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IMPACT OF SOFT ERRORS ON SCIENTIFIC SIMULATIONS

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Abstract

The trends in computing processor technology are driving toward multicores through miniaturization that can pack many processors in a given chip area. This miniaturization has led to a significant increase in the occurrence of soft errors, where a single bit flip impacts the output of the computing system. This in-turn affects the performance of the application running on the system. In this thesis, we attempt to understand and characterize the impact of soft errors on scientific simulations. We consider the impact of a single soft error on the widely used preconditioned conjugate gradient method (PCG), an important kernel in such scientific simulations. We first show that a single error in PCG can propagate through a sequence of sparse matrix vector multiplication (SpMV) operations that form the core computations in PCG. Consequently, we demonstrate that a single soft error in PCG can lead to performance degradation by factors of 200 or more. Next, we consider the Community Earth System Model (CESM), an extensively used coupled climate model that allows simulation of the earth's climate system. Our experimental results indicate that although the soft errors cause variations in the output of the models, these variations are within the allowable range of perturbations. However, the models are not robust enough and fail upon soft errors in the pointer data structures. These results indicate the need for further study of the impact of soft errors on scientific simulations and the need to develop methods for detection and mitigation.

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Acknowledgments

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Dedicated to my parents who have always been my inspiration.

Chapter 1

Introduction

Back in 1965, during the early years of the chip making Dr. Gordon Moore wrote "The number of transistors incorporated in a chip will approximately double every 24 months" [30]. The prediction has indeed been true and it is expected to continue. However as the dimensions and operating voltages of electronic units shrink to accommodate the increasing number of cores within a given chip area, there has been a significant increase in the occurrence of soft errors [9], where a single bit flip can leave the output of the computing system in a corrupt state. In this thesis we focus on the impact of soft errors on scientific simulations that run on multicore systems.

Soft error or transient errors can be described as errors that lead to bit flips in memory and errors in the logic circuit output that leaves the state of the computing system corrupt. The errors can be caused by cosmic radiations [5], radiation from packaging materials [8], as well as voltage fluctuation [5]. Soft-error rate in microprocessor logic has become a reliability concern [32, 16, 38]. With increases in the transistor densities, the soft error rates have been growing exponentially, with typical values ranging between 1k and 10k FIT/Mb [8] (FIT is failure per billion hours of operation). The 106,496 dual-processor compute node BlueGene/L, for example [11], is reported to experience one soft error in its L1 cache every 4-6 hours induced due the radioactive decay in lead solders. Michalak et al. [28] report that the ASCI Q experienced 27.7 CPU failures per week due to radiation. There have been various studies to investigate their effects on caches in single processor systems [39, 32, 23], on software systems [6, 38, 16], and parallel applications [24].

Given the increase in the occurrence of soft errors, various techniques have been suggested and implemented to overcome these effects. But with technology moving towards the chip multiprocessors, it is becoming important to study the behavior of these errors in today's systems. With levels of memory and caches well protected against the insertion of soft errors, the processor itself is still left susceptible. Soft errors induced at the processor level go untraced and can affect the final output of the application that was running during that period. This poses a reliability challenge in the field of high performance computing as most of the applications have long execution time. A majority of large-scale scientific applications run on supercomputers. Super computers consists of multiple multicores, thus increasing the occurrence of the soft errors in these systems.

A majority of the long running scientific applications involve partial differential equation (PDE) based systems, such as those found in heat diffusion, computational fluid dynamics (CFD) and structural mechanics. Such applications typically use software tool kits such as PETSc [26], in conjunction with iterative linear solver packages like Hypre [14] and Trilinos [19]. The basic underlying computation in these software packages is a sequence of sparse matrix vector multiplication (SpMV) operations of the form $y \leftarrow A.v$ that are performed iteratively within an iterative sparse linear solver such as conjugate gradient (CG) and its preconditioned forms. Reliable and accurate fast simulations can be viewed as depending on the performance of the SpMV kernel and the propagation of numerical attributes through relevant sequence of SpMV operations.

In this thesis, we first present the effect of soft errors on performance of iterative linear solvers, in particular CG and preconditioned CG (PCG) . Our experiments indicate that a single soft error has the potential to degrade the performance of PCG by as much as a factor of 200x. We also attempt to characterize the propagation pattern of soft errors in the SpMV kernel within PCG. Next, we present a case study on a real life scientific application, the Community Earth System Model (CESM), a community climate code. We conclude that the climate codes are robust when the data in physics based model are corrupted by single soft errors but fail when pointers to the data are corrupted.

The thesis is organized as follows. Chapter 2 first begins with a brief overview of the recent research related to soft error detection, and characterization followed by a discussion of the basic concepts of linear solvers and community climate models. Chapter 3 explores the effect of the sparsity pattern of a matrix on the propagation of a single soft error and presents the impact of a soft error on the performance of an iterative linear solver. Chapter 4 presents a case study of the impact of soft errors on community climate models. Finally, Chapter 5 contains a summary of the thesis with brief comments on future research directions.

Chapter 2

Related Research and Background

In this chapter, we provide a brief overview of the related research done in the area of soft error detection, mitigation and characterization. Later in the chapter, we provide basic background information about the linear solvers and the conjugate gradient method, an iterative linear solver that we use in our experiments. We also give a short overview of the Community Earth System Model, a community climate model used as a case study in the thesis.

2.1 Related Research

The research in the field of soft errors can be categorized into 3 areas: (i) soft error detection [16, 38, 33, 20] which involves online or static methods of detecting soft errors, (ii) protection against soft error [7, 29, 22, 35] which involves selective protection of the systems against the soft errors using external techniques, and (iii) soft error characterization [40, 31, 15] where the behavior of the application or system under soft error attack is understood to come up with protection and mitigation schemes based on the characterization.

2.1.1 Soft Error Detection

The first area of an error detection technique called fingerprinting is proposed by Smolens et al. [16], which detects differences in execution across a dual modular redundant (DMR) processor pair. In fingerprinting a processor's execution history is summarized in a hash-based signature. The comparison of their fingerprints expose the differences between two mirrored processors. Fingerprinting is based on the schemes used for fault tolerance techniques. This technique needs special hardware modifications to the processor pipeline.

Software based detection techniques have been developed to detect soft error [33, 20] to avoid large hardware overhead. Rebaudengo et al. [33] propose a technique that automatically transforms programs written in any high level language to be able to detect most of the errors affecting data and code. The proposed transformation rules can be implemented into a compiler as a pre-processing phase, thus making it completely transparent to the programmer. Hu et al. [20] focus on utilizing the compilers to duplicate instructions for error detection in the VLIW datapath. The instruction duplication mechanism is further supported by a hardware enhancement for efficient result verification, thus avoiding the need for additional comparison instructions. In their proposed approach, the trade off between performance, reliability and energy consumption is achieved through the compiler by determining degree of instruction duplication.

2.1.2 Protection Against Soft Errors

The next area of research in this field focus on protecting processors from soft errors. SHIELD [29] is an architecture that increases the resistance of register files to soft errors. Based on the observation that the data stored in a register is only useful for a small fraction of the lifetime of the registers and that not all registers are equally vulnerable to soft errors, SHIELD selectively protects registers by storing the ECCs of the most vulnerable registers while they contain useful data, and checks their integrity off the critical path. Latif et al. [22] assessed the benefits of inherent error detection and optional error correction on the software side. They study programming patterns that exhibit properties for inherent detection of transient faults compared to techniques that use instruction duplication, their technique can, not only save execution time but reduce code size.

2.1.3 Soft Error Characterization

Another area of research deals with soft error characterization. Zhang et al. [40] made the first attempt to characterize microarchitecture soft error vulnerabilities across the stacked chip layers under 3D integration technologies. They use models and simulations that capture soft error physical mechanism and circuit/architecture level impact. Their study reveals the opportunities of leveraging 3D integration to achieve enhanced reliability. The second feature enables the deployment of error resilience device techniques to achieve a reliability target while minimizing manufacturing cost. They also propose a set of microarchitecture techniques, which can effectively exploit the reliability benefits offered by 3D technologies.

There have also been studies that focus on the soft error vulnerability of specific applications. Lu and Reed [5] evaluate the soft error vulnerability of three MPI applications. They show the correlation between error injection sites and the application's vulnerability to such errors. Skarin, et al. [37] evaluate the soft error vulnerability of a brake-by-wire system for automobiles using a similar approach. Although both studies thoroughly evaluate the soft error vulnerability of the selected target application, they provide little insight about the vulnerability of other applications. This makes any generalizing of the results difficult. Alternatively, Messer et al. [27] evaluate the soft error vulnerability of a realistic software stack. They show the soft error properties of other applications running on the same OS and the same application running on different OSs.

In this thesis we focus on the impact of soft errors on scientific applications, in particular sparse linear solver preconditioned conjugate gradient method. There has been recent interest in understanding this as well as the protection of these applications against soft errors. Bronevetsky et al.[11] report observations on the effect of soft errors on iterative solvers like, CG, preconditioned Richardson, and Chebyshev methods in SparseLib [13]. Based on the experimental observations, the paper the impact of soft errors as (i) no effect, (ii) silent error, (iii) application hangs observations, and (iv) application crashes. The paper also proposes and evaluates several soft error detection and tolerance schemes, like, residual tracking, checkpointing and data structure encoding that could potentially lead to significant improvements in the reliability of these libraries. Malkowski et al. [25] consider PCG and GMRES and they focus on utilizing the manner in which the coefficient matrix A is resident in L1 and L2 caches in these methods. They use the concept of vulnerable time to propose and evaluate energy and reliability tradeoffs for two schemes, for adaptively turn-off the Error Correction Code (ECC) for L1 cache and L2 caches. They assume little or no cache reuse for the vector v and therefore is not protected. The data structures having higher resident time in the caches than their corresponding vulnerable time, are protected.

2.2 Linear Solver Basics

There are basically two classes of methods to solve a linear system of the form $Ax = b$ (where A is a $n \times n$ coefficient matrix, b is an $n \times 1$ known vector and x is an $n \times 1$ vector of unknowns): (i) direct methods (ii) iterative methods,

Direct methods attempt to solve the problem using a finite sequence of operations. These methods yield an exact solution in the absence of rounding errors. They are typically used to solve moderately sized systems with a dense coefficient matrix. Gaussian elimination is one of the most widely used methods to solve such a system. It uses the the idea of modifying the matrix into an upper triangular form ($Ux = b'$ where b' is the corresponding change in the known right hand side vector) while still maintaining the solution to the original system. The obtained triangular system is then solved by back substitution. The triangularization of the coefficient matrix A is achieved by using the LU factorization method, where L stands for lower triangular matrix and U stands for upper triangular matrix. In LU factorization, the coefficient matrix is factorized into an upper and lower triangular matrices ($A = LU$) and then solved using back substitution successively on the two triangular matrices L and U to solve the system. Direct methods can be used on sparse matrices as well. A modified LU factorization algorithm that attempts to find sparse factors L and U could be used here. The number of non-zero elements determine the computational cost of these algorithms in the case of sparse systems. The runtime also depends on the sparsity structure of the coefficient matrix. In the case of a dense coefficient matrix, the runtime depends only on size; and is independent of data, structure, or sparsity.

Indirect or iterative methods [34] aim to yield a sequence of improving approximate solutions for a class of problems. An iterative method uses an initial guess and generates successive approximations to a solution. The rate at which an iterative method converges depends greatly on the eigen spectrum [18] of the coefficient matrix. Iterative methods usually involve a transformation matrix called a preconditioner that transforms the coefficient matrix into a matrix with a more favorable spectrum. A good preconditioner improves the convergence of the iterative method. Without a preconditioner the iterative method may fail to converge.

2.2.1 Conjugate Gradient

Algorithm 1 Conjugate Gradient

procedure CG(A, b,x_0, maxit, TOL)

$r = b - A * x$

$iters = 0$

$nb = norm(b)$

$rsq = r' * r$

$p = r$

while iters < maxit && sqrt(rsq)/nb > TOL **do**

  $iters = iters + 1$

  $t = SpMV(A, p)$

  $v = r' * r$

  $alpha = v/(p' * t)$

  $x = x + alpha * p$

  $r = r - alpha * t$

  $rsq = r' * r$

  $beta = (r' * r)/v$

  $p = r + beta * p$

end while

The conjugate gradient method (CG) is the most prominent iterative method for solving sparse systems of linear equations. CG is used to solve systems of the form

$Ax = b$, where x is an unknown vector, b is a known vector, and A is a known, symmetric, positive-definite matrix. These systems arise in many scientific settings, such as finite difference and finite element methods for solving partial differential equations, structural analysis and circuit analysis. CG works on the vectors represented by an SpMV sequence, $span(v, Av, \ldots A^n v)$ to find a solution for the linear system, where, A is the coefficient matrix and v is the initial residual vector. This span of vectors is known as Krylov subspace [17]. Hence each iteration of CG requires a SpMV operation of the form $t \leftarrow A.p$ [line 9 in Algorithm 1]. Thus the SpMV operation dominates the computation time of CG. In many cases, naive CG takes a long time to converge to a solution. Hence, preconditioning is necessary to ensure fast convergence of the CG algorithm. This variant of CG with the preconditioning stage is called preconditioned conjugate gradient (PCG), and is a widely used linear iterative solver in scientific applications.

2.3 Community Climate Models

The Community Earth System Model (CESM) [2] is a fully-coupled, global climate model aimed to provide state-of-the-art computer simulations of the Earth's past, present, and future climate states. CESM is sponsored by the National Science Foundation (NSF) and the U.S. Department of Energy (DOE). CESM is maintained by the Climate and Global Dynamics Division (CGD) at the National Center for Atmospheric Research (NCAR).

Figure 2.1 illustrates the Community Earth System Model. The model is composed of four separate model, atmosphere, ocean, land surface and sea-ice. These models are used to simultaneously simulate the earth's climate. The central coupler component is used to couple the four models together. CESM has been used to conduct fundamental research into the earth's past, present and future climate states.

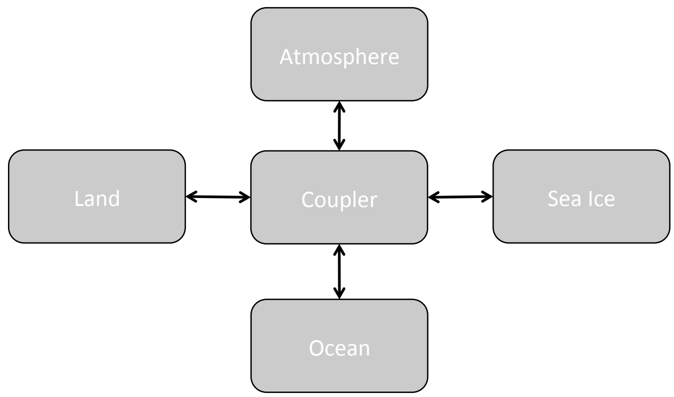


Fig. 2.1 Community Earth System Model

In this thesis, we study the effect of soft errors on the atmosphere and ocean models.

Figure 2.2 gives an overview of the atmosphere model. The atmospheric model is a numerical model based on the physical laws of fluids. The model uses simplified forms of the equation of motion and assumes that the atmosphere is in hydrostatic balance, while, the compression due to gravity is balanced by a pressure gradient force. Parameterization, the process of including the effect of unresolved phenomena is used to include radiation, effects of unresolved turbulence and gravity waves, effects of convection on heat, moisture and momentum budgets in the atmospheric model.

The ocean model [21] solves the three-dimensional primitive equations for fluid motions on the sphere under hydrostatic and Boussinesq approximations [10]. Finite-difference discretization are used to compute spatial derivatives. The ocean model is

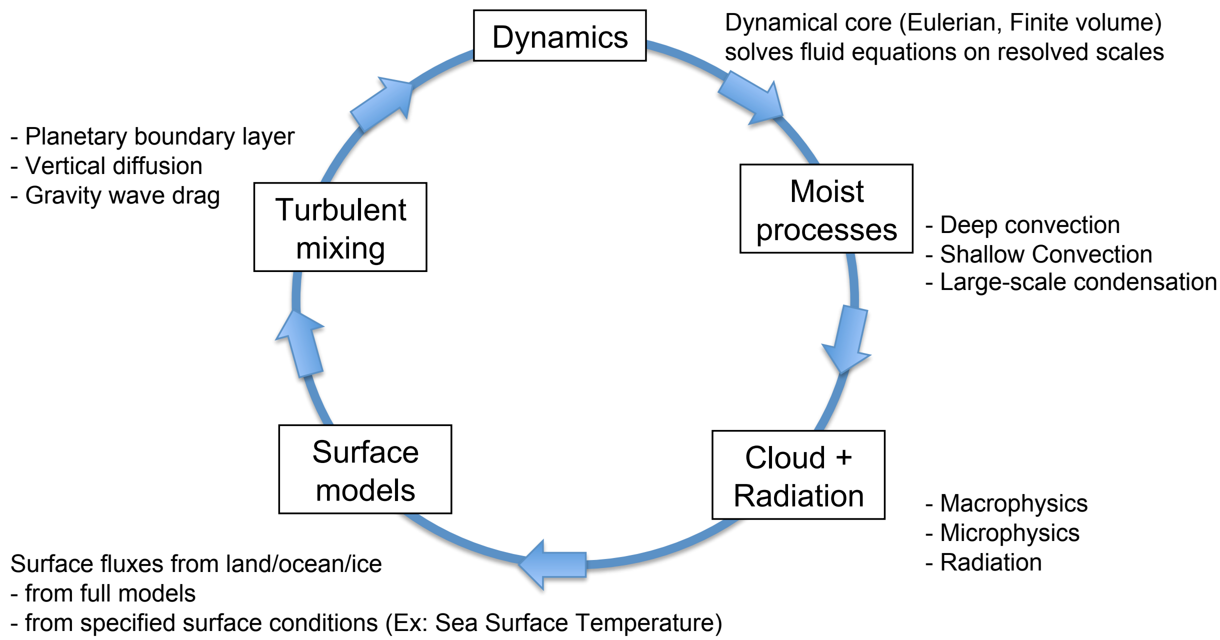


Fig. 2.2 Atmosphere model workflow

required to obtain the air-sea coupling, to understand and get a good representation of the meridional transport of heat circulation, and also to get a good representation of the carbon cycle. A wide variety of physical parameterizations are done in the model to achieve the same.

These models can be run in both serial or parallel mode and can also use thread-based (OpenMP) parallelism, message-passing (MPI) or a hybrid of the two. Preconditioned conjugate gradient solver is used to solve for the two-dimensional surface pressure.

Chapter 3

Propagation of Soft Errors in Preconditioned Conjugate Gradient

In this chapter, we explore the effect of sparsity pattern of a sparse matrix on propagation of single soft error during the SpMV operation and present the impact of a soft error on the performance of an iterative linear solver, in partiular PCG. To facilitate better understanding, we first provide notation and terminology used in this chapter.

Notation and Terminology. Vectors and matrices are represented as *italicized* lowercase and uppercase letters respectively. For example, vector y and matrix A. Unless mentioned otherwise, vectors are of size $n \times 1$ and matrices are of size $n \times n$. The i^{th} element of a vector y is represented as y_i. Following are the definitions of the terms we use in this chapter.

Sparsity pattern of a sparse matrix is the connectivity structure of the sparse matrix in its graph representation.

Krylov subspace generated by A and r is equal to span$\{r$,Ar, A^2r ... A^kr $\}$.

Consider a sparse linear system, $Ax = b$, where, A is a sparse symmetric positive definite coefficient matrix, b and x are known and unknown vectors, respectively of size $n \times 1$. Let the conjugate gradient (CG) method solve this system. The CG method works on the vectors represented by a SpMV sequence $(y \leftarrow Av; v \leftarrow y)$, $span(v, Av, \ldots A^n v)$ to find a solution for the linear system, where v is the initial residual vector. The resultant vector is written back and used in the next iteration. Therefore, across the iterations any perturbation in the value of elements in A, v or y shows up in an element of v in the following iteration. Therefore, we focus on the effect of soft errors in v.

We characterize the propagation and growth of a single soft error in the vector v^0 for a sequence of SpMV operations given by $(v^0, Av^0, \ldots, A^k v^0)$.

3.1 Effect on Performance

In this section, we show the impact of soft errors on the performance of PCG. We use PCG with incomplete Cholesky preconditioner with threshold. We use 24 symmetric positive definite matrices from The University of Florida Sparse Matrix Collection [12]. Table I gives the properties of the these matrices. The first column represents matrix ids and the second column gives matrix names. The third and fourth columns represent, respectively, the matrix dimension and number of non-zero elements in the matrix.

We use the single bit error model in our experiments. We simulate small and large perturbations caused due to single bit flips by bit flips in the significand and exponent of the values. We conduct exhaustive experimentation by simulating error in every position of the vector v to understand the performance impact of a soft error.

Figure 3.1 shows the variation in the number of iterations to converge to a solution due to single errors at different positions in the vector using the matrix $crystm01$. Observe that certain positions more sensitive to soft errors than the others. We provide a plausible reason in Section 3.2.

The Figure 3.2 presents the relative slowdown (observed as increased iterations count) in the convergence of PCG due to single soft errors (with an error simulated in each position in v) on the test matrices. We observe that a soft error causes an increase

Matrix ID	Matrix	n	nnz
1	bcsstk01	48	400
2	mesh1e1	48	306
3	lund_b	147	2,441
4	mesh2e1	306	2,018
5	mesh2em5	306	2,018
6	mhdb416	416	2,312
7	bcsstk07	420	7,860
8	nos5	468	5,172
9	nos6	675	3,255
10	msc00726	726	34,518
11	bcsstk09	1,083	18,437
12	plbuckle	1,282	30,644
13	bcsstk15	3,948	117,816
14	mhd4800b	4,800	27,520
15	crystm01	4,875	105,339
16	bcsstk16	4,884	290,378
17	Kuu	7,102	340,200
18	Muu	7,102	170,134
19	fv1	9,604	85,264
20	fv2	9,801	87,025
21	fv3	9,801	87,025
22	tedB	10,605	144,579
23	t2dahe	11,445	176,117
24	bcsstk18	11,948	149,090
25	cbuckle	13,681	676,515
26	crystm02	13,965	322,905
27	gyrom	17,361	340,431
28	bodyy4	17,546	121,550

Table 3.1 The UFL benchmark matrices. For each matrix n indicates the dimension and nnz indicates the number of non-zeroes.

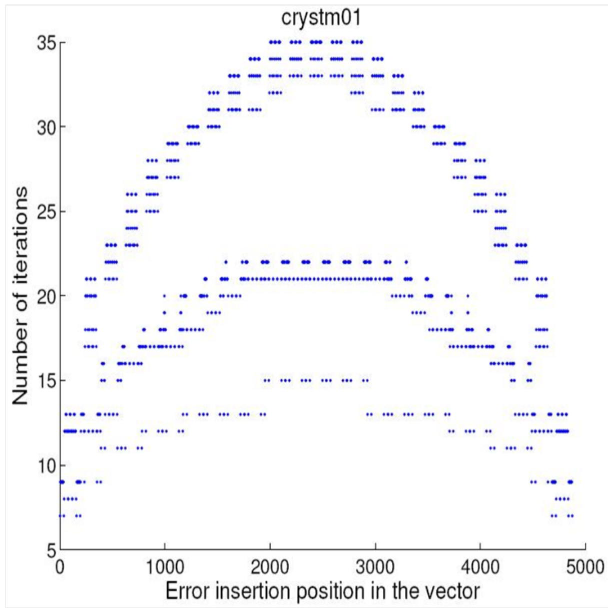


Fig. 3.1 Sensitivity to error insertion position.

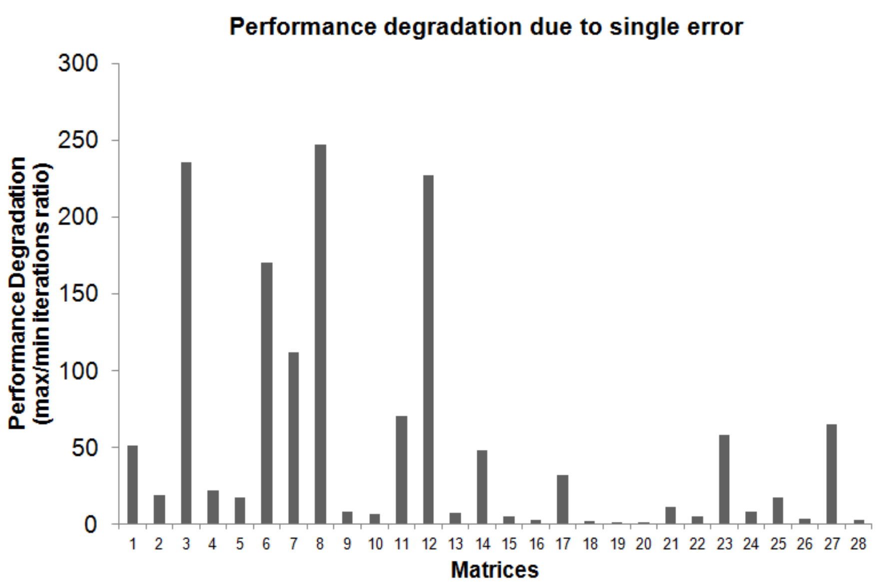


Fig. 3.2 Ratio of maximum to minimum number of iterations required for convergence of PCG after a single error insertion.

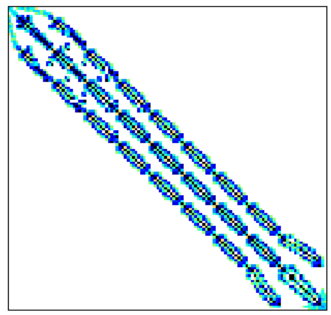
in the number of iterations by a factor of 250x. It is evident from this figure that a soft error could be very expensive from a performance perspective. The observations made in Figure 3.2 clearly indicate the effect of a single soft error on the performance of an iterative solver like PCG. The iterative solver tend to run longer to converge to a solution or to the iteration threshold. This in turn indicates the increase in the power consumption as the application tend to run longer due to the error. With long running scientific applications this would pose as a major issue that needs attention.

3.2 Soft Error Propagation Pattern

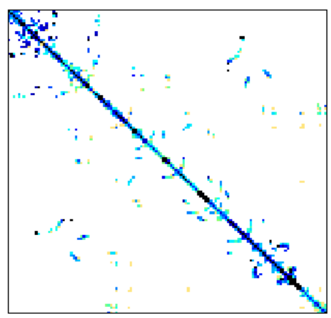
In this section, we show that soft error propagation pattern is related to the sparsity structure of the coefficient matrix A. The plots in Figure 3.3 shows sparsity structure of different example matrices.

Consider a sparse symmetric coefficient matrix A, an vector y^0, and a sequence of SpMV operations that generate the vector set $y^0, y^1, \ldots, y^k$ where $y^i = A^i y^0$. Consider a single soft error inserted in y^0 in the i^{th} position (y_i^0). At the end of the k^{th} SpMV operation, the vector y^k will have errors in all its components, for some k.

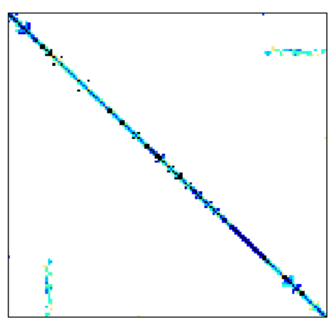
We now illustrate this propagation pattern. Figure 3.4 shows a sparse symmetric coefficient matrix A, where 'X' represents a non-zero value; an initial vector y^0, where 'x' represents a non-erroneous value and δ represents erroneous value; and the resultant vectors of a sequence of SpMV operations ($\bar{y}^1, \bar{y}^2, \bar{y}^3, \bar{y}^4, \bar{y}^5$). Figure 3.5 shows the growth of the tree in which elements of y_i are corrupted. In these figures, we assume that the 1^{st} element of y^0 is affected by a soft error initially. Figure 3.6 shows the order and positions (1, 7, 5, 4, 6, 2, 3) in which the elements of y^i are affected. We observe that



(a)



(b)



(c)

Fig. 3.3 Sparsity structure of matrices (a) bcsstk34, (b) bcsstk35 and (c) pwtk.

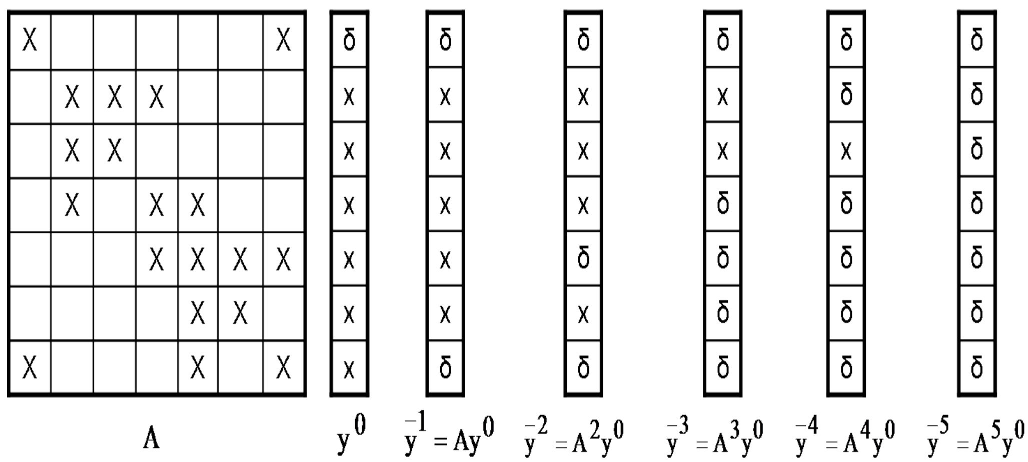


Fig. 3.4 Sparse matrix A, vector y, and the sequence of SpMV operations on A and y

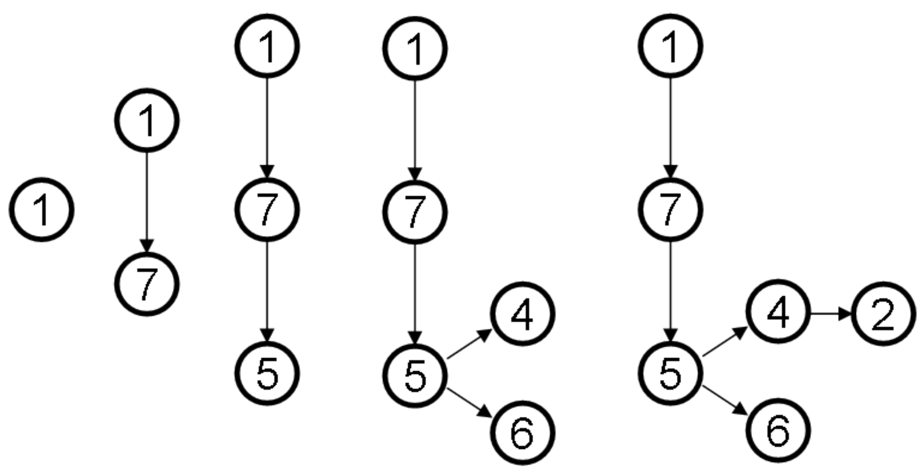


Fig. 3.5 Intermediate tree representations (0 - 4 iterations)

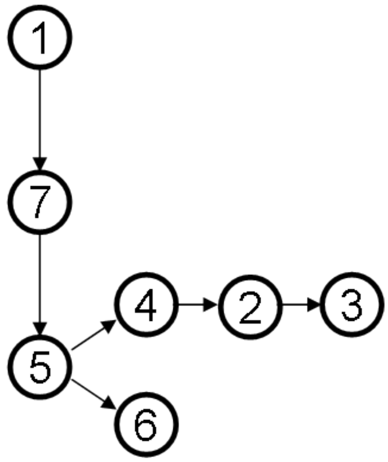


Fig. 3.6 Final tree representation

the resultant vector at the end of the 5^{th} iteration has an error in all of its components and the height of the tree is 5, which is equal to k.

We illustrate on an example matrix the corruption of the Krylov space due to the propagation of the single error. Figure 3.7 shows the relative norm of the corrupt Krylov vectors (with respect the Krylov vectors without errors, i.e., relative norm error $= \frac{abs(norm(y^i - \bar{y^i}))}{norm(y^i)}$) for a test matrix *lund_b*. The figure indicates the propagation on the insertion of a single error in the vector y^i. Observe that the error increases in magnitude as it propagates with the iterations.

This work on the characterization of soft errors was presented as a poster [1] at the Super Computing Conference in 2010 and was awarded the Best Poster award. An extended version of this work is also published in the International Conference on Supercomputing 2011 [36].

In this chapter, we have illustrated that a single soft error can cause multiple errors by propagating through a sequence of SpMV operations. This could be the probable

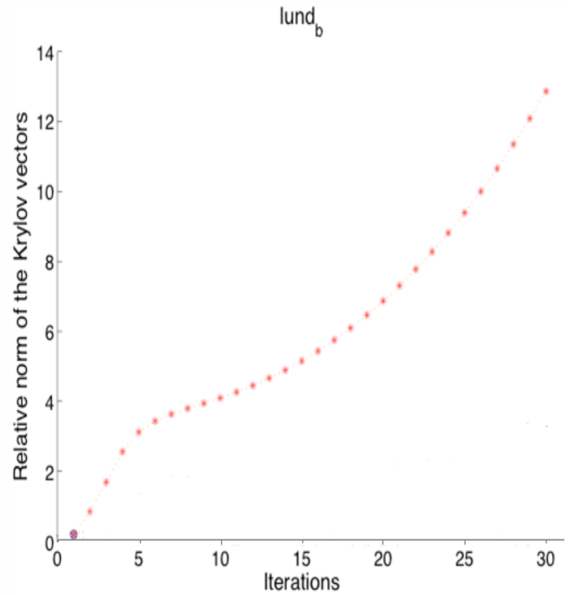


Fig. 3.7 Relative error in the Krylov subspace.

cause for the potentially disastrous performance impact on PCG. In the following chapter (Chapter 4), we present a case study of the effect of soft errors on a real life scientific application, the Community Earth System Model (CESM), a community climate code.

Chapter 4

Impact of Soft Errors on the Community Earth System Model

The Community Earth System Model (CESM) is a coupled climate model that allows simulation of the earth's climate system. The model is a long running scientific application that is run on multiple cores. Any error that affects the application can potentially lead to loss of performance as well as power. This makes the study of the effect of soft errors on this applications useful in building a more robust application.

We use the atmosphere model (CAM) and ocean model (POP) for our experiments. Figure 4.1 illustrates the location of the error insertion in the atmosphere model. The experiments are conducted in the spectral transform dynamical core of the model.

We conduct experiments with single bit error insertion model, wherein, the error in simulated by flipping a single bit of the exponent or significand in the target variable. The error inserted is used to simulate a large or small change in magnitude of the variables. We also simulate a change in sign of the value by flipping the sign bit. In our experiments, we run the model on 32 cores of the Kraken [4] and Frost [3] for a model time of 1 month with a resolution of $T31\_gx3v5$. The resolution can be understood as approximately 3.75 degree latitudinal resolution with longitudinal resolution of 3.6 degrees. We analyze the values of the global integrals given out by the model to determine the effect of the error on the output. The global integrals that we use are mean energy going into physics, mean energy coming out of physics, heating rate, and surface pressure.

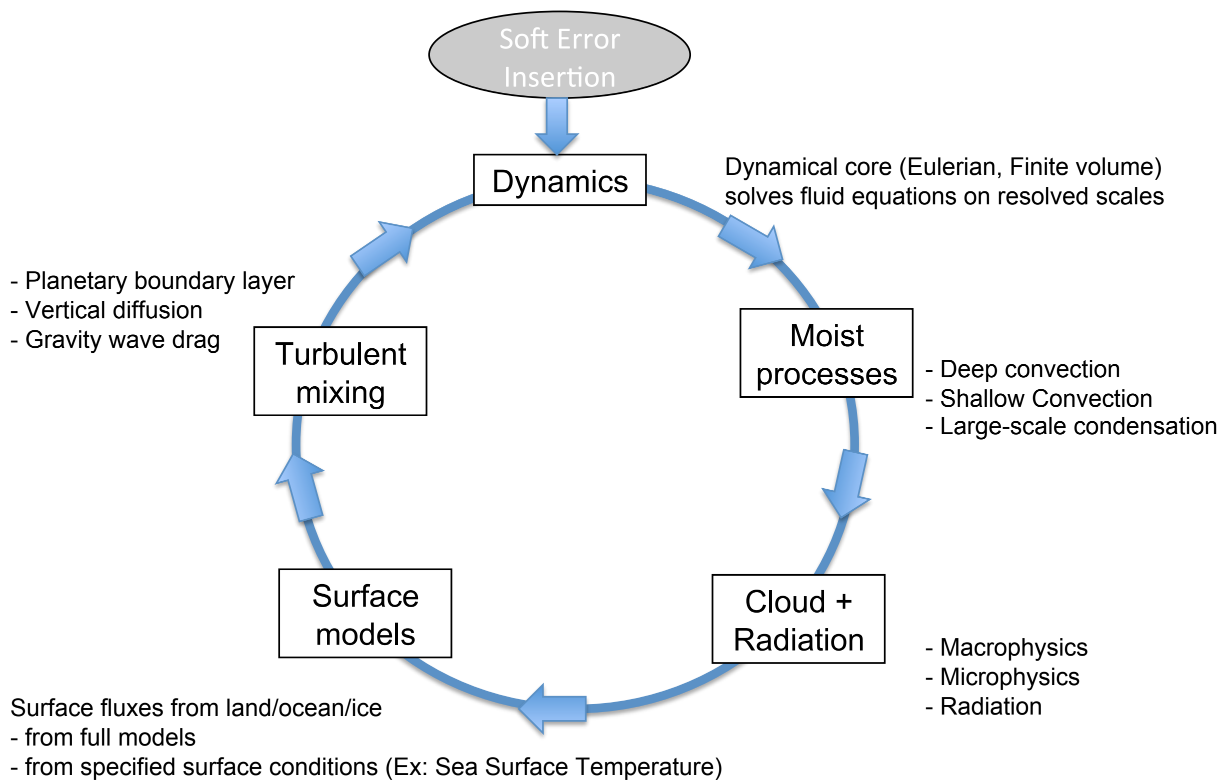


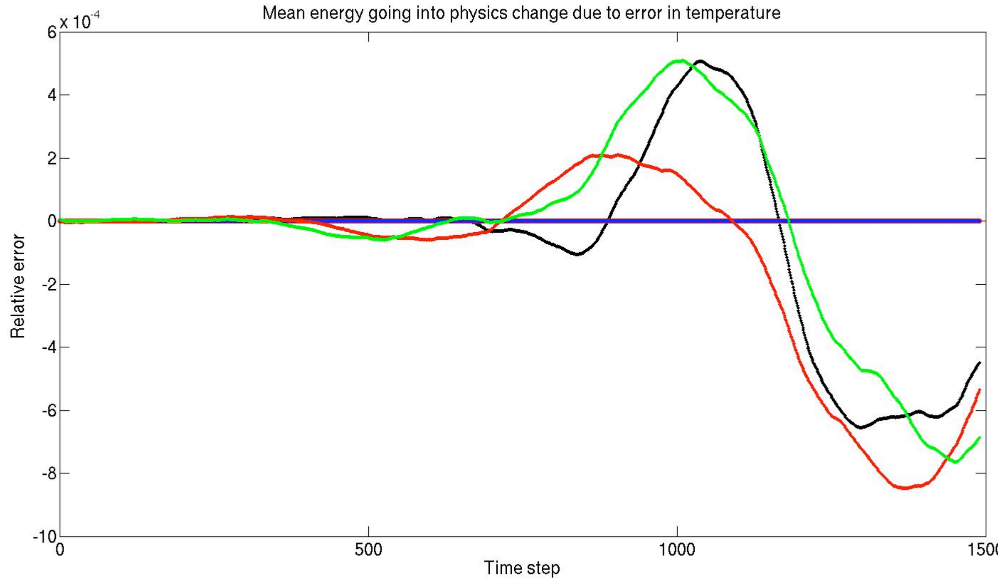
Fig. 4.1 Atmosphere model workflow with soft error insertion

We first observe the effects of the single error in data, in the PCG solver, within the finite volume model of the atmosphere model. We do not observe any change in the output as a result of this error. Analysis showed that the PCG solver within the model have a lower threshold for the number of iterations to convergence. The solvers discards instances where the solution does not converge within the allowed threshold.

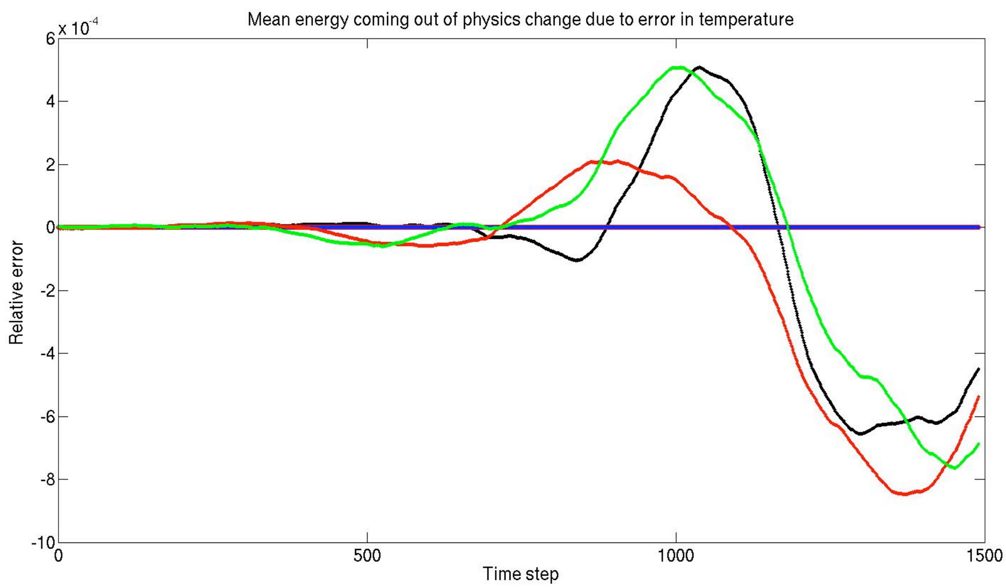
We next investigate the effect of single soft errors in the physical variables like temperature, velocity and volume within the atmosphere model.

Figure 4.2 shows the relative error in the global integrals: mean energy going into physics and mean energy coming out of physics when a single error is simulated in the temperature field in the atmosphere model. Figure 4.3 shows the relative error in the global integrals: heating rate and surface pressure. The relative errors are calculated against the integral values in the case of no error insertion. The model also allows an error margin to accommodate the round-off errors due to different machine epsilon values (the black line on the plot indicates the allowed relative error.)

The plots can be understood with the following legend. The blue line indicates the effect of the error when the 10^{th} bit of the exponent of the temperature field (value read: 12.7062067059385075) is flipped (leading to a value 0.170362373879794680E+156). The green line indicates the effect of the error when the sign bit is flipped (leading to a value of -12.706207). The red line indicates the effect when the 2^{nd} bit of the exponent is flipped (leading to a value of 362.482372). The plots show that the relative error lies within the range of the perturbation limits allowed by the model, thus concluding that the model is very robust against single bit flips in the physical variables.

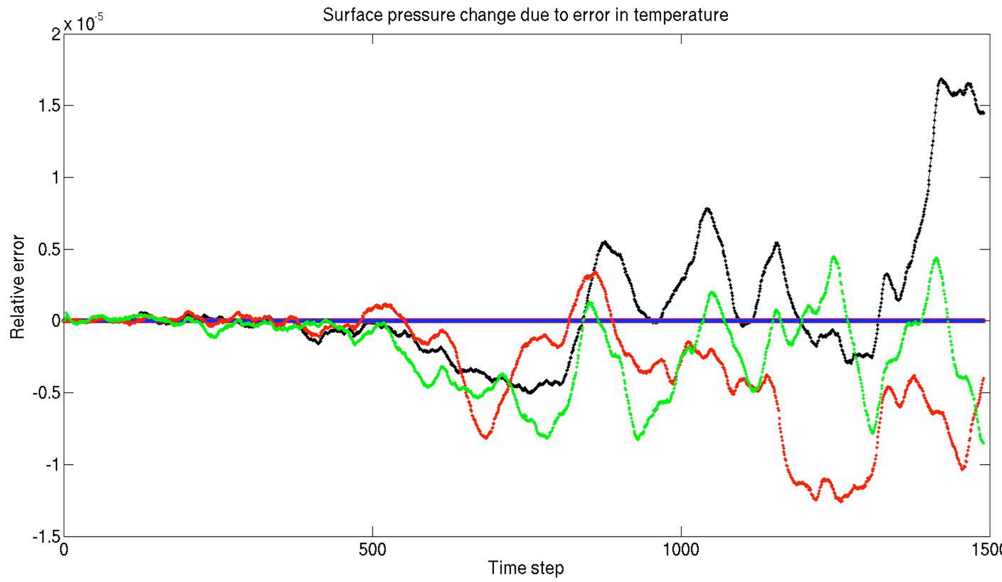


(*a*)

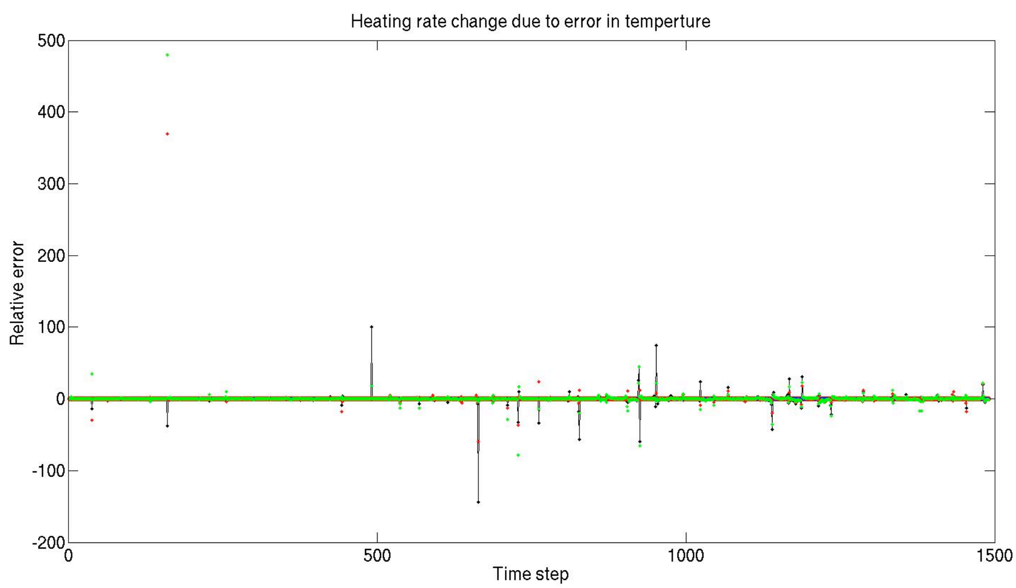


(*b*)

Fig. 4.2 Effect of a single bit flip in the temperature field in the atmosphere model on the mean energy

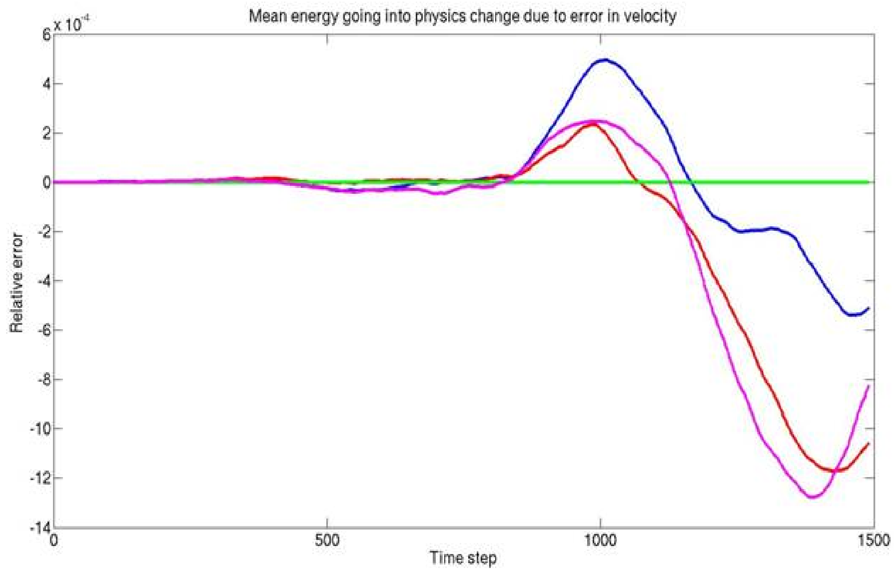


(c)

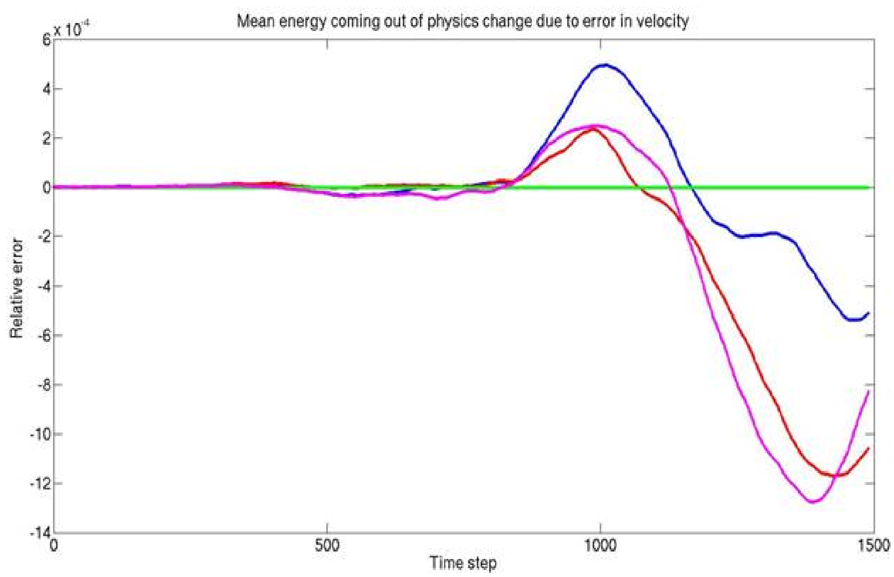


(d)

Fig. 4.3 Effect of a single error in the temperature field in the atmosphere model on surface pressure and heating rate

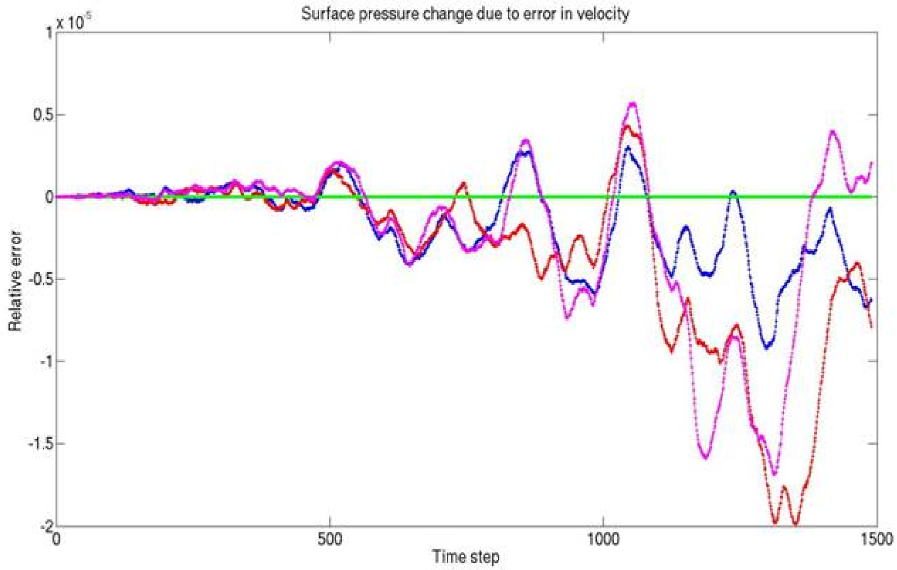


(a)

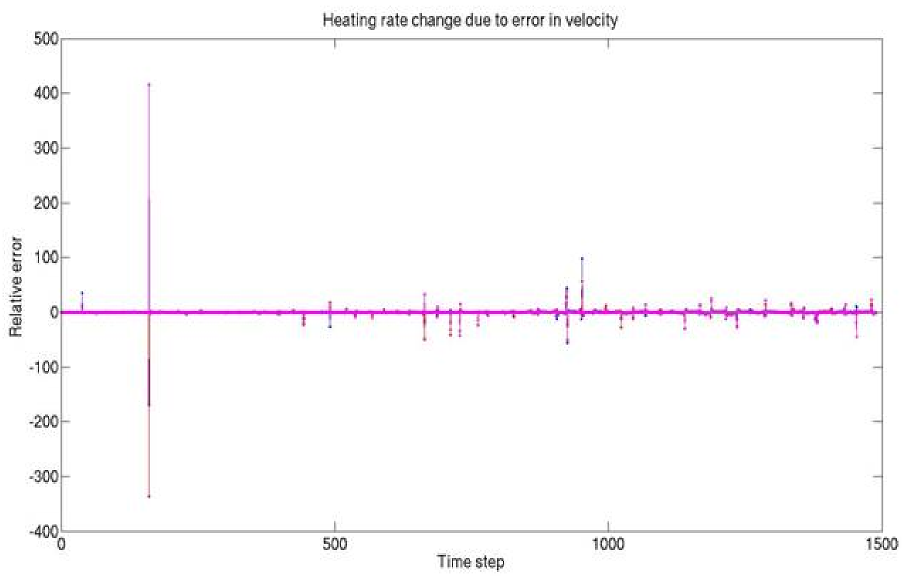


(b)

Fig. 4.4 Effect of a single bit flip in the velocity field in the atmosphere model on the mean energy



(c)



(d)

Fig. 4.5 Effect of a single error in the velocity field in the atmosphere model on surface pressure and heating rate

Similar results are observed when a single error was inserted in the velocity component of the atmosphere model. Figure 4.4 shows the relative error in the global integrals: mean energy going into physics and mean energy coming out of physics and Figure 4.5 shows the relative error in the global integrals: heating rate and surface pressure. As before, the relative errors are calculated against the integral values in the case of no error insertion. The error margin allowed by the model is marked with the cyan line. The red line indicates the effect of the error when the 10^{th} bit of the exponent of the temperature field (value read: -1.35923482838048648) is flipped (leading to a value 0.101376364837761051E-153). The blue line indicates the effect of the error when the sign bit is flipped (leading to a value of 1.35923482838048648). The green line indicates the effect when the sign bit of the maximum value in the velocity component is flipped (leading to a value of 362.482372).

We also conducted experiments using the ocean model. Here the error insertion was done into the time management module. The error was inserted into the pointers to the data unlike in the data in the atmosphere model. The ocean model consistently fails with segmentation faults.

On analyzing the behavior of the models to data corruption and the behavior on pointer corruption we conclude that the models are robust against single bit data corruptions in the physics based model. The models are deterministic and are capable of factoring out any reliability issue due to single bit data corruption. But the models are not robust enough to handle errors in the pointer data structures and result in segmentation faults. The case study was brief and is not complete. The study of the effects of the errors on the climate models will be continued as a part of the future work.

Chapter 5

Conclusion

In this thesis, we have demonstrated that soft errors can negatively impact long running scientific applications on advanced computer hardware. We study the impact of soft errors on the preconditioned conjugate gradient method (PCG), which is an iterative linear solver that is at the core of many such applications. Our results show that a single soft error has the potential to degrade the performance of PCG by a factor of 200 or more. We also study the effect of soft errors on the Community Earth System Model (CESM), a widely used scientific application to conduct fundamental research into the earth's past, present and future climate states. Our study on CESM indicates that the physics based models are robust against single bit data corruptions. However, the models are not robust enough and fail to handle such errors in the pointer data structures. The results in this thesis indicate the need for further study of the impact of soft errors on scientific simulations and the need to develop methods for detection and mitigation.

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