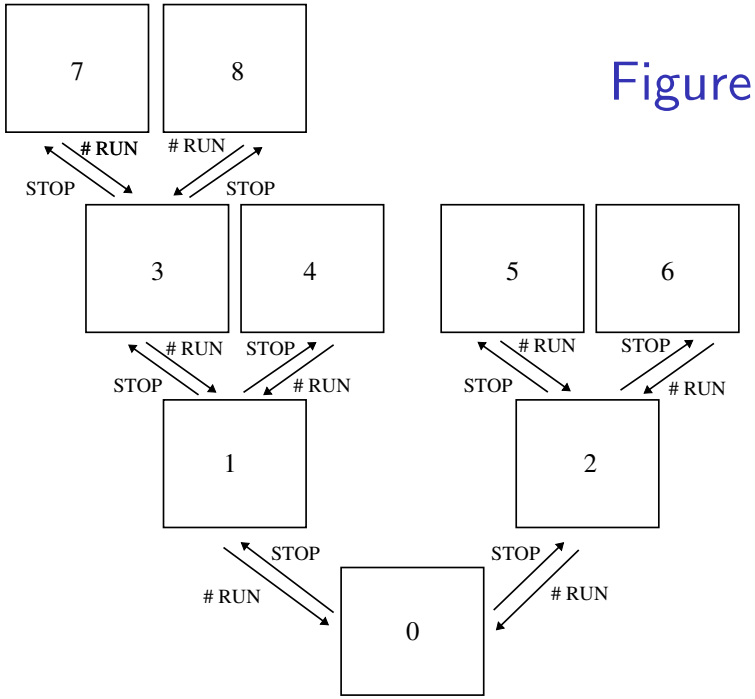


Figure : Binary Tree

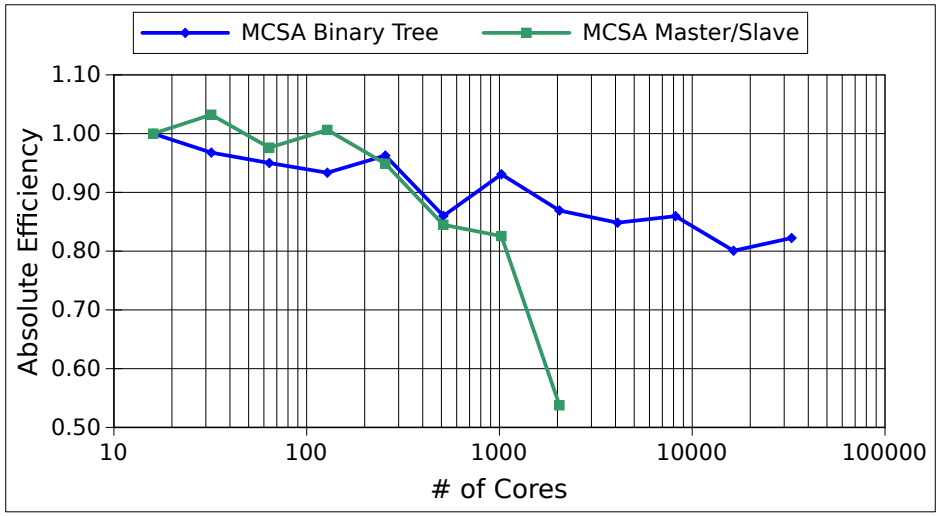


Figure : Weak scaling absolute efficiency

OAK RIDGE National Laboratory

Replication

Different batches of Monte Carlo samples can be combined in summation via superposition if they have different random number streams. For two different batches:

$$\mathbf{M_{MC}x} = \frac{1}{2}(\mathbf{M_1} + \mathbf{M_2})\mathbf{x}$$

Consider each of these batches independent *subsets* of a Monte Carlo operator where now the operator can be formed as a general additive decomposition of N_S subsets:

$$\mathbf{M_{MC}} = \frac{1}{N_S}\sum_{n=1}^{N_s}\mathbf{M_n}$$

We replicate the linear problem and form each subset on a different group of parallel processes. Applying the subsets to a vector requires an AllReduce to form the sum. Each subset is domain decomposed.

OAK RIDGE National Laboratory

Scaling Studies

OAK RIDGE National Laboratory

Parallel Test - Simplified P_N (SP_N) Assembly Problem

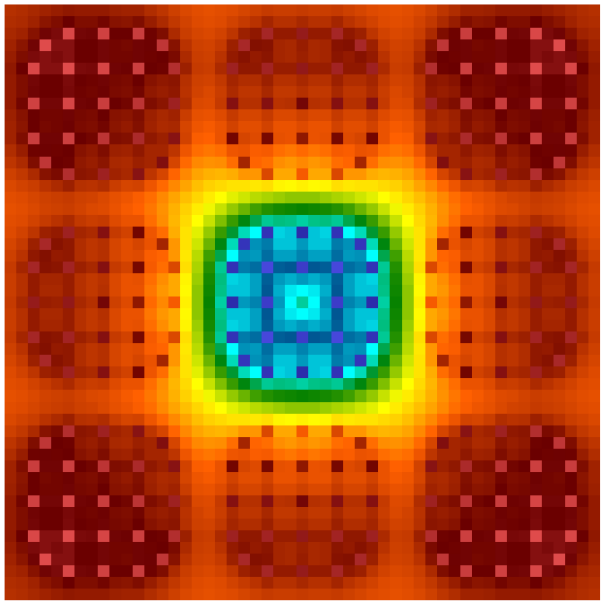


Figure : SP_N solution example

The (SP_N) equations are an approximation to the Boltzmann neutron transport equation used to simulate nuclear reactors

$$-\nabla\cdot\mathbb{D}_n\nabla\mathbb{U}_n+\sum_{m=1}^{4}\mathbb{A}_{nm}\mathbb{U}_m=\frac{1}{k}\sum_{m=1}^{4}\mathbb{F}_{nm}\mathbb{U}_m$$

Scaling problem – 1×1 to 17×17 array of fuel assemblies with 289 pins each resolved by a 2×2 spatial mesh and 200 axial zones

- 7 energy groups, 1 angular moment, 1.6M to 273.5M degrees of freedom
- 64 to 10,800 computational cores via domain decomposition
- We are usually interested in solving generalized eigenvalue problem - we use the operator from these problems to test the kernel scaling

OAK RIDGE National Laboratory

Monte Carlo Communication Parameters

		Message Check Frequency			
		128	**256**	**512**	**1024**
Mesage Buffer Size	**256**	1.054	1.061	1.076	1.076
	512	1.103	1.146	1.211	1.270
	1024	1.062	1.088	1.133	1.176
	2048	1.030	1.042	1.072	1.107
	4096	1.010	1.012	1.025	1.050
	8192	1.001	1.000	1.008	1.018
	16384	1.017	1.003	1.010	1.009

- 64 cores, 1.6M DOFs, history length of 15, 3 histories per DOF
- Buffer size dominates the trend
- 27% decrease in runtime observed for bad parameter choices
- Worth the time to do this parameter study when running on new hardware

OAK RIDGE National Laboratory

Monte Carlo Strong Scaling

OAK RIDGE National Laboratory

Monte Carlo Weak Scaling

OAK RIDGE National Laboratory

Monte Carlo Replication Scaling

Algorithm Variations

Monte Carlo Synthetic Acceleration

- Devised by Evans and Mosher in the 2000's as an acceleration scheme for radiation diffusion problems (LANL)
- Can be abstracted as a general linear solver with Monte Carlo as a preconditioner
- Combine with Richardson iteration as a "smoother" in between Monte Carlo steps:

$$\begin{aligned}
\mathbf{r}^k &= \mathbf{b} - \mathbf{A}\mathbf{x}^k \\
\mathbf{x}^{k+1/2} &= \mathbf{x}^k + \mathbf{r}^k \\
\mathbf{r}^{k+1/2} &= \mathbf{b} - \mathbf{A}\mathbf{x}^{k+1/2} \\
\mathbf{x}^{k+1} &= \mathbf{x}^{k+1/2} + \mathbf{M}_{\mathbf{MC}}\mathbf{r}^{k+1/2}
\end{aligned}$$

OAK RIDGE National Laboratory

Matrix-Free Algorithm

- At each application of $\mathbf{M_{MC}}$, execute the Monte Carlo process
- Must perform Monte Carlo every time you want to apply with a better approximation requiring more time and more operations
- Variations in random number streams are amortized over iterations

OAK RIDGE National Laboratory

Stochastic Approximate Inverse Algorithm

- Construct $\mathbf{M_{MC}}$ as a sparse matrix by executing the Monte Carlo process once and tallying the row entries
- Use this operator as a stochastic approximation to the inverse
- A better approximation to the inverse requires more setup time and more storage
- Will investigate a drop tolerance strategy

L	N_S	NNZ	NNZ Ratio	MC Time (s)	Setup Time (s)	MCSA Iters
3	2	484,714	0.41	0.104	0.671	255
3	3	622,123	0.52	0.145	0.705	255
5	2	783,153	0.66	0.158	0.737	185
5	3	1,032,573	0.87	0.237	0.831	171
5	4	1,241,442	1.05	0.302	0.906	171
10	3	1,969,540	1.66	0.433	1.061	95
10	4	2,416,572	2.04	0.570	1.214	95
15	3	2,867,005	2.42	0.645	1.317	132
15	4	3,544,181	2.99	0.833	1.534	67
15	5	4,157,269	3.50	1.029	1.765	66

Table : MCSA Performance. A had $115,600$ rows and $1,186,464$ non-zero entries.

OAK RIDGE National Laboratory

Unpreconditioned Algorithm Comparison

Conclusions and Future Work

OAK RIDGE National Laboratory

Conclusions

- Monte Carlo methods offer great potential for both resilient and highly parallel solvers
- A fully asynchronous algorithm provides a scheme without collectives
- Good scaling demonstrated so far on reasonably load balanced problems
- Replication a potential resiliency strategy with some overhead
- Matrix-free and stochastic approximate inverse algorithms are complementary - trade operations for storage

OAK RIDGE National Laboratory

Conclusions

- Vectorization an area of active research with a focus on heterogenous architectures (Titan and Summit)
- Multiple threading models are being explored (Kokkos, HPX, etc.)
- Extending methods to broader problem areas is significant algorithmic challenge and an attractive area for continued research
- Performance modeling and resiliency simulations this FY

OAK RIDGE National Laboratory