FAULT TOLERANT VARIANTS OF THE FINE-GRAINED PARALLEL INCOMPLETE LU FACTORIZATION

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ABSTRACT

This paper presents an investigation into fault tolerance for the fine-grained parallel algorithm for computing an incomplete LU factorization. Results concerning the convergence of the algorithm with respect to the occurrence of faults, and the impact of any sub-optimality in the produced incomplete factors in Krylov subspace solvers are given. Numerical tests show that the simple algorithmic changes suggested here can ensure convergence of the fine-grained parallel incomplete factorization, and improve the performance of the use of the resulting factors as preconditioners in Krylov subspace solvers if faults do occur.

Keywords: Fault tolerance, parallel preconditioning, incomplete factorization, GPU acceleration.

1 INTRODUCTION

Fault tolerance methods are devised to increase both reliability and resiliency of high-performance computing (HPC) applications. On future exascale platforms, the mean time to failure (MTTF) is projected to decrease dramatically due to the sheer size of the computing platform (Cappello, Geist, Gropp, Kale, Kramer, and Snir 2014). There are many reports (Asanovic et al. 2006, Cappello et al. 2014, Snir et al. 2014, Geist and Lucas 2009) that discuss the expected increase in the number of faults experienced by HPC environments. This is expected to be a more prevalent problem as HPC environments continue to evolve towards larger systems. As the landscape of HPC continues to grow into one where experiencing faults during computations is increasingly commonplace, the software used in HPC applications needs to continue to change alongside it in order to provide an increased measure of resilience against the increased number of faults experienced. Sparse linear solvers constitute one of the major computational areas for applications that are run in HPC environments. These solvers are used in a variety of applications. In order to improve the performance of these solvers, oftentimes a preconditioner is used in conjunction with the Krylov subspace solver. One of the most commonly used classes of preconditioners is incomplete LU factorization. Future HPC environments are likely to include a heterogeneous mixture of computing resources containing different types of accelerators (e.g., GPUs and MICs), and therefore algorithms that can take advantage of the computing structure of accelerators naturally will be advantageous. The fine-grained parallel incomplete LU (FGPILU) algorithm proposed in (Chow and Patel 2015) is such an algorithm. The main contribution of this work is to analyze the ability of this algorithm to complete successfully despite the occurrence of a computing fault, and to offer variants of the original algorithm that aid in this goal.

Typically, faults are divided into two categories: hard faults and soft faults (e.g., Bridges, Ferreira, Heroux, and Hoemmen 2012). Hard faults cause immediate program interruption and typically come from negative effects on the physical hardware components of the system or on the operating system itself. Soft faults represent all faults that do not cause the executing program to stop; they are the focus of this work. Most often, these faults refer to some form of data corruption that is occurring either directly inside of, or as a result of, the algorithm that is being executed. Currently, they often manifest as bit-flips. As the rate that faults occurring in HPC environments continues to increase, it becomes increasingly important to ensure that these solvers are able to execute without suffering the negative consequences associated with a fault occurring. In order to properly investigate the impact of soft faults, one needs to select a fault model that fully encapsulates all of the potential impacts of a soft fault, implement the selected fault model into the algorithm to be investigated, and conduct the necessary experiments to determine the potential impact of a fault occurring during the selected algorithm. This paper examines the potential impact of soft faults on the fine-grained parallel incomplete LU factorization, and also investigates the use of fine-grained parallel incomplete LU algorithm generated preconditioners on Krylov subspace solvers. The structure of this paper is organized as follows: in Section 2, a brief summary of some related studies is provided, in Section 3, details concerning the fault model that is used throughout this work are given, in Section 4, background information is provided for the fine-grained parallel incomplete LU algorithm, in Section 5, a theoretical examination of the fine-grained parallel incomplete LU algorithm with respect to its stability in the presence of faults is undertaken, in Section 6, a series of numerical results are provided, while Section 7 concludes.

2 RELATED WORK

The expected increase in faults is detailed in Asanovic et al. 2006, Cappello et al. 2014, Snir et al. 2014, Geist and Lucas 2009. The self-stabilizing variant of the FGPILU algorithm introduced here was inspired by the self-stabilizing iterative solvers presented in Sao and Vuduc 2013, which in turn are built upon the ideas of selective reliability Bridges et al. 2012. The work done in this study to show the effectiveness of iterative methods when using a (possibly faulty) FGPILU preconditioner is done using the CG algorithm Saad 2003. The analysis of the potential performance of a Krylov subspace method using a potentially sub-optimal FGPILU algorithm is related to the analysis in Sao and Vuduc 2013. The results for the experiments conducted for this effort are presented similarly to the results in Chow and Patel 2015, Chow, Anzt, and Dongarra 2015, but with more of a focus on the impact that a soft fault can have on the execution of both the FGPILU algorithm, and the performance of an FGPILU preconditioner in a linear solver.

3 FAULT MODEL

Soft faults typically manifest as bit-flips. However, for the purposes of this study, a more numerical approach was taken to model the impact of a soft fault. It is important when looking forward towards producing fault tolerant algorithms for future computing platforms not to become too dependent on the precise mechanism that is used to model the instantiation of a fault. Much of the current research (e.g., Bronevetsky and de Supinski 2008) treats faults exclusively as a bit flip; which reflects the current method in which faults occur. Regardless of how a fault manifests in future hardware, the result will be a corruption of the data that is used by the algorithm. To this end, a more generalized, numerical scheme for simulating the occurrence of a fault is adopted. Several numerically based fault models have been utilized in recent studies. These include a perturbation-based fault model that injects a random perturbation into every element of a key data structure (Coleman and Sosonkina 2016b), and a numerical fault model that is predicated on shuffling the components of an important data structure (Elliott, Hoemmen, and Mueller 2015). Other numerical models, such as inducing a small shift to a single component of a vector have been considered as well Bridges, Ferreira, Heroux, and Hoemmen 2012. The fault model used in this paper is a modified version of the one initially developed in Coleman and Sosonkina 2016b and is related to the fault model developed in Elliott, Hoemmen, and Mueller 2015. Specifically, similar to Coleman and Sosonkina 2016b, the modified model (denoted here as mFTM) targets a single data structure and injects a small random perturbation into its each component only episodically, as opposed to doing so persistently contrary to in Coleman and Sosonkina 2016b. For example, if the targeted data structure is a vector x and the maximum size of the perturbation-based fault is ε, then proceed as follows: Generate a random number $r_i \in (-\varepsilon, \varepsilon)$ for every component x_i, where i ranges over entire length of x. Then set $\hat{x}_i = x_i + r_i$ for all i's. The resultant vector $\hat{x}$ is, thus, perturbed away from the original vector x. After a fault occurs, it is possible for an algorithm to detect the error and correct it. It was shown in Elliott, Hoemmen, and Mueller 2015 that the numerical soft-fault model proposed there corresponds to a "sufficiently bad" impact of a soft fault rather than tries to determine the "damage" *exactly* of a soft fault. By construction, the mFTM follows in the footsteps of the ones in Elliott, Hoemmen, and Mueller 2015. An exploration of the similarities and differences between the two models is presented in (Coleman and Sosonkina 2016a). Hence, simulating these numerical soft fault models for iterative algorithms may force them to run consistently through bad errors only. Furthermore, by varying the size of the perturbation in mFTM, it is possible to produce steadily impactful errors.

4 FINE-GRAINED PARALLEL INCOMPLETE LU FACTORIZATION

In the same manner as other incomplete LU factorizations, the fine-grained parallel incomplete LU (FGPILU) factorization attempts to write an input matrix A as the approximate product of two factors L and U where, $A \approx LU$. In traditional incomplete LU factorizations (for an overview, see Saad 2003), the individual components of both L and U are computed in a manner that does not lend itself naturally to parallelization. The recent FGPILU algorithm proposed in Chow and Patel 2015 allows each element of both of the factor to be computed asynchronously (i.e. independently), and progress towards the "true" incomplete LU factors in an iterative manner. To do this, the FGPILU algorithm progresses towards the factors L and U by using the property $(LU)_{ij} = a_{ij}$ for all (i,j) in the sparsity pattern S of the matrix A, where $(LU)_{ij}$ represents the (i,j) entry of the product of the current iterate of the factors L and U. This leads to the observation that the FGPILU algorithm (given in Algorithm 1) is defined by two non-linear equations:

$$l_{ij} = \frac{1}{u_{jj}}\left(a_{ij} - \sum_{k=1}^{j-1} l_{ik}u_{kj}\right) \qquad\qquad u_{ij} = a_{ij} - \sum_{k=1}^{i-1} l_{ik}u_{kj}\ . \tag{1}$$

Following the analysis presented in (Chow and Patel 2015), it is possible to collect all of the unknowns l_{ij} and u_{ij} into a single vector x, then express these equations as a fixed-point iteration $x^{(p+1)} = G\left(x^{(p)}\right)$, where the function G implements the two non-linear equations described above. In a fault-free environment, it can be proven that the FGPILU algorithm is locally convergent in both the synchronous and asynchronous cases (see Section 3 in Chow and Patel 2015). The FGPILU algorithm is given in Algorithm 1. Keeping with the terminology used in (Chow and Patel 2015, Chow, Anzt, and Dongarra 2015) each of the passes that the algorithm makes in updating all of the l_{ij} and u_{ij} elements is referred to as a "sweep". After each sweep of the algorithm, the L and U factors progress closer to the L^* and U^* factors that would be found with a traditional incomplete LU factorization. To do this, the factors L and U are first seeded with an initial guess. In this study, the initial L factor will be taken to be the lower triangular part of A and the initial U will be taken to be the upper triangular portion of A. Adopting the approach in both (Chow and Patel 2015, Chow, Anzt, and Dongarra 2015) a scaling of the input matrix is first performed on A such that the diagonal

Algorithm 1: FGPILU algorithm as given in (Chow and Patel 2015)

```
Input: Initial guesses for $l_{ij} \in L$ and $u_{ij} \in U$
Output: Factors $L$ and $U$ such that $A \approx LU$
1 for $sweep = 1, 2, \ldots, m$ do
2     for $(i,j) \in S$ do in parallel
3         if $i > j$ then
4             $l_{ij} = (a_{ij} - \sum_{k=1}^{j-1} l_{ik} u_{kj}) / u_{jj}$
5         else
6             $u_{ij} = a_{ij} - \sum_{k=1}^{i-1} l_{ik} u_{kj}$
```

elements of A are equal to one. This can be accomplished by performing a similarity transformation with an appropriate scaling matrix D and using it to update A so that, $A = DAD^T$. As pointed out in (Chow and Patel 2015), this diagonal scaling is imperative to maintain reasonable convergence rates for the algorithm, so the working assumption throughout this paper is that all matrices have been scaled appropriately.

5 FAULT TOLERANCE FOR THE FGPILU ALGORITHM

In this section, some theoretical bounds on the impact of a fault on the FGPILU algorithm are developed, and these projected impacts are used to develop fault tolerant adaptations to the original FGPILU algorithm. Using the fault model described in Section 3, if a fault occurs at the computation of the k^{th} iterate (affecting the outcome of the $(k+1)^{st}$ vector, it is possible to write the corrupted $(k+1)^{st}$ iteration of x as

$$\hat{x}^{(k+1)} = G\left(x^{(k)}\right) + r\,, \tag{2}$$

where the vector r accounts for the occurrence of a fault. Note that the magnitude of r corresponds only to the soft fault that was injected (as implemented in mFMT) and is not a part of the FGPILU algorithm itself: For a no-fault sweep, $r = 0$. To track the progression of the FGPILU algorithm, it was proposed in (Chow and Patel 2015) to monitor the non-linear residual norm. This is a value $\tau = \sum_{(i,j)\in S} \left| a_{ij} - \sum_{k=1}^{\min(i,j)} l_{ik} u_{kj} \right|$, which decreases as the number of sweeps progresses the algorithm closer to the conventional ILU factorization. If a fault occurs then one or both non-linear equations from the FGPILU algorithm will have some amount of error. In particular, the update equations for l_{ij} and u_{ij} will become

$$l_{ij} = \frac{1}{u_{jj}} \left(a_{ij} - \sum_{k=1}^{j-1} l_{ik} u_{kj} \right) + r_{ij}\,, \qquad u_{ij} = a_{ij} - \sum_{k=1}^{j-1} l_{ik} u_{kj} + r_{ij}\,, \tag{3}$$

where r_{ij} represents the component of the vector r that maps to the (i,j) location of the matrix. This shows that if a fault occurs during the computation of the incomplete LU factors that the non-linear residual norm τ will be affected. In order to ensure that a fault does not negatively affect the outcome of the algorithm, a simple monitoring of the non-linear residual norm is proposed. In principle, since $S \subset A$, when the FGPILU algorithm converges, the non-linear residual norm will be at a minimum. Further, since there is a contribution from every $(i,j) \in S$, the individual non-linear residual norms for each $(i,j) \in S$, denoted here by τ_{ij}, can be defined as $\tau_{ij} = \left| a_{ij} - \sum_{k=1}^{\min(i,j)} l_{ik} u_{kj} \right|$, where the total non-linear residual norm can always be recovered by taking the sum of all the individual non-linear residual norms over all $(i,j) \in S$. To establish a baseline for fault tolerance, define individual non-linear residual norms τ_{ij} for each $(i,j) \in S$ based on the initial guess that is used to seed the iterative FGPILU algorithm. In particular, if L^* and U^* are the initial guesses for the incomplete L and U factors, then take $l_{ij}^* \in L$ and $u_{ij}^* \in U$ and define baseline individual non-linear residual norms τ_{ij}^* using the original values τ_{ij} and the values $l_{ij}^* \in L$ and $u_{ij}^* \in U$.

Since for each sweep of the FGPILU algorithm, the components $l_{ij} \in L$ and $u_{ij} \in U$ can be computed, by testing the individual non-linear residual norms it is possible to determine if a large fault occurred. Specifically, it is of interest to determine if a fault occurred that was large enough to cause a potential divergence of the algorithm. To do this, first a tolerance t is set and then a fault is signaled if $\tau_{ij} > t$. Since the individual non-linear residual norms are generally decreasing as the FGPILU algorithm progresses, set $t = \max(\tau^*_{ij})$ initially (Line 3 of Algorithm 2), and then update t during the course of the algorithm if desired. Note that if a fault is signaled by any of the individual non-linear residual norms, it is only known that a fault occurred somewhere in the current row of the factor L or the current column of the factor U. As such, the conservative approach would require the rollback of both the current row of L and the current column of U to their values at the previous checkpoint (e.g., Lines 5 to 9 of Algorithm 2). Further, it is possible for the individual non-linear residuals as defined to increase by a small amount, especially at early iterations. To counteract the potential for reporting false positives on fault detection, the derivative of the global non-linear residual can be checked to ensure that it is also increasing before switching the current row and/or column (see Line 15 of Algorithm 2). This algorithm is detailed in Algorithm 2.

Algorithm 2: Checkpoint-Based Fault Tolerant FGPILU (CP-FGPILU)

```
Input: Initial guesses for $l_{ij} \in L$ and $u_{ij} \in U$
Output: Factors $L$ and $U$ such that $A \approx LU$
1  for $(i,j) \in S$ do in parallel
2      $\tau_{ij} = \left| a_{ij} - \sum_{k=1}^{\min(i,j)} l_{ik}u_{kj} \right|$
3  $t = \max(\tau_{ij})$
4  for $sweep = 1,2,\ldots,m$ do
5      if $Fault$ then
6          Set $i = \max_{i,j}(k^1_{ij})$ and $j = \max_{i,j}(k^2_{ij})$
7          Rollback $\{l_{ik}\}_{k=1}^{i-1}$ and $\{u_{kj}\}_{k=1}^{j-1}$
8          $Fault$ = FALSE
9          $sweep = sweep - 1$
10     else
11         for $(i,j) \in S$ do in parallel
12             if $i > j$ then $l_{ij} = (a_{ij} - \sum_{k=1}^{j-1} l_{ik}u_{kj})/u_{jj}$
13             else $u_{ij} = a_{ij} - \sum_{k=1}^{i-1} l_{ik}u_{kj}$
14             $\tau_{ij} = \left| a_{ij} - \sum_{k=1}^{\min(i,j)} l_{ik}u_{kj} \right|$
15             if $\tau_{ij} > t$ and $\tau' > 0$ then
16                 Set $k^1_{ij} = i$ and $k^2_{ij} = j$
17                 $Fault$ = TRUE
```

Note that if a fault is detected, the algorithm only restores (i.e., "Rollback") the affected row of L and column of U. Additionally, since in practice it has been proposed (Chow and Patel 2015, Chow, Anzt, and Dongarra 2015) to use a limited number of sweeps of the FGPILU algorithm as opposed to converging the algorithm according to the global non-linear residual norm, the number of sweeps conducted is decremented so that all elements of L and U are updated *at least* the desired number of times. Also, while no global communication is required to check for the presence of a fault, if a fault is detected there will be some communication required between processes to fix the effects of the fault. Note also that when using the CP-FGPILU algorithm, the size of the faults that are not caught by the algorithm are determined by the tolerance that is set. In particular, $||r|| \leq t$, where r represents a fault that was not caught by the proposed checkpointing scheme, since if $||r|| > t$ than the fault would be caught by the check on Line 15 of Algorithm 2. This, in turn, affects the update equations Eqs. (2) and (3).

Algorithm 3: Self-Stabilizing Fault Tolerant FGPILU (SS-FGPILU)

```
Input: Initial guesses for $l_{ij} \in L$ and $u_{ij} \in U$
Output: Factors $L$ and $U$ such that $A \approx LU$
1  for $sweep = 1, 2, \ldots, m$ do
2      if $sweep \equiv 0 \mod F$ then
3          for $(i, j) \in S$ do in parallel
4              if $\{\|l_{ij}\|, \|u_{ij}\|\} \gg \|a_{ij}\|$ or $|\{l_{ij}, u_{ij}\} - a_{ij}|/|a_{ij}| > \beta$ or $\{l_{ij}, u_{ij}\} = \{0, \mathtt{NaN}\}$ then
                   $\{l_{ij}, u_{ij}\} = a_{ij}$
5              if $i > j$ then $l_{ij} = (a_{ij} - \sum_{k=1}^{j-1} l_{ik} u_{kj})/u_{jj}$
6              else $u_{ij} = a_{ij} - \sum_{k=1}^{i-1} l_{ik} u_{kj}$
7      else
8          for $(i, j) \in S$ do in parallel
9              if $i > j$ then $l_{ij} = (a_{ij} - \sum_{k=1}^{j-1} l_{ik} u_{kj})/u_{jj}$
10             else $u_{ij} = a_{ij} - \sum_{k=1}^{i-1} l_{ik} u_{kj}$
```

It is also possible to develop a variant of the checkpoint-based fault tolerant algorithm that replaces the entire factors L and U as opposed to only the affected areas - call this variant the Checkpoint All variant (CPA-FGPILU). In this case, a fault is declared if the currently computed global non-linear residual norm τ is some factor α greater than the previously computed non-linear residual norm τ_{i-1}. Note that, due to a combination of the asynchronous nature of the the FGPILU algorithm, the non-linear residual norm will not be strictly monotonically decreasing, especially as the algorithm proceeds closer to convergence. Therefore using the factor $\alpha = 1$, i.e., expecting a strict monotonic decrease, may cause the algorithm to report false positives, especially when nearing convergence.

The other variant of the FGPILU algorithm is a so-called *self-stabilizing* version that relies on completing an update sweep successfully with some regularity in order to ensure that the resulting L and U factors will form an effective preconditioner. While the two checkpoint-based fault tolerance schemes introduced above can be shown to be effective numerically (see Section 6), it is possible to recover from the occurrence of a fault without the need for storing intermediate copies of the computed L and U factors. The update sweep must be computed reliably; in particular, it cannot be negatively affected by the occurrence of a fault. In the algorithm as shown in Algorithm 3, an update sweep is expected every F iterations. The expectation is that the steps that are undertaken during the "update sweep" will be able to mitigate any potential consequences of a fault occurring during the prior $F-1$ iterations.

5.1 Convergence of the fault tolerant FGPILU algorithm variants

In Chow and Patel 2015, the convergence of the original FGPILU algorithm (Algorithm 1) is examined by investigating the properties of the non-linear equations that define the algorithm, which are captured in the fixed point function $G(x)$ and the associated Jacobian $G'(x)$. In order to examine the convergence of both the CP-FGPILU and SS-FGPILU algorithms, consider the modified version of $G(x)$ that allows for the occurrence of a fault Since, the mFTM from Section 3 considers faults as a corruption of data via one-time perturbation, the modified Jacobian is equal to the original Jacobian. This implies that the local and global convergence results from Chow and Patel 2015 hold for the modified equations that describe the fault tolerant variants of the FGPILU algorithm. Generally, convergence for all of the variants relies on their producing the elements in the original domain of the problem (using either checkpointing or a stabilizing step); as the elements are updated convergence will eventually occur. For the proposed self stabilizing FGPILU, following Theorem 2 from Sao and Vuduc 2013, a result about the convergence may be stated as:

Theorem 1. *For any state of $l_{ij} \in L$ and $u_{ij} \in U$, if a correction is performed in the k^{th} sweep, all subsequent iterations are fault-free, no elements in the final L and U factors differ by more than β percent from the original factors in the matrix A, and β is chosen such that if a fault occurs a fault is signaled, then the SS-FGPILU algorithm will converge.*

Proof. This follows from noticing that the correcting (or "stabilizing") step (Lines 2 to 6 of Algorithm 3) ensures that the state $l_{ij} \in L$ and $u_{ij} \in U$ of the incomplete L and U factors will be in the original domain of the problem and then invoking the convergence arguments for the original FGPILU algorithm (see Chow and Patel 2015) which rely upon the assumptions and base arguments from Frommer and Szyld 2000. □

Note that finding an appropriate value for the the constant β may be difficult in practice in situations where approximate L and U factors cannot be determined by alternative means. The theorem only guarantees that if such parameters exist and can be found that the algorithm will converge successfully. The convergence of the checkpoint-based variants of the FGPILU variants follows directly from the convergence of the original FGPILU algorithm. Assuming that faults do not occur after a certain number of sweeps, the algorithm will converge under the assumption that it was successfully returned to a state not affected by a fault. Note that if a fault is detected, the state is restored to the last known good state - how recent that state is depends on the frequency with which the checkpoint is stored. More frequent storage of a "good" state via checkpointing will slow down the overall progression of the algorithm, but will provide a more recent fail-safe state if a fault is detected.

Finally, note that for all variants of the FGPILU algorithm if a fault occurs that is not caught by either the stabilizing step in Algorithm 3, or by the checkpointing step in Algorithm 2 it is possible for the Jacobian to move to a regime where the fixed point mapping that represents the FGPILU algorithm is no longer a contraction. In this case, the fault tolerance mechanisms of the FPGILU variants will not help, and subsequent iterations of the algorithm will not aid in convergence. Since the application of the FGPILU preconditioner is effectively only an approximate application of the conventional, fault-free ILU preconditioner, the application of the generated preconditioners can be expressed as, $\widetilde{z_j} \approx P^{-1} v_j$. Both Chow and Patel 2015, Chow, Anzt, and Dongarra 2015 have shown that it is possible to successfully use the incomplete LU factorization resulting from the FGPILU algorithm before the algorithm has converged according to the progress of the non-linear residual. It is possible that any adverse affects that a fault may have on the convergence of the FGPILU generated incomplete LU factors will not have a meaningful impact on the convergence of the overarching iterative method (e.g. CG, GMRES, etc). This impact will be explored numerically in Section 6.

6 NUMERICAL RESULTS

The experimental setup for this study is an NVIDIA Tesla K40m GPU on the Turing High Performance Cluster at Old Dominion University. The nominal, fault-free iterative incomplete factorization algorithms and iterative solvers were taken from the MAGMA open-source software library (Innovative Computing Lab 2015). All of the results provided in this study reflect double precision, real arithmetic. The test matrices that were used predominantly come from the University of Florida sparse matrix collection maintained by Tim Davis (Davis 1994), and the matrices selected for this study are the same as the ones that were selected for the study (Chow, Anzt, and Dongarra 2015) that detailed the performance of the FGPILU algorithm on

GPUs without the presence of faults. There are six matrices selected from the University of Florida sparse matrix collection, and mimicking the approach in Chow, Anzt, and Dongarra 2015, all six of these matrices were reordered using the Reverse Cuthill-McKee (RCM) ordering in an effort to decrease the bandwidth and help to improve convergence. The two other test matrices that were used come from the finite difference discretization of the Laplacian in both 2 and 3 dimensions with Dirichlet boundary conditions. For the 2D case, a 5-point stencil was used on a 500×500 mesh, while for the 3D case, a 27-point stencil was used on a $50 \times 50 \times 50$ mesh. All of the matrices considered in this study are symmetric positive-definite (SPD) and as such the symmetric version of the FGPILU algorithm (i.e. the incomplete Cholesky factorization) was used. Also, recall from Section 4 that each of the eight matrices used in this study will be symmetrically scaled to have a unit diagonal in order to help improve the performance of the FGPILU algorithm. A summary of all of the matrices that were tested is provided in Table 1.

Table 1: Summary of the 8 symmetric positive-definite matrices used in this study.

Matrix Name	Abbreviation	Dimension	Number of Non-zeros
APACHE2	APA	715,176	4,817,870
ECOLOGY2	ECO	999,999	4,995,991
G3_CIRCUIT	G3	1,585,478	7,660,826
OFFSHORE	OFF	259,789	4,242,673
PARABOLIC_FEM	PAR	525,825	3,674,625
THERMAL2	THE	1,228,045	8,580,313
LAPLACE2D	L2D	250,000	1,248,000
LAPLACE3D	L3D	125,000	3,329,698

The experiments are divided into two sets. This first set of experiments focuses on the convergence of the FGPILU algorithm despite the occurrence of faults and features comparisons of the L and U factors produced by the preconditioning algorithms. Faults are injected into the FGPILU algorithm following the methodology described in Section 3. Due to the relatively short execution time of the FGPILU algorithm on the given test problems, a fault is induced only once during each run, at a random sweep number before convergence. Three fault-size ranges were considered: $r_i \in (-0.01, 0.01)$, $r_i \in (-1, 1)$, and $r_i \in (-100, 100)$. Results for the three ranges are averaged and presented in Section 6.1. The second set of experiments shows the impact of using in a Krylov subspace solver the preconditioners obtained from the first set of experiments. Note that in all of the experiments conducted, the condition $u_{jj} = 0$ was never encountered. Since all the test matrices are SPD, the preconditioning algorithms are Incomplete Cholesky variants, and the the solver is the preconditioned conjugate gradient (PCG), as implemented in the MAGMA library.

6.1 Convergence of FGPILU algorithm

In order to obtain representative results, a fault from each range is injected once, on a single iteration and the results are averaged over approximately 30–40 runs per problem, all of which are successfully converged cases. For the purposes of this study, the FGPILU algorithm is said to have converged successfully if the non-linear residual norm progresses below 10^{-8}. Although this threshold is unnecessarily small from a practical point of view,—it is possible to achieve good performance from a preconditioner with a larger non-linear residual norm—it was chosen so that more sweeps would have to be conducted before the algorithm converges to better judge the impact of faults. The progression of the non-linear residual norm for a single fault-free run of each problem is depicted in Fig. 1(left), which is a as an example of the typical progression of the non-linear residual norm as the algorithm progresses towards convergence.

To illustrate the potential impact of a fault, Fig. 1(right) shows the impact a fault can have on the FGPILU algorithm when it is injected (and ignored) at the beginning, the middle, or near the end of how long it would

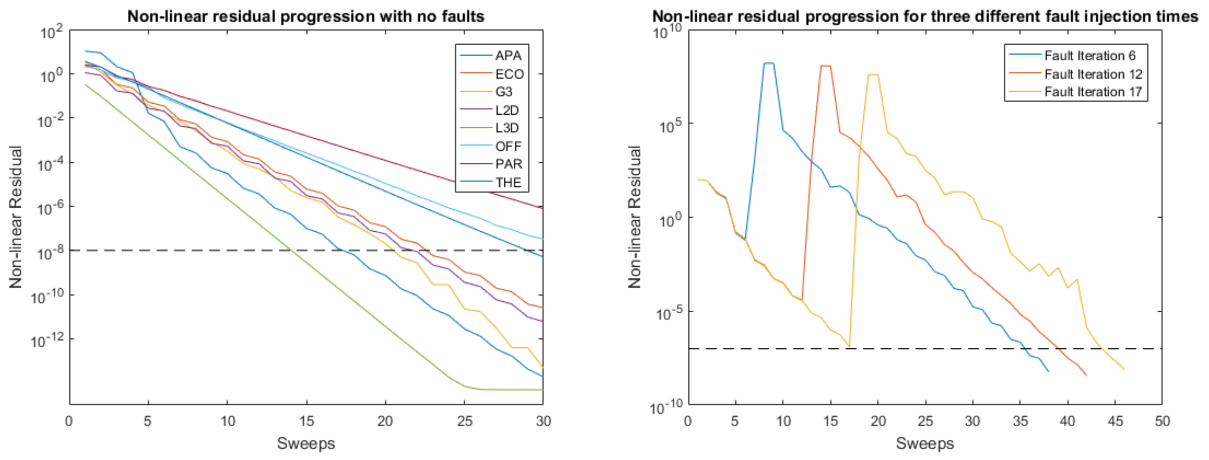


Figure 1: The progression of the non-linear residual for 30 sweeps of a typical fault-free run for each of the 8 test problems (left). The progression of the non-linear residual for the Apache test problem for three different fault injection times and fault size in the $(-1,1)$ range (right). The horizontal dashed line is indicated the FGPILU convergence tolerance of 10^{-8}.

take the algorithm to converge with no faults present. Note from Fig. 2(left) that the Apache test problem converges in 20 iterations when faults are not present. From Fig. 1(right), it may be observed that it took about twice as many sweeps for FGPILU to converge under a single occurrence of a fault; and the number of these extra sweeps is similar for the three injection places. Although the example shown in Fig. 1(right) is typical of what what was observed experimentally with the test cases selected, it is by no means general or conclusive: Faults may cause the FGPILU algorithm to diverge entirely or the resulting L and U factors may cause the PCG solver to either stagnate or even diverge. A major point of the example in Fig. 1(right) is to report the beneficial effects on FGPILU convergence of larger number of sweeps if faults are ignored in FGPILU and to show the non-monotonous decrease of the FGPILU residual norm after a fault takes place.

Aggregate results for the performance of several variants of FGPILU algorithm are provided in Fig. 2 as follows: when no attempt is made to mitigate the impact of the faults (denoted `No FT`), the CPA-FGPILU variant wherein the L and U factors may be replaced in their entirety (`CPA`), CP-FGPILU described in Algorithm 2 (`CP`), SS-FGPILU which is given in Algorithm 3 (`SS`). As in Fig. 1, additional sweeps of the FGPILU algorithm are conducted until the non-linear residual norm falls below 10^{-8}. Since the fault injection could occur on any single sweep, results from all runs are averaged to find the total number of sweeps necessary for the algorithm to converge.

Figure 2(left) shows the average number of sweeps to reach convergence for the cases that were successful. Note that this number is generally lower for the checkpoint-based schemes, but that this is not the case for all of the problems that were tested. However, the higher success rate of the CPA-FGPILU and CP-FGPILU algorithms combined with the generally faster convergence of those methods suggests that, with the parameters used in this study, they are more effective at mitigating faults. The small degradation in the number of sweeps to convergence depicted in Fig. 2(left) for certain problems (i.e., L3D) for the `No FT` variant reflects the fact that only successful runs are included in the averages here. In Fig. 2(right), a corresponding drop in the "success rate" can be seen for the problems where the increase in the number of sweeps required is not as large as expected for variants without fault mitigation. Here, a preconditioner is deemed as resulting in success if the PCG solve using it terminates before the maximum number of iterations is reached. For the FGPILU variants tested, the success rates captured in Fig. 2(right) show that both of the checkpoint-based variants are usually more successful than the self-stabilizing one at mitigating faults and producing acceptable preconditioners. It is important to note that a large, unoptimized value of

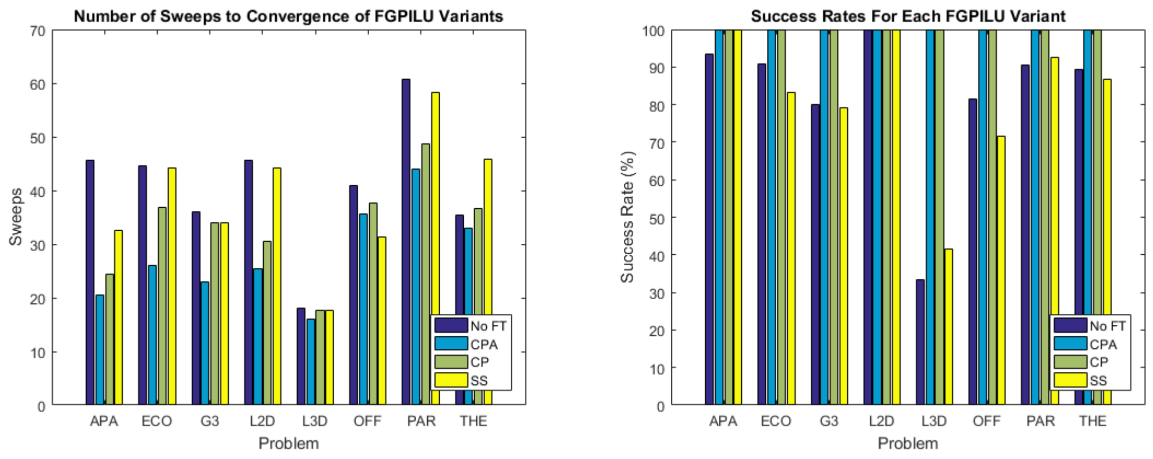


Figure 2: The numbers sweeps required for convergence for each of the 8 test problems (left). The percentage of runs that produced a preconditioner that corresponded to a successful PCG solve (right).

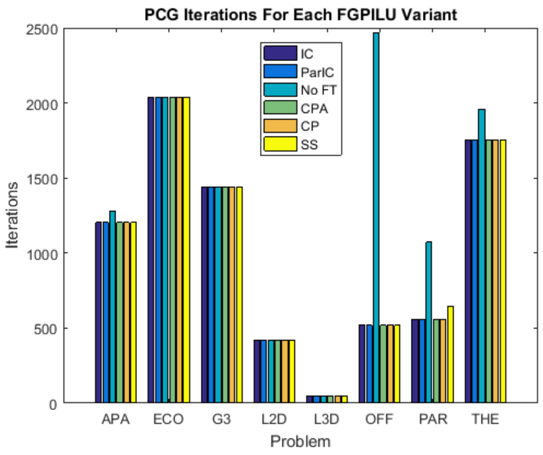
$\beta = 4$ was used for the percent difference check inside of the `SS` runs, and that this value may certainly be improved and tuned for the particular case at hand. The lower success rates associated with the SS-FGPILU algorithm are due to the fact that some of the smaller faults are not caught by this large value of β and the Jacobian moves to a portion of the domain where the mapping is not a contraction. Finding a way to obtain optimal parameters for the SS-FGPILU algorithm efficiently from intrinsic properties of the linear system in question is left as future work.

6.2 Preconditioner Performance in Iterative Methods

In this set of experiments, a maximum number of 3000 PCG iterations was used; any run that had not converged by that point was declared to have diverged. While all of the preconditioners to be evaluated are forms of incomplete LU decomposition, they are constructed by algorithms described in Section 6.1. For the purpose of an extended comparison, results are provided for the traditional Incomplete Cholesky (`IC`) and the Fine Grained Parallel Incomplete Cholesky (`ParIC`); neither of these two variants is subjected to faults. Figure 3 captures only the cases in which a preconditioner was successfully prepared (c.f. Fig. 2(right)). Figure 3(left) indicates that a successful FGPILU variant is typically capable of accelerating the PCG solve to the levels similar to those achieved by the no-fault constructions of incomplete LU. The timing results presented in Fig. 3(right) are for the total time required for the preconditioner preparation and PCG solve. While the former may vary much depending on which variant is considered, the latter is rather uniform across the variants due to their similar numbers of iterations performed to convergence. More efficient implementations of the fault tolerance mechanisms and a more realistic tolerance for the non-linear residual norm may improve the performance of the three fault-tolerant variants of the FGPILU algorithm.

7 CONCLUSIONS

This paper has investigated the potential of the FGPILU algorithm to tolerate and mitigate certain soft faults arising in the construction of L and U factors. Three recovery techniques were presented. Namely, they are (1) checkpointing of the entire data structure comprising the factors, (2) checkpointing of select pieces of the data structure, or (3) self-stabilizing of the algorithm to avoid checkpointing altogether. Comparisons of the three techniques suggest that, while checkpointing appears to be somewhat more robust, the self-stabilizing algorithm is competitive and may be preferred due to its greater flexibility of fault mitigation,



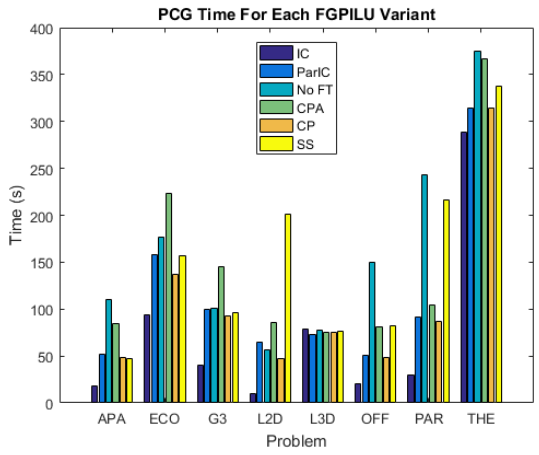


Figure 3: The numbers of iterations required for the successful PCG solves for each of the 8 test problems (left). The time required for the successful PCG solves for each of the 8 test problems (right).

e.g., when its parameters are are tuned for a better success rate on a given problem. Conversely, if the selective checkpointing scheme is optimized (e.g., by checkpointing less frequently or by rolling back fewer elements) the cost of checkpointing may be further reduced. The fault-tolerant techniques and findings presented in this paper may be readily applied to the asynchronous iterative methods in general to make them more robust in the presence of soft faults. While it has been shown that it is possible to generate a suitable ILU preconditioner with a small number of sweeps of the FGPILU algorithm in prior work, the use of asynchronous preconditioning algorithms is increasing in general, and as new asynchronous preconditioning algorithms are developed some may use the FGPILU algorithm as a building block and require the FGPILU algorithm to execute successfully inside of a more complex preconditioning scheme. In these cases, it may be important to have the FGPILU algorithm converge more completely, and the work presented here could be used as a starting point towards ensuring that can happen successfully even when computing faults happen to occur.

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