

Overview of Direct Sparse Linear Solvers for Power Grid Optimization Problems

Presenter: Leslie Cook
Midwestern State University

ORNL is managed by UT-Battelle LLC for the US Department of Energy



OAK RIDGE
INSTITUTE
FOR SCIENCE
AND EDUCATION



EXASCALE COMPUTING PROJECT



MIDWESTERN STATE UNIVERSITY



U.S. DEPARTMENT OF
ENERGY

Problem Statement

Solving large sparse linear systems of equations

$$\mathbf{Ax} = \mathbf{b}$$

- \mathbf{A} is a known coefficient matrix with dimension $n \times n$
- \mathbf{b} is a known RHS vector with dimension $n \times 1$
- \mathbf{x} is an unknown solution vector with dimension $n \times 1$

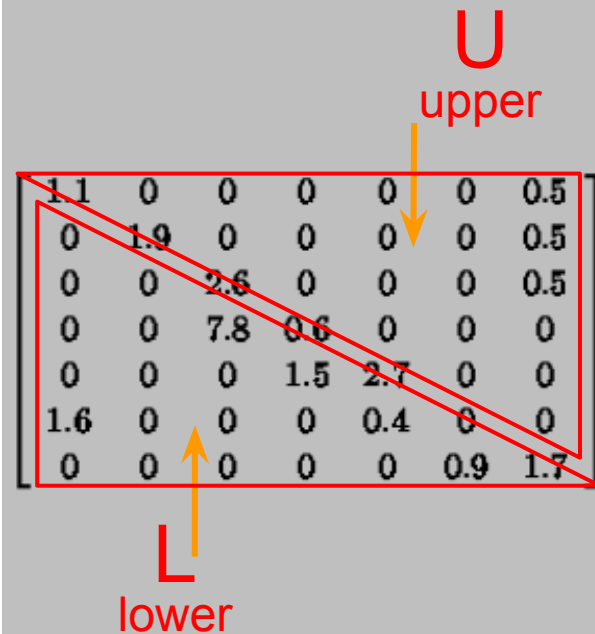
Factorize \mathbf{A} into lower \mathbf{L} and upper \mathbf{U} triangulars, where

$$\mathbf{A} = \mathbf{LU}$$

Solving $\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$ directly is too computationally expensive, so we solve by the substitutions,

1. $\mathbf{Ly} = \mathbf{b}$ solve $\mathbf{y} = \mathbf{L}^{-1}\mathbf{b}$
2. $\mathbf{Ux} = \mathbf{y}$ solve $\mathbf{x} = \mathbf{U}^{-1}\mathbf{y}$

Sparse Matrix



Problem Statement

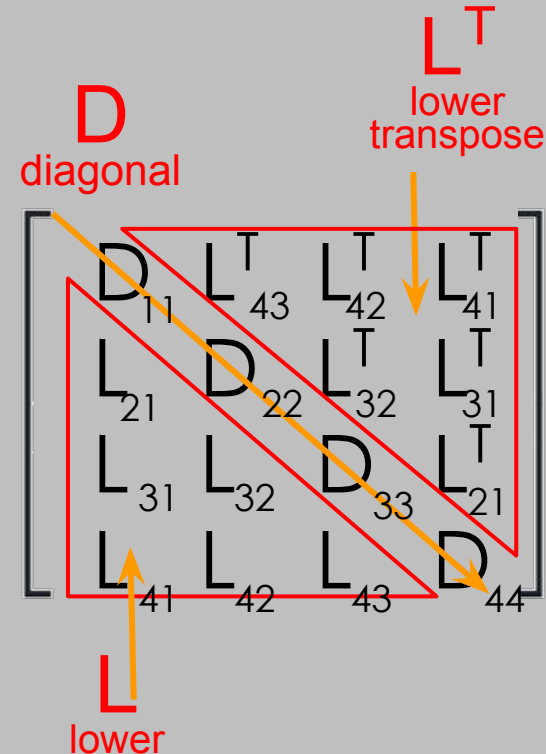
If we know we have a symmetric sparsity pattern, we can exploit matrix symmetry to further reduce computational cost by factoring A as,

$$A = LDL^T$$

- L is the lower triangular matrix
- D is a (1x1) or (2x2) the diagonal block
- L^T is the transpose of the lower triangular matrix

Solve $LDL^T x = b$ with the substitutions,

1. $Ly = b$ solving $y = L^{-1}b$
2. $DL^T x = y$ solving $x = (DL^T)^{-1}y$ which gives
 $x = D^{-1}Ly$ where only the lower triangular is needed for efficient solving.



Problem Statement

The residual vector \mathbf{r} is calculated to determine the accuracy of our solution, the closer to zero the better.

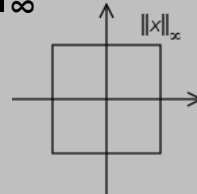
$$\mathbf{r} = \mathbf{b} - \mathbf{A}\mathbf{x}$$

We calculate the norm of the residual vector \mathbf{r} and the norm of the RHS vector \mathbf{b} . The ratio of the norm of solution vector to the norm of the RHS vectors gives the relative residual. This is a measure of how well our solution converges.

$$\|\mathbf{r}\| / \|\mathbf{b}\|$$

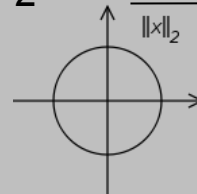
INF-norm

$$\|\mathbf{x}\|_{\infty} = \max_i |x_i|$$



2-norm

$$\|\mathbf{x}\|_2 = \sqrt{\sum |x_i|^2}$$

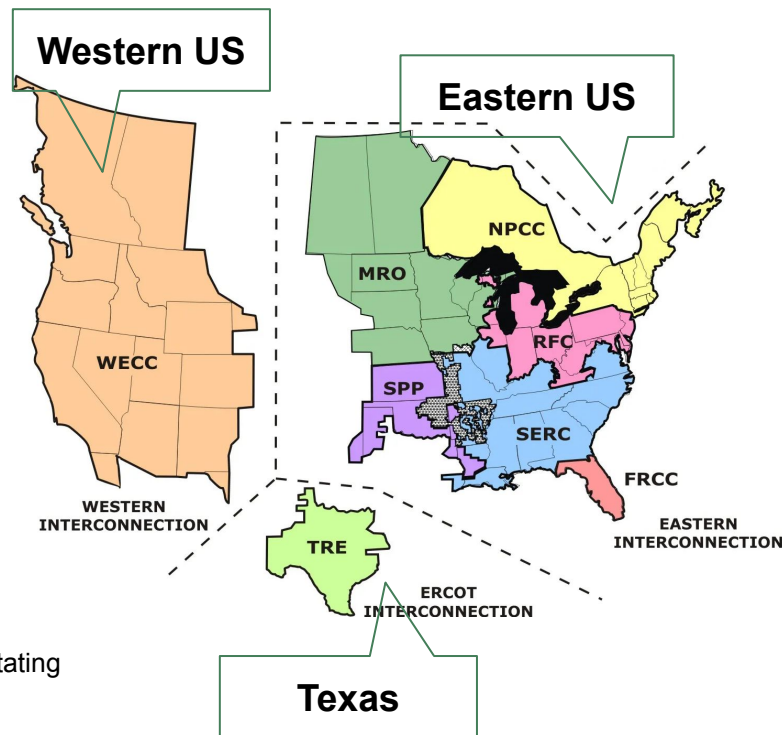


Note: The 2-norm may obscure errors compared to INF-norm, making the INF-norm preferable

Test Cases

Synthetic linear systems extracted from AC power flow analysis for power grids of Texas, Western US, and Eastern US.

Grid Model	rows	columns	NNZ	*Bus size
Texas 2000-bus	55667	55667	173710	2000
Western US 10k-bus	238072	238072	723720	10,000
Eastern US 70k-bus	1640411	1640411	4991820	70,000



* Buses serve as junction points within an electrical network, facilitating the connection of different elements of the electrical system.

Testing Environments

Oak Ridge Leadership Computing Facility

- Summit

21 cores with each node consists of 2x IBM POWER9™ CPUs and 6 NVIDIA Volta v100 GPUs

- Frontier

64 cores with each node consists of 1x HPC and AI Optimized 3rd Gen AMD EPYC CPU and 4 Purpose Built AMD Instinct 250X GPUs



Sparse Linear Solver Packages

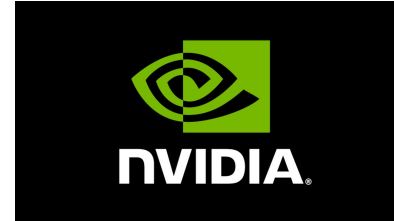
CPU

- HSL
 - MA57 (baseline)
- Trilinos Amesos2
 - KLU2
 - ShyLUBasker



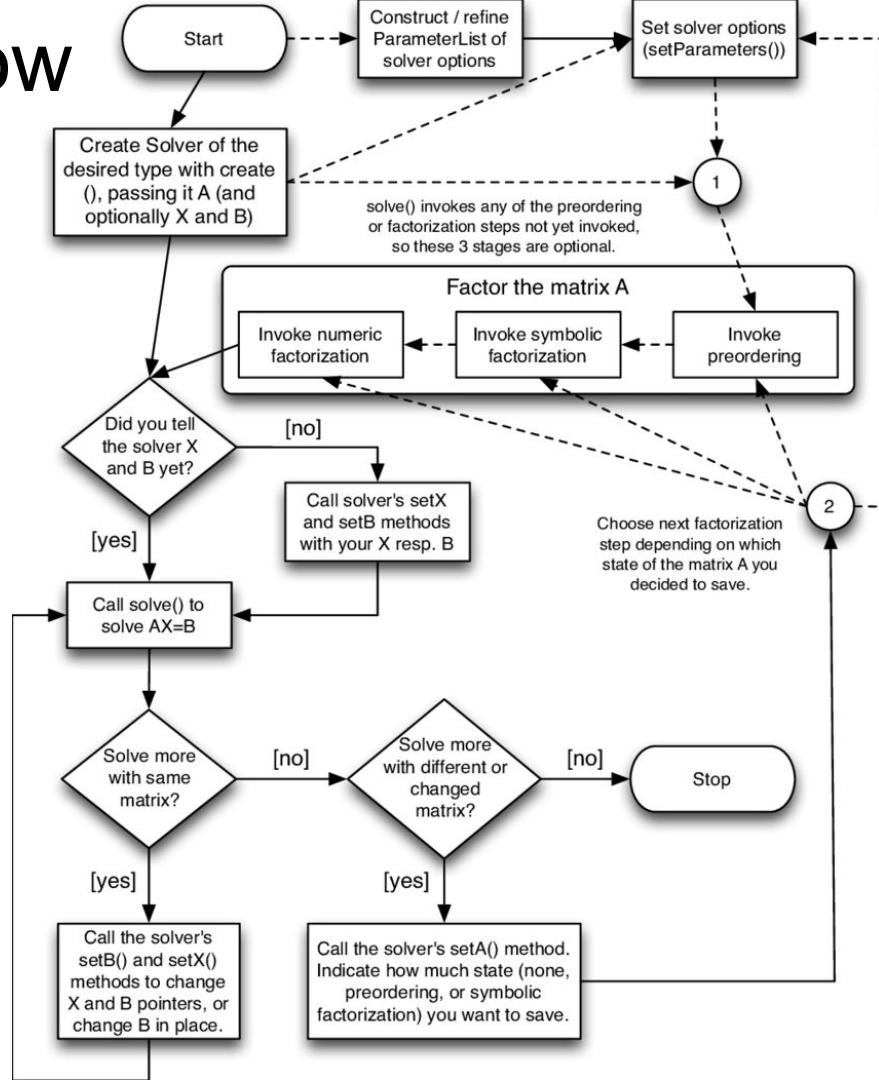
GPU

- cuSolver
 - KLU-GLU
 - KLU-RFwFGMRES
- rocSOLVER
 - rocSolver-KLU-RF



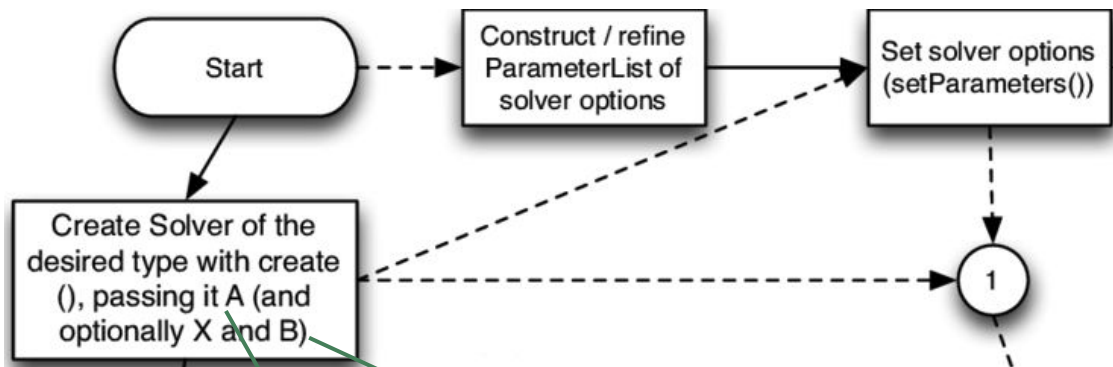
Solver	MA 57	KLU2	ShyLU Basker	cuSolver KLU-GLU	cuSolver KLU-RF wGMRES	rocSolver KLU-RF
Exploits symmetry	Yes	No	No	No	No	No
Primary algorithm	LDL ^T	LU	(I)LU	LU refact	LU refact	LU refact
Follows with IR	Yes	No	Yes	Yes	Yes	Yes
Norm eq used	INF-norm	2-norm	2-norm	INF-norm	INF-norm	INF-norm
GPU accelerated	No	No	No	Yes	Yes	Yes
compiler	gcc	gcc	gcc	nvcc	nvcc	hipcc
Open source	No	Yes	Yes	No	No	No

Workflow



- Tasked with building a test bench for Amesos2 solvers in the ORNL Linear-Solver-Testing GitLab repository

Workflow

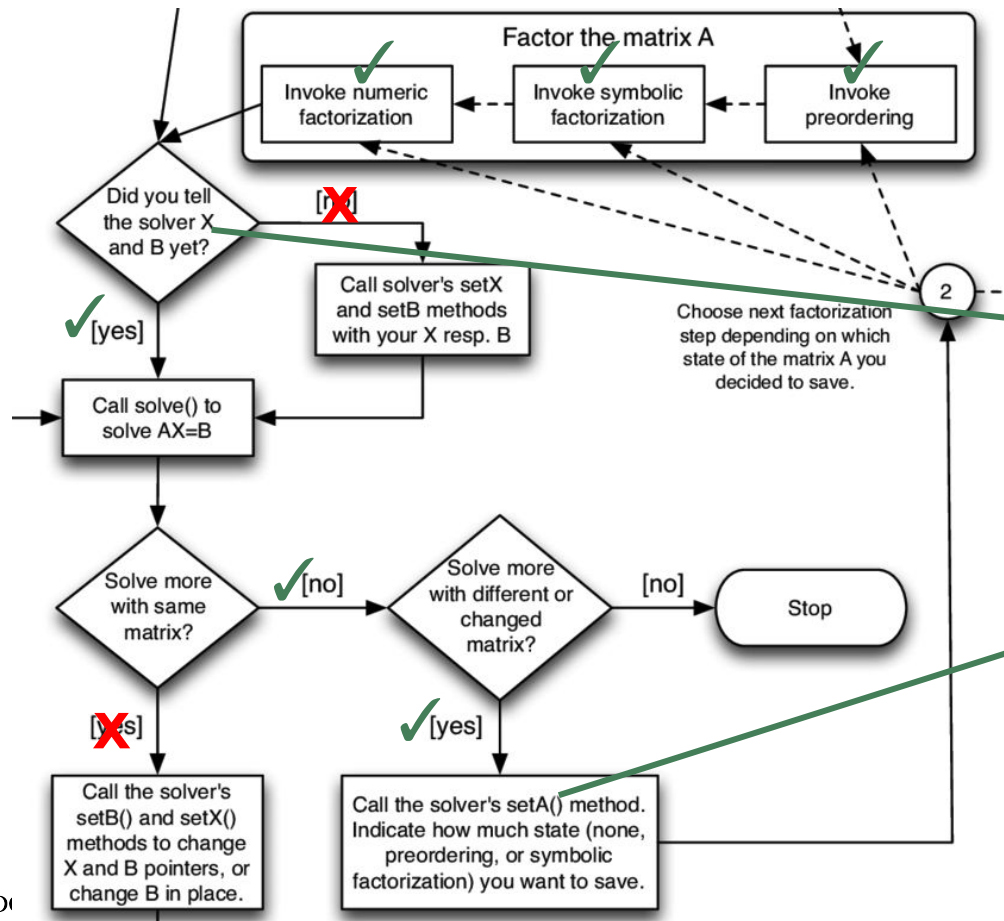


matrix A	vector B
reads in a series of given matrix market files	reads in a series of matching RHS matrix market files

Parameters

KLU2	ShyLUBasker
Equilibrate before solve	Set num threads (64)
Is contiguous	Use pivot
	Replace tiny pivot
	Use metis

Workflow



X is set to randomized values

setA(A, Amesos2::SYMBFACT)
reuse symbolic factorization

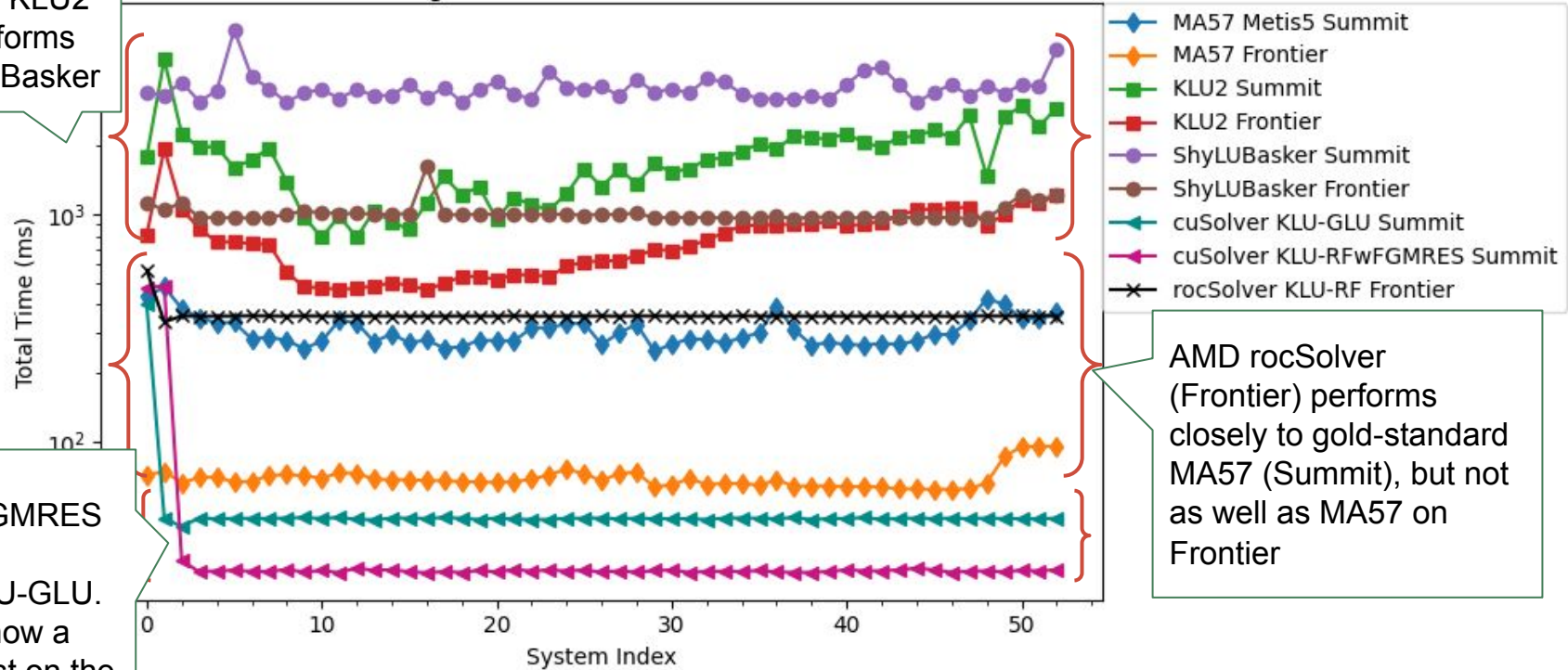
RESULTS

The background of the slide is a vibrant teal and green gradient. It features a complex pattern of binary code (0s and 1s) that appears to be flowing or receding into the distance. Overlaid on this are several geometric and molecular motifs: a series of white hexagons arranged in a honeycomb-like pattern, some of which are filled with a lighter shade of green; and a network of small white dots connected by thin lines, resembling a molecular or data network. The overall aesthetic is high-tech and scientific.

Total Computation Time - Texas Grid

ACTIVSg2000: 55667 x 55667 nnz: 173k

Amesos2 test bench: KLU2 outperforms ShyLUBasker



AMD rocSolver (Frontier) performs closely to gold-standard MA57 (Summit), but not as well as MA57 on Frontier

cuSolver KLU-RFwFGMRES outperforms cusolver KLU-GLU. Index 0-2 show a one time cost on the CPU before deployment on GPUs

Figure 1. Total runtimes for the Texas (2000-bus) grid model highlight performance disparities of linear solvers on different hardware architectures.

Stability issues for rocSolver and ShyLUBasker indicated poor solution accuracy

Relative Residuals - Texas Grid

ACTIVSg2000: 55667 x 55667 nnz: 173k

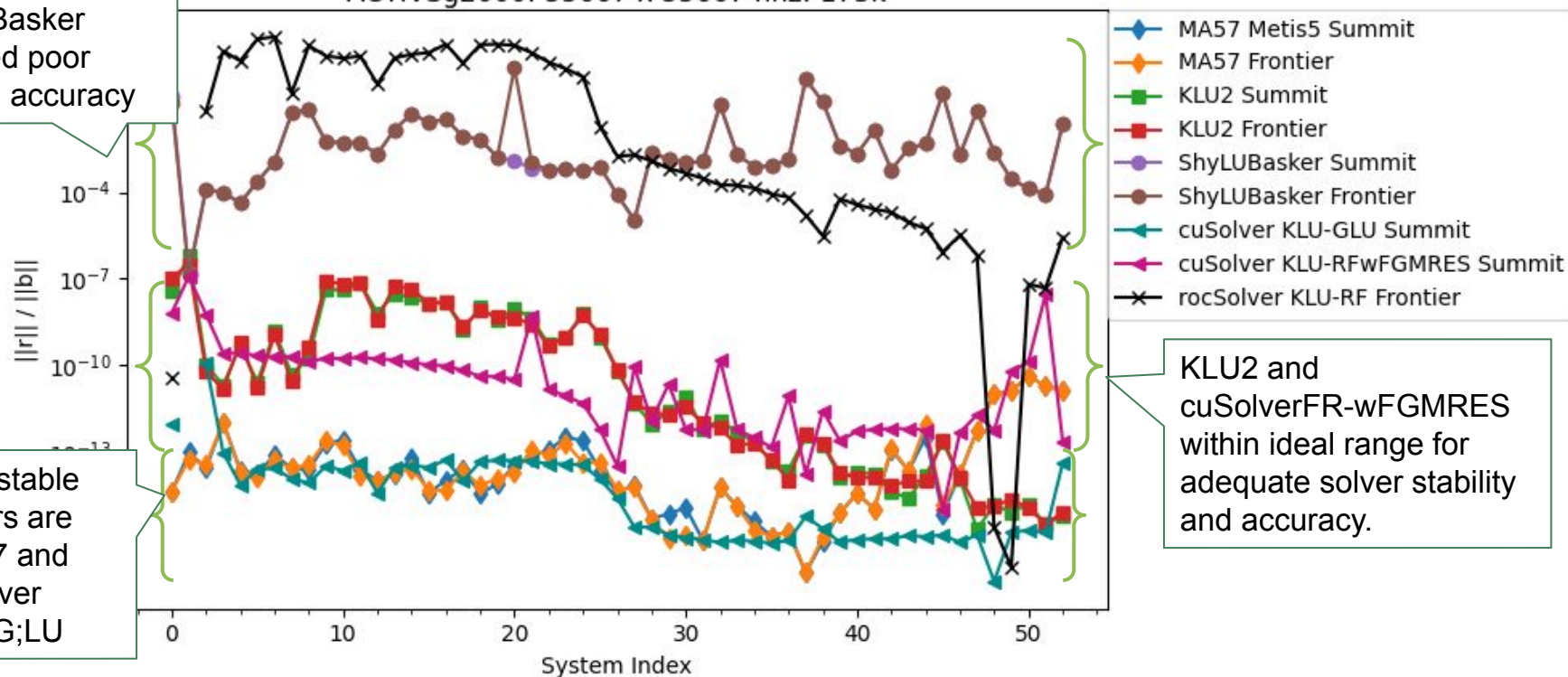


Figure 2. Relative residuals for the Texas (2000-bus) grid model accentuates the stability and accuracy of each solver. Note: A data point for rocSolver at index 1 is omitted due to convergence failure

Total Computation Time - Western US Grid

ACTIVSg10k: 238072 x 23807 nnz: 723k

Amesos2 test bench:
ShyLUBasker outperforms KLU2

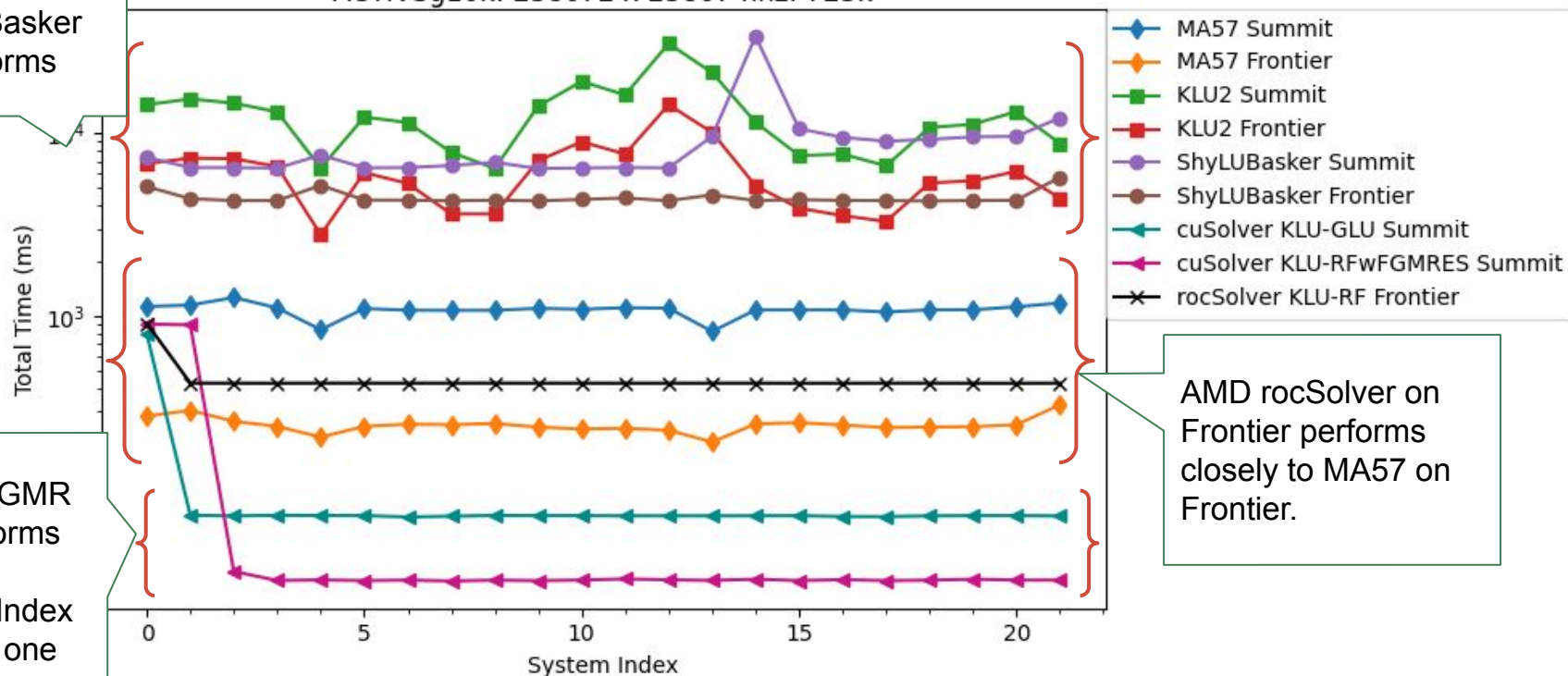


Figure 3. Total runtimes for the Western US (10k-bus) grid model highlights performance discrepancies of each solver

Some stability issues for rocSolver and ShyLUBasker indicate poor solution accuracy.

Relative Residuals - Western US Grid

ACTIVSg10k: 238072 x 23807 nnz: 723k

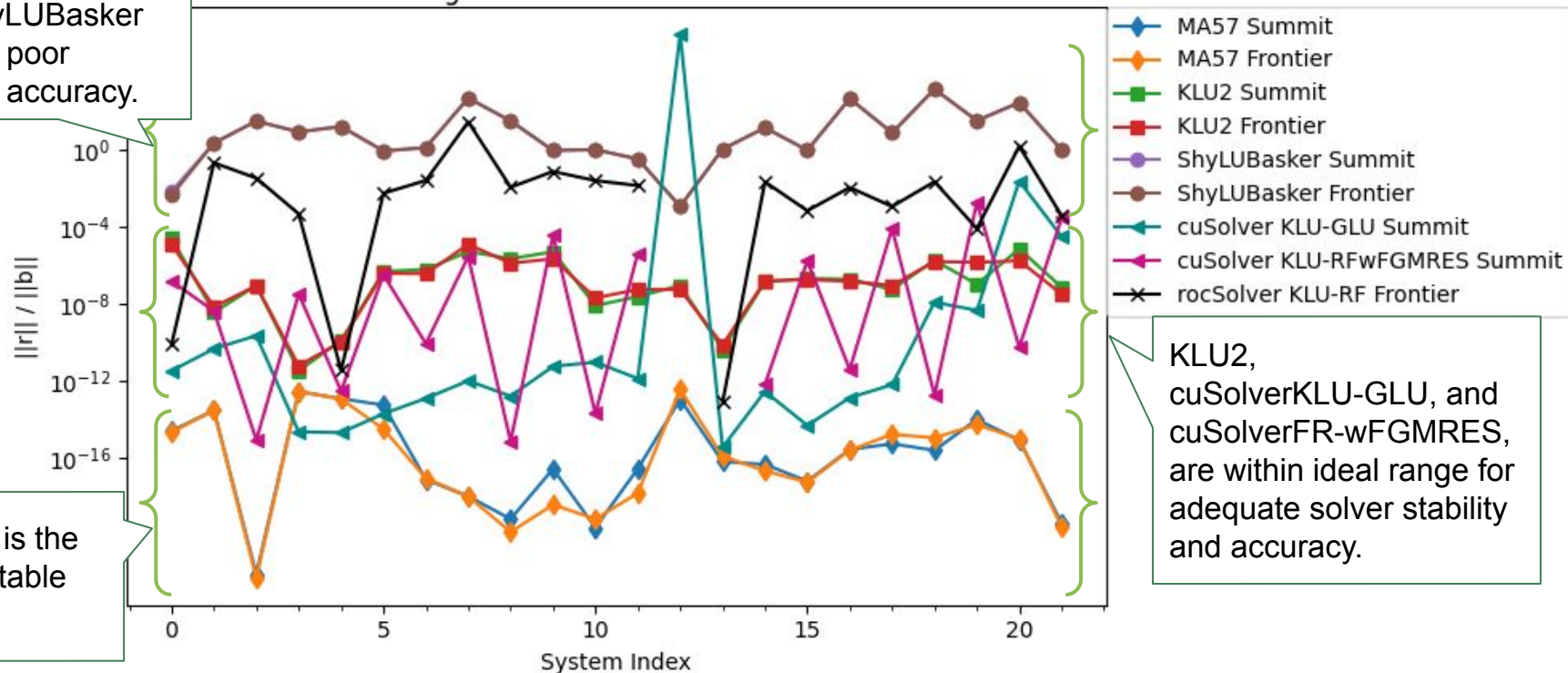


Figure 4. Relative residuals for the Western US (10k-bus) grid model accentuates the stability and accuracy of each solver. Note: A data point for rocSolver at index 12 was omitted due to convergence failure.

Total Computation Time - Eastern US Grid

ACTIVSg70k: 1640411 x 1640411 nnz: 5m

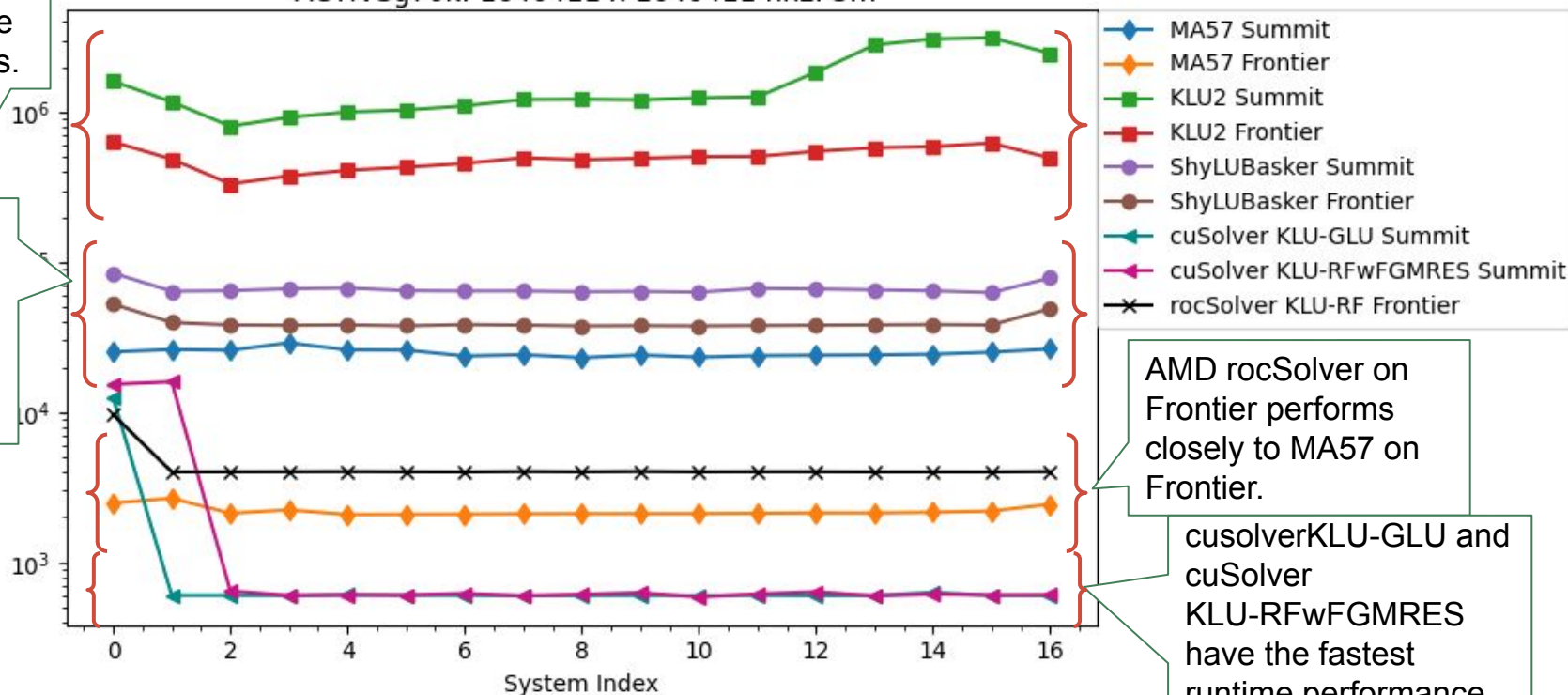


Figure 5. Total runtimes for the Eastern US (70k-bus) grid model highlights performance discrepancies of each solver.

Stability issues for rocSolver and ShyLUBasker indicate poor solution accuracy.

Relative Residuals - Eastern US Grid

ACTIVSg70k: 1640411 x 1640411 nnz: 5m

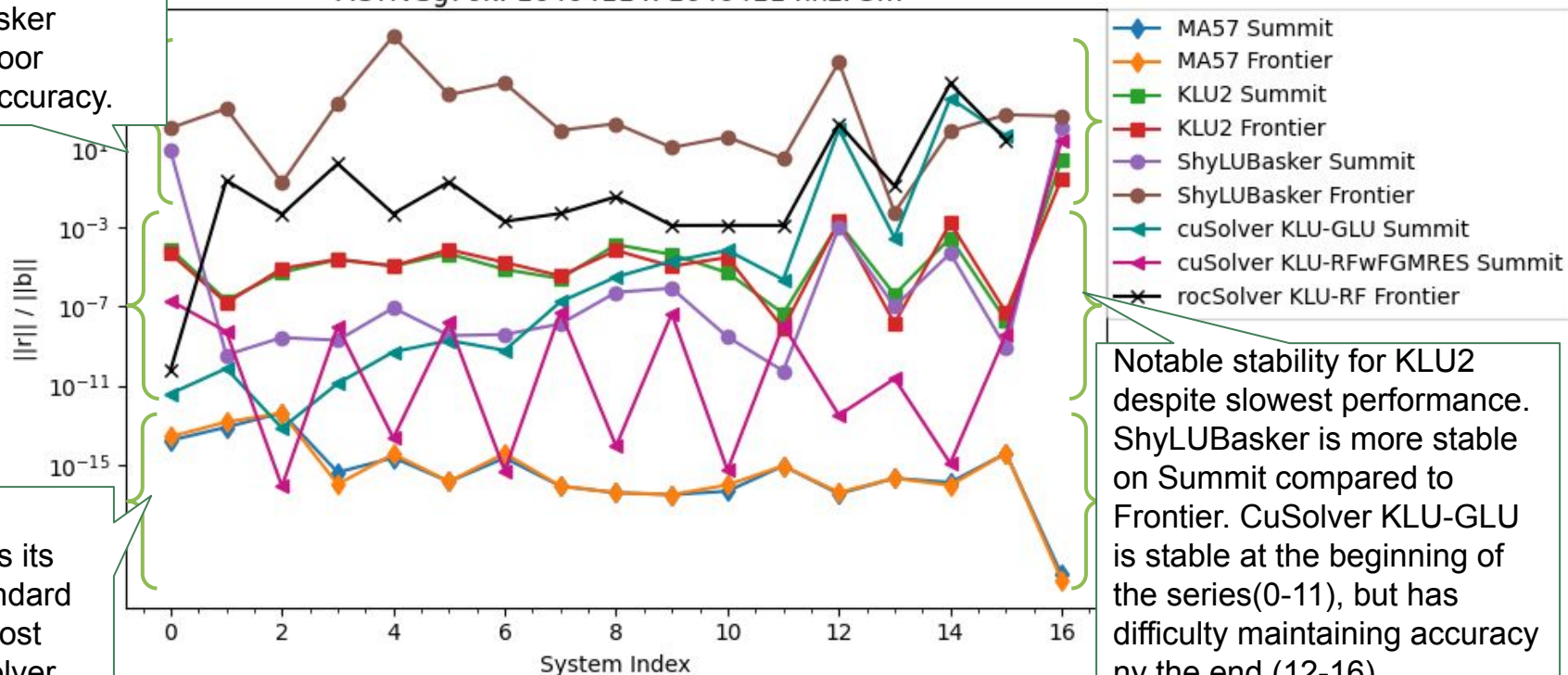


Figure 6. Relative residuals for the Eastern US (70k-bus) grid model accentuates the stability and accuracy of each solver. Note: Data points for rocSolver and cuSolverKLU-GLU at index 16 were omitted due to convergence failure.

Results and Discussion

- CUDA GPU linear solvers significantly outperform CPU based solvers for all test cases provided.
- RocSolver performed closely to the MA57 “gold standard” CPU benchmark, some stability issues observed and worth further investigation.
- Amesos2 ShyLUBasker solver performance scales well with the number of threads, however, we observed serious stability issues for some test cases,
- Amesos2 KLU2 solver has limited parameters to adjust compared to vanilla KLU, e.g. it did not support COLAMD ordering, but proved to maintain a notable level of stability throughout despite longer runtimes.
- Amesos2 solvers highlight a trade off that can occur in runtime performance versus solver stability.

This report has been authored in part by UT-Battelle, LLC, under contract DE-AC05-00OR22725 with the US Department of Energy (DOE). The US government retains and the publisher, by accepting the work for publication, acknowledges that the US government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the submitted manuscript version of this work, or allow others to do so, for US government purposes. DOE will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (<https://energy.gov/doe-public-access-plan>).

Questions?

ACKNOWLEDGMENTS

A special thank you to ORNL mentor Slaven Peles and to Kasia Swirydowicz of PNNL for the help and guidance throughout the GRSI program. Thank you Nicholson for answering all of my srun jsrun, and profiling questions and Maksud for quick access to his machine and installing the cuDSS packages. Thank you to the Exascale Computing Project team for additional support and great teamwork.

ORNL is managed by UT-Battelle LLC for the US Department of Energy



OAK RIDGE
INSTITUTE
FOR SCIENCE
AND EDUCATION



EXASCALE COMPUTING PROJECT



MIDWESTERN STATE UNIVERSITY



U.S. DEPARTMENT OF
ENERGY

References

Świrydowicz, K., Koukpaizan, N., Abhyankar, S., & Peleš, S. (2023). Towards efficient alternating current optimal power flow analysis on graphical processing units. 2023 XXIX International Conference on Information, Communication and Automation Technologies (ICAT). 10.1109/icat57854.2023.10171317

Świrydowicz, K., Darve, E., Jones, W., Maack, J., Regev, S., Saunders, M. A., Thomas, S. J., & Peleš, S. (2022). Linear solvers for power grid optimization problems: A review of GPU-accelerated linear solvers. Parallel Computing, 111, 102870. 10.1016/j.parco.2021.102870

Bavier, Eric & Hoemmen, Mark & Rajamanickam, Siva & Thornquist, Heidi. (2012). Amesos2 and Belos: Direct and Iterative Solvers for Large Sparse Linear Systems. Scientific Programming. 20.241-255. 10.1155/2012/243875.

Rajamanickam, Siva. KLU2 Direct Linear Solver Package. Computer software. <https://www.osti.gov//servlets/purl/1253280>. Vers. 00. USDOE. 4 Jan. 2012. Web.

[KLU2 header](#)