SCALABLE MESSAGE-LOGGING TECHNIQUES FOR EFFECTIVE FAULT TOLERANCE IN HPC APPLICATIONS

BY

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DISSERTATION

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Abstract

An important set of challenges emerge as the High Performance Computing (HPC) community aims to reach extreme scale. Resilience and energy consumption are two of those challenges. Extreme-scale machines are expected to have a high failure frequency. This is an inevitable consequence of the mismatch between two trends. The number of components assembled in supercomputers grows exponentially. However, the improvement on the reliability of each individual component is much slower. At the same time, the vast number of components in a single machine will consume a non-trivial amount of energy. To keep a supercomputer within operational margins, HPC systems have to be both reliable and energy-aware. For an application to be able to run and make progress in spite of constant interruptions, it has to incorporate some fashion of fault tolerance. Rollback-recovery techniques provide a framework to overcome crashes in the system by periodically saving the state of the application and rolling back to checkpoints in case of failures. Two well-known rollback-recovery techniques are checkpoint/restart and message-logging. The former is easier to implement and has become the *de facto* standard to make applications fault tolerant. It has, however, a high performance and energy cost during recovery. Message-logging, on the other hand, makes it possible to recover faster from a failure and to consume less energy. The downside of message-logging is the overhead it exhibits in the failure-free scenario. Memory and performance overheads may offset its advantages. This thesis focuses on techniques to alleviate the downsides of message-logging. It presents a mechanism based on high-level programming language constructs to decrease the performance overhead of message-logging. It also introduces two strategies to reduce the memory overhead created by the message log. Additionally, it addresses important architectural constraints of modern supercomputers. Based on large-scale experimental results and projections from an analytical model, we conclude message-logging is a promising strategy to provide fault tolerance at a low energy cost for extreme-scale machines.

To Abuelita Balbina.
For teaching me what resilience means in real life.

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CHAPTER 1

Introduction

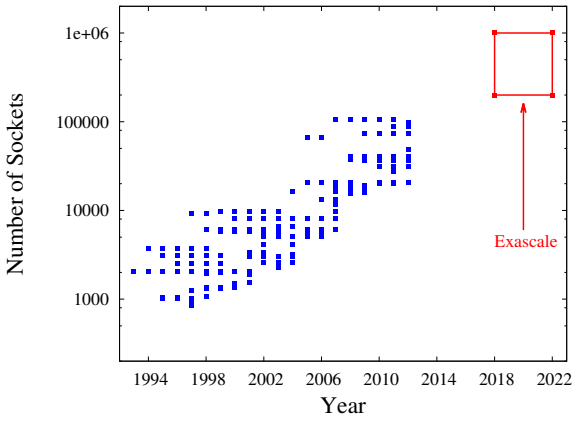
Self-healing materials are among the most amazing engineering inventions. These bio-inspired polymers have the ability to recover from a crack, or snap back after a puncture, reestablishing the original structural properties of the material. It is not a surprise that space agencies are very interested in materials with self-healing properties. Building a spacecraft with such materials will make missions to outer space safer. Otherwise, fast-moving debris may hit the spaceship and jeopardize the goals of the mission. With such a resilient cover, the astronauts can be safe and free to focus on the fundamental goal of the trip: explore the unknown portions of the Universe.

The same way astronauts use a spaceship to get to previously hidden places outside our planet, many computational scientists rely on supercomputers to extend the body of knowledge in their research area. A supercomputer is sometimes their vehicle to find groundbreaking facts about Nature. It used to be the case that supercomputers were highly resilient. They had low failure rates and crashes were considered a rarity. However, as we approach exascale and the size of the machines increases substantially, the tenet of reliable supercomputers will fall and what is currently the former rarity will most likely become the standard. A machine at exascale will face frequent failures. The high performance computing (HPC) community, and particularly the system builders, must provide computational scientists with the illusion of a self-healing supercomputer. The same way smart materials let astronauts concentrate on their work by providing a safe spaceship, resilience protocols in supercomputers should allow computational scientists to concentrate on extending the frontiers of what we know and keep enjoying the wonderful journey of Science.

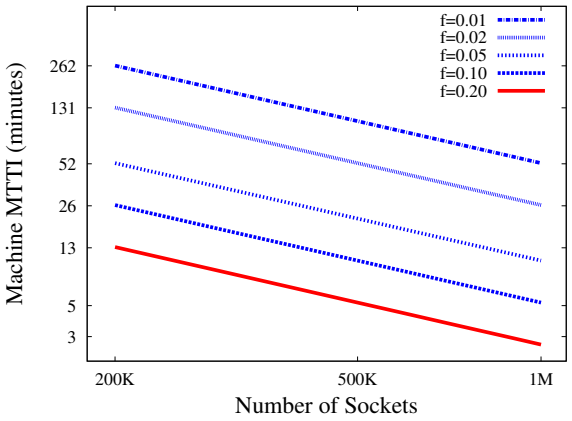
1.1 Justification

Computational scientists are among the main users of high performance parallel computing. They usually run codes to simulate a physical process. Their programs use models that can be accurate enough to avoid running an experiment in real life. Running an experiment in real life may sometimes be too costly. Additionally, models can predict what will happen in different scenarios that may be infeasible to replicate in reality. In applications that range from molecular dynamics to weather forecasting, computational scientists are always ready to consume as many FLOPS as a machine can provide.

In order to satisfy the demand for faster supercomputers, the architects of these machines relied on three major factors during the last decades: Moore's Law, increase in the clock frequency and an increment in the number of sockets per machine. As Moore's Law comes to an end, and the clock speed has stagnated, the main source to boost the performance in a supercomputer is the number of sockets.



(a) Historical view of the number of sockets in the top 10 largest systems. An exascale machine is expected to have more than 200,000 sockets and to be available between 2018-2022.



(b) MTTI of a machine for various failure rates (f) per socket. An exascale machine is expected to face several failures per hour.

Figure 1.1: The trend in the size of supercomputers and their associated MTTI make failures an unavoidable concern for exascale machines.

Figure 1.1 presents a perspective on the size of the supercomputer and the implications it will have for the future. A historical view of the number of sockets per machine is presented in Figure 1.1(a). The trend is clear, the number of sockets increases exponentially. An exascale machine, already on the horizon, is estimated to have more than 200,000 sockets [1]. The implication of such a large number of sockets is depicted in Figure 1.1(b), where the mean-time-to-interrupt (MTTI) of a supercomputer is calculated for different numbers of sockets

and different failure rates per socket per year (f). The value $f = 0.2$ has been adopted as a good estimate for exascale [2]. The MTTI of a machine has been calculated assuming socket failures are independent and they follow an exponential distribution. The results show that failures will occur rather frequently, with several failures per hour. These predictions are not pessimistic; other estimates forecast a MTTI value worse than one hour [1, 3].

Failures will happen so often that it will be impossible to ignore them. In order to provide a productive system for computational scientists to keep pushing the envelope in their field, resilience has to be adopted as a major concern for deploying supercomputers. However, providing resilience has been historically challenging [4], mostly because it disrupts the natural cycle of developing parallel applications. Ideally, we do not want application scientists to take on the resilience issue. They should focus on modeling the scientific problems. The vehicle they use to simulate those phenomena should appear reliable, even when it is not in reality. The runtime system, that interfaces the applications with the machine, has to deal with failures and provide the illusion of a resilient supercomputer. The application writer should have a minimal participation in this process.

The runtime system has to offer an efficient fault-tolerance solution. The way to determine how efficient a resilient solution is relates to the original motivation for high performance computing. Computational scientists use powerful machines to either solve their problem faster or to solve a larger problem. In either case, time to solution is the adopted metric to decide which technique is better in solving a particular scientific problem. We believe the same should apply for fault tolerance strategies. A good resilient technique keeps the *progress rate* as high as possible with a tolerably low rate of irrecoverable failures. In that sense, recovering the lost work quickly after a failure is fundamental. Our philosophy for a successful fault tolerance algorithm is one that has low overhead and recovers fast, even at the expense of not surviving all possible failure scenarios. What really matters is to *probabilistically* survive the vast majority of failures.

Figure 1.2 presents a *progress diagram*, the visualization tool we will use to understand how efficient a fault tolerance strategy is. This diagram depicts time versus progress, where progress refers to the total computational effort needed to solve a scientific problem. Progress can be given in terms of iterations, number of FLOPS, or any other work unit defined by the application. The slope of the curve is the progress rate. The two curves in Figure 1.2 correspond to an execution without faults and with one fault using fault tolerance support. All the possible latency overheads of a fault tolerance technique are expressed in the figure. First, fault tolerance support may provoke a *slowdown* in the speed of the program. This is seen as the difference in the slopes of the two curves. Second, a *checkpoint* may delay the execution of a program. Third, upon a failure hitting the system, *recovery* from that failure

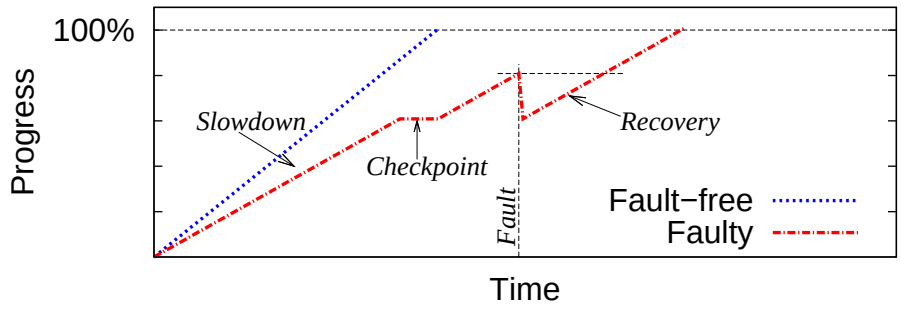


Figure 1.2: Progress diagram. It shows the progress rate as the measure to determine how efficient a fault tolerance solution is.

may consume a non-trivial amount of time. In order to optimize a fault tolerance method, the three sources of latency overhead must be addressed.

The HPC community has a typical answer for failures in supercomputers. For years, checkpoint/restart has been successfully used. This simple scheme requires all the tasks in an application to periodically store their state. If a failure strikes the system, all tasks rollback to the most recent checkpoint and restart execution. There are reasons to believe a simple version of this scheme will be insufficient at exascale [3]. There are two major reasons we believe this will be true. First, checkpoint/restart alone may not tolerate the high frequency of failures at exascale [2]. With such a high failure rate, most of the execution time will be spent on rolling back and re-executing lost work. According to our definition of an efficient fault tolerance solution, checkpoint/restart falls short. It does not provide a way to accelerate recovery. Second, checkpoint/restart wastes a lot of energy. Imagine a system with millions of nodes, rolling back all just because one fails. It is a tremendous waste of energy to re-execute all the tasks even if a minuscule percentage fails. Energy is important, because power considerations will be a major restriction in designing exascale systems [1].

In order to overcome the limitations of checkpoint/restart, we need to examine a promising extension called message-logging. In this technique, application messages are stored and re-sent in case of a failure. That means, if a failure occurs in the system, only the crashed tasks are rolled back, decreasing the waste of energy. Furthermore, with a technique called *parallel recovery* [5], the time for the crashed tasks to catch up can be substantially reduced, making the progress rate of the application high even in the presence of failures.

1.2 Research Challenges

Message-logging can potentially overcome the two major limitations of checkpoint/restart. If failures are frequent, it can substantially reduce the total energy spent in the computation. Additionally, it can recover faster from a failure, reducing the execution time. There are, however, several limitations and challenges before this technique can be widely adopted.

The first problem to solve is the latency overhead. Message-logging requires handling meta-data about messages to guarantee a correct recovery from a failure. Depending on the characteristics of the application, the amount of meta-data and the required time to process it may be onerous. Furthermore, popular parallel programming constructions, such as collectives, aggravate this problem [6]. The main challenge is to find a way to reduce the amount of meta-data required for a consistent recovery. That way, the latency overhead can be reduced or even overlapped with communication delays. Also, it is important to understand how the overhead behaves to avoid those cases where it peaks. Control flow in an application should be considered in order to minimize the amount of meta-data needed.

A major criticism to message-logging is its obvious drawback: memory overhead. If messages have to be stored to be re-sent in case of a failure, then those messages can potentially consume a great deal of memory. A trade-off must be found to alleviate memory pressure in message-logging. Is it possible to design a protocol that stores only a subset of the messages? Not storing some messages may result in a higher cost at recovery. For instance, more tasks may need to get rolled back. However, if properly done, it could dramatically reduce memory consumption at a relatively small cost. It is necessary to explore the communication graph of an application and use that information to create that trade-off. Also, parallel programming constructs must be analyzed in order to decrease memory requirements.

As multicore nodes are becoming the building blocks of parallel machines, it is important to understand how this architecture affects the design of message-logging protocols. A fundamental challenge is to determine the granularity at which machines fail. Finding an appropriate failure unit will determine how the protocols are built and what guarantees are provided. A multicore node has shared memory among the constituting cores and that resource has to be used to improve the resiliency and performance of the message-logging protocol.

A way to predict the performance of message-logging for different scenarios is instrumental in understanding the impact of the different optimizations. A performance model that incorporates all the different sources of overhead and speedup can shed some light on the potential of message-logging for exascale. At the same time, it may categorize applications according to how suitable message-logging is for them.

1.3 Thesis Organization

This thesis is organized in three major parts. Part one contains chapters 2, 3 and 4. This part introduces all the necessary theoretical background and justifies why message-logging is a promising technique to provide fault tolerance at scale. Chapter 2 presents a survey of the background work for this thesis. It focuses on the migratable-objects model for parallel programming and how various resilience methods have been implemented. Experimental results on the various approaches are presented, including execution time and energy measurements. Chapter 3 shows how message-logging can be implemented efficiently and how it can be scaled. Next, Chapter 4 offers both a performance and energy model for checkpoint/restart, message-logging and parallel recovery.

Part two of the thesis contains chapters 5, 6 and 7. It presents a series of optimizations that make message-logging a more usable approach. Chapter 5 introduces the first protocol of a set of strategies to decrease memory pressure in message-logging. It starts with a technique that trades off memory consumption for recovery cost. It does it by creating *teams* of nodes and treating each team as a recovery unit. The next strategy is presented in Chapter 6. It shows a protocol for collective communication operations and how memory overhead is reduced in that case. The new features of multicore systems are addressed in Chapter 7 and a new protocol is shown. That chapter also contains a discussion on the appropriate unit of failure and a reliability analysis for real-world data.

The last part of the thesis contains Chapter 8 and Appendix A. In Chapter 8 we present the conclusions of the work on the thesis as well as a list of promising future work. A couple of opportunities to further explore the potential of message-logging are presented in Appendix A. The first idea relates to performing message-logging at the application level. The second idea deals with certain types of applications where communication is asymmetric and a different trade-off can be made.

CHAPTER 2

Background

Fault tolerance has been a constant concern in computer systems. From the very beginning of the field, the processing of information on a faulty infrastructure was a common concern. A good example of this is the way Shannon's theorem was incorporated in many areas of computer science, ranging from communications to data storage. Shannon's theorem determines the maximum rate at which data can be transmitted over a channel that has a given degree of noise and data corruption. It is a fundamental concept in Information Theory because it provides a key insight on what type of techniques should be used to effectively communicate over a faulty medium.

The memory hierarchy provides a couple additional examples that illustrate the integration of fault tolerance into the design of computer systems. The *redundant array of independent disks* (RAID) offers a fault-tolerant method for secondary storage. RAID consists in assembling different disk drives into a single logical storage unit [7]. RAID has different levels, depending on the degree of reliability. Naturally, each increase in reliability comes at the expense of decreased efficiency in space or a decrease in performance. As for main memory, *error correcting codes* (ECC) have been found to be successful in alleviating the impact of soft errors. These errors appear when electrical or magnetic interference cause a bit in main memory to flip, creating a potential error in the data of the application. An ECC memory works by adding redundant bits to detect and, in some cases, correct soft errors in memory.

More recently, the deployment of large-scale services over distributed systems has brought resilience into the picture. A remarkable example can be found in peer-to-peer platforms that implement distributed hash tables [8, 9]. These data structures are a cornerstone in building file sharing services. One salient feature of peer-to-peer systems is the dynamical nature in the membership of its components. Computers participating in the system may connect intermittently. Thus, peer-to-peer systems must handle a high churn in its members.

Having computers joining and leaving the system at any time requires a resilient solution.

This chapter covers the main approaches in HPC to provide fault tolerance. We survey the most relevant rollback-recovery techniques, including checkpoint/restart methods and message-logging protocols. These two strategies are fundamental for the development of the following chapters because checkpoint/restart is the most popular alternative to build a resilient HPC system and, as such, it is the baseline for all comparisons. Along this thesis we will use and empower message-logging. We believe message-logging has the potential to bring two cardinal advantages over traditional checkpoint/restart. First, using a particular computational model, it is possible to have message-logging accelerating recovery and significantly decreasing total execution time in an environment with frequent failures. Second, it consumes less energy, not just because it finishes faster but because during recovery most of the nodes may stay idle and draw a fraction of the power.

Checkpoint/restart is a very intuitive strategy to overcome failures. However, it requires a *global rollback* in case of a failure. That is, the whole set of nodes is forced to roll back and resume execution from the previous checkpoint. Conversely, message-logging only requires a *local rollback*, namely just the crashed node and (potentially) a few others need to roll back. The vast majority of the system may either make progress or stay idle if the application is tightly coupled. This fact opens up some opportunities to improve both the execution time and the energy consumed.

The highlights of this chapter include:

- We offer a discussion on how the fault tolerance goals differ between parallel computing and distributed systems (§2.1). We argue that progress rate is the right metric to compare resilience solutions in HPC.

- We present a survey of the most relevant rollback-recovery techniques, categorized into checkpoint/restart (§ 2.3) and message-logging (§ 2.4).

- A description of the migratable-objects model is presented. This computational model allows parallel recovery, arguably a technique that is a key factor for scalability (§ 2.5).

- The simple causal message-logging protocol is introduced (§2.6). This protocol combines the advantages of the causal protocol with parallel recovery.

- An empirical evaluation of several of the protocols presented in the chapter is offered (§ 2.7).

2.1 Fault Tolerance Goals

One of the most popular terms related to fault tolerance is *RAS* [10]. It stands for *reliability, availability* and *serviceability* and it was initially introduced by IBM to describe a robust mainframe computer. RAS provides a scale in which high levels of RAS represent a highly assured system, guaranteeing data integrity and the possibility of access the system for long and uninterrupted periods of time.

To better understand the RAS guarantees, let us define the three pillar terms:

Reliability is a function that expresses the probability of the system to survive during a particular time period [11]. To increase the reliability of a system, different techniques aim at avoiding, detecting and repairing component failures. A reliable system must always provide an error free operations. Thus, if the system detects an error, it will try to fix the error by retrying the set of operations that went wrong. If it cannot fix the error, it will halt and declare a fatal error has occurred. At that point, manual intervention will be required to bring the system back up. This definition represents reliability as a function of time, therefore a typical measure used is mean-time-to-failure (MTTF).

Availability is the fraction of the time the system is up for use. In real systems, after a fatal error occurs, the system is inspected and some components are replaced or repaired. Eventually, the system is brought up again and continues providing the service. Thus, if the system is not operational, it will reduce the availability. Sometimes, the system may continue its operation without the failed component, but at a reduced capacity. This will increase availability at the cost of efficiency.

Serviceability is the easiness with which a system can be repaired. Serviceability is also known as maintainability. Among the methods to reduce the repair time, there are early detection and fast diagnosing mechanisms. These methods aim at decreasing the down time of the system and lower the cost of manual intervention to repair the components.

The RAS principles have been applied to a wide range of areas in computer systems, from databases to processors. RAS represents a common ground to understand how robust a system is.

In distributed systems, the reliability goals adopt a slightly different form [12]. The first concern is *recoverability* or the ability of the system to automatically restart after a failure. The second concern is *continuous availability* or the ability of the system to continue

providing correct results despite the failure of a limited number of components. The rest of operational components guarantee a consistent behavior and avoid a down time of the system. This last objective sets the research direction of reliability in distributed systems. The major goal is to avoid a fatal crash of the system by tolerating the failure of up to t components. The larger t, the more reliable the system is, because there are fewer cases that bring down the system into a catastrophic crash.

We believe that the same set of goals should not be applied to evaluate the reliability solutions in high performance computing. The major goal of a supercomputer is not so much to provide a highly available service, but to speed up the computational programs of the users. Most of the jobs on a supercomputer are run offline, which means sacrificing a little of response time is not going to have a huge impact on the satisfaction of the users. In fact, users of HPC installations usually have a limited amount of computational units to use. This allocation time must be carefully budgeted to make the best use of precious time on the supercomputer. Therefore, accelerating their code is still the main goal in HPC.

In a faulty HPC environment the goal should remain the same, i.e., to finish the execution as soon as possible despite frequent component failures. Therefore, we propose **progress rate** as the metric to compare and evaluate fault tolerance solutions in HPC. Average time to completion and not reliability should be the main focus when designing new fault tolerance solutions. Since there is a tradeoff between making a system more robust to different failures taking down up to t components and running the application fast, speedup should be the fundamental consideration. This approach does not mean that reliability should be ignored altogether. Rather, fault tolerance techniques should provide a level of reliability above a reasonable threshold. Therefore, the probability of an unrecoverable failure must be small. Additionally, with extreme scale systems on the horizon, energy consumption and power management considerations become more prevalent. Our philosophy is that a successful fault tolerance mechanism in HPC should decrease the average execution time of an application subject to the power limitations.

The distributed systems community has worked on reliability for several decades. In that time frame, they have built a significant body of knowledge on the topic, including many implementations, models and studies. It is natural to port that knowledge into high performance computing, which has not dealt with reliability as much time. However, there is a risk in blindly adopting the same reliability techniques, because the goals of the two areas are different and so must be the kind of tools.

2.2 System Model

We assume a parallel application is divided into a set Γ of G *tasks*. There is no global shared memory in the application. Each task has its own private memory to store part of the application's data. The only way to share information between tasks is through message exchange. We assume the underlying machine is composed of a set Σ of S *nodes*. The nodes are connected through a network that delivers messages in-order between any pair of nodes. The network is reliable, but latency is unbounded.

The tasks are distributed among the nodes with potentially more than one task per node. This is $G \geq S$. When a nodes crashes, all the tasks residing on that node are lost and their state must be recovered from another entity in the system, either other node or the storage system. Although there are several components that can fail in the system, we will only consider node crashes. A node **failure** is defined as a behavior that deviates from that required by the specifications [11]. If a node can not provide the service it is supposed to, the system can detect that failure. A failure is typically the manifestation of an **error**. An error is a deviation from correctness or accuracy in the state of a component. It is usually caused by a **fault**. Faults are usually physical defects or flaws in hardware or software.

A failure in the system will render one or more nodes unusable. In other words, we follow the *fail-stop* model, where the failed component ceases to work and never comes back. We assume the underlying machine has a pool of spare nodes that will replace the failed ones. That way, a failed task can be relaunched in one fresh node. We will call *forward path* any portion of the execution that does not include a failure. This concept will be important, given that different fault tolerance strategies present a tradeoff between overhead in the forward path and a slowdown during recovery.

Figure 2.1 presents an example of the system model where a machine has 2 nodes (X and Y) and a set of 4 tasks (A, B, C and D). Tasks A and B execute on node X, while tasks C and D on Y. The arrows in the figure represent messages exchanged between the tasks. The forward path corresponds to the time period between the start of the execution until the first failure. Once node X crashes, the runtime system will automatically find a replacement for X. In this case, node X' takes over all the responsibility of X, including tasks A and B.

The fail-stop model is a good representation of *hard errors*, which implies a component breaks and suffers a permanent physical change. The system can not continue with the execution of the application until the component is replaced. A different type of failures, called *soft errors* occur when there is an fault in the system, but the system may still be completely functional and able to finish execution. An example of a soft failure is a bit-flip in a memory region. Cosmic rays may cause this type of phenomenon. Applications

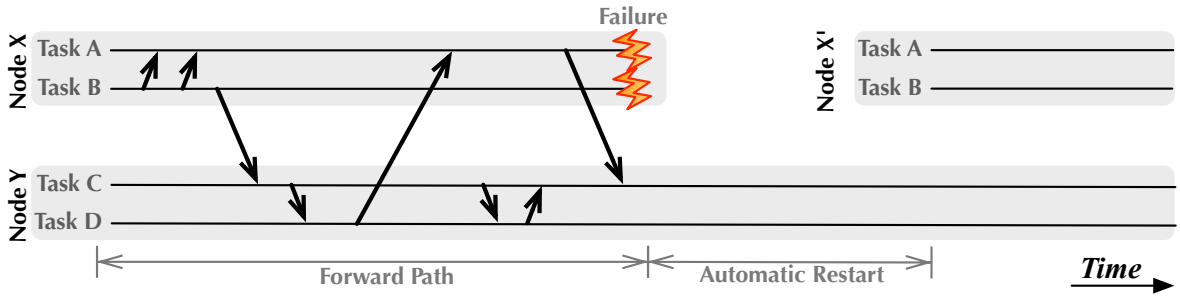


Figure 2.1: System model. The machine is composed of a set of nodes on which a set of tasks run.

are typically very susceptible to this latter kind of error [13, 14], unless they incorporate some sort of resilience in their algorithms. A particular kind of programs can tolerate soft errors by incorporating *resilient algorithms* [15]. These algorithms usually work by using error-correction codes (ECC) and specific properties of the numerical methods. Once an inconsistency is detected, the result can be reconstructed using correct values of the computation. The development of resilient algorithms is usually confined to particular types of applications. Despite the relevance of soft errors to the HPC community, they will not be targeted in this thesis. We will concentrate on hard errors and mechanisms to overcome them.

Rollback-recovery is the name of the common method of providing fault tolerance by periodically saving the state of an application. If a failure strikes the system, a natural way to recover is to roll the system back to the most recent saved state. There are two major techniques in rollback-recovery: checkpoint/restart and message-logging.

2.3 Checkpoint/Restart

The most popular rollback-recovery strategy to deal with failures is checkpoint/restart [16]. The fundamental idea behind this approach is that every task periodically saves, or checkpoints, its state. The state of a task may include the state of the node it is running on, depending on whether application-level, system-level or runtime-based checkpoint is used. Application-level checkpoint decreases the amount of data to be stored, but requires the programmer or a compiler to determine what to checkpoint [17]. System-level checkpoint will dump the state of the whole system, including registers and buffers. Runtime-based checkpoint splits the checkpoint responsibility between the programmer (who writes the

checkpoint method for the tasks) and the runtime system (which checkpoint all the internal data structures).

If the system experiences a failure, all the tasks roll back to the most recent checkpoint and restart from there. There are two major issues that should be addressed. First, there is a question of how often to checkpoint. The optimum checkpoint period depends, among other things, on the MTTF of the machine and the time to checkpoint. The specifics of how to compute the best checkpoint interval can be found elsewhere [18, 19]. The second point is how to guarantee a consistent state when checkpointing. There are two options on this regard, the checkpoint can be either *uncoordinated* or *coordinated*.

In uncoordinated checkpoint, each task checkpoints at its own frequency, without synchronizing with the rest of the system. However, a failure may require the rollback of multiple checkpoint periods. Imagine that a task A sends message m to task B. If A sends the message before it checkpoints and B receives the message after it checkpoints, the message is called *in-flight*. If both tasks roll back to the previous checkpoint, it will make the system inconsistent, since B would wait for a message that will never come. In that case, to get A to resend the message will require forcing it to rollback to an older checkpoint. This reasoning can lead to a *cascading rollback* until a consistent state is obtained. There is no bound in the number of checkpoint periods that must be rolled back and it exists the possibility that a single error may roll back the whole application to the very start of the execution.

Coordinated checkpoint, instead, guarantees that no cascading rollback will occur in any failure. In order to achieve this, it avoids in-flight messages and other types of inconsistencies. All tasks have to checkpoint a global but consistent state. There are two major approaches for this: blocking and non-blocking. The former case implies that all tasks must come to a halt and wait until all outgoing messages have been received. At that point, the state of the tasks is safely stored. The non-blocking case is based on an algorithm that does not interrupt the execution of the application, but instead uses markers to initiate a *global snapshot* of the system [20]. Those markers are propagated across the entire system and the algorithm guarantees that the set of states is globally consistent. A comparison of these two versions of coordinated checkpoint can be found in other sources [21].

A coordinated checkpoint can be achieved through looking at some properties of the application. For instance, barrier operations require all tasks to reach a point without letting any task continue execution before every other task has reached the barrier. Barriers and other synchronization operations are commonly used in HPC applications. If those synchronization points are used to trigger checkpoint, then a *synchronized* checkpoint is obtained.

Usually, each task will store its checkpoint in stable storage. However, saving the state

to disk (particularly if NFS is used) may congest the file servers and delay the checkpoint. A way to reduce the jitter to the file system is by aggregating writes at a node level and submitting one single write operation [22]. Another approach to reduce the checkpoint bandwidth is to have tasks performing *incremental checkpoint* [23]. Under this approach, after a task saves its full checkpoint, it may submit a differential checkpoint with only the portions of the data that have changed since the last checkpoint. Using all those incremental changes, the system may reconstruct the latest state of a task. It is possible to build a hybrid scheme, combining full and incremental checkpoints. Such a scheme has been applied to HPC applications [24]. In the hybrid scheme, a task will occasionally perform a full checkpoint. Between full checkpoints, it will just do an incremental checkpoint. A combination of both types of checkpoints reduces bandwidth consumption and storage requirements.

Another possibility to alleviate the problem of making disks a bottleneck is to use double in-memory checkpointing [25]. The fundamental assumption is that system memory is enough to hold the application's data and the checkpoint. Recent studies suggest that HPC applications do not exhaust the physical memory [26]. Under this approach, each task checkpoints its state into the memory of two nodes. One is the local node on which it is running. The other is the checkpoint *buddy* of the local node. Then, if a node fails, the system will relaunch the tasks of the failed node on a replacement node. After that, the runtime system will get the checkpoint from the buddy node. All other tasks in the system retrieve their checkpoint from the local node. Figure 2.2 shows an example of how double in-memory checkpoint/restart works. There are four tasks in this case and they checkpoint in coordination. The collection of all those checkpoints is called a *recovery line*. Imagine the application sends some messages between tasks before a failure hits node X. At that point, the runtime system detects the failure and proceeds to react to that failure. We call *restart* interval the time lapse between the failure detection and the point where all tasks are ready to resume execution. That time includes relaunching the tasks on another physical node and retrieving the checkpoints. Since we assume spare computational nodes, tasks A and B are relaunched on a free physical node and they get their checkpoints from the checkpoint buddy (node Y in this example). Once all tasks are ready to continue with execution, then *recovery* starts and this phase lasts until all the work lost due to the failure is redone. Note that figure 2.2 shows that messages m_1 and m_2 are received in different order during recovery and before the failure. This is possible and legitimate, since message reception is in general non-deterministic.

Double in-memory requires $2MG$ space in memory for a system with G tasks and each task having M bytes of application's data. Essentially, every task multiplies its memory footprint by 3. It is possible to reduce that overhead by using redundancy codes [27]. That

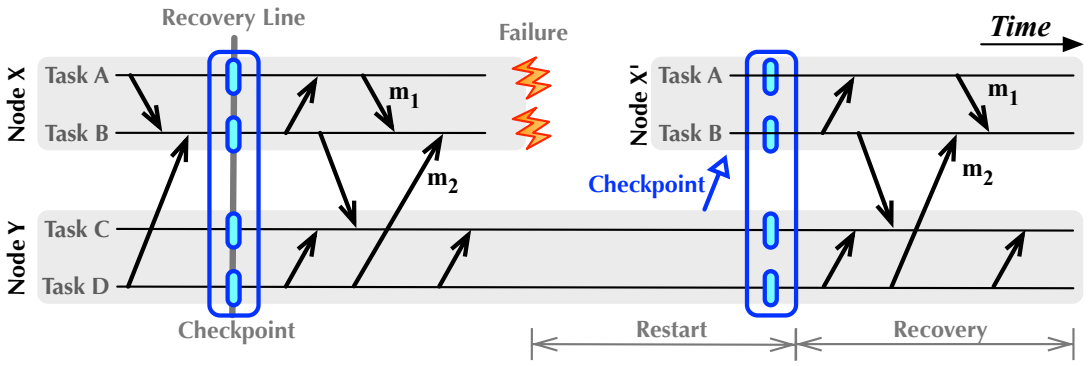


Figure 2.2: Coordinated Checkpoint/Restart. All tasks in the system checkpoint in a coordinated fashion. Often times the programmer triggers the checkpoint at global synchronization points in the application.

means, instead of each task storing M bytes for its own checkpoint and M bytes for its buddy, it may store only $2kM/G$ bytes for its buddy, where k is the number of concurrent failures to be tolerated. A simple way to achieve this is to apply a `xor` operator to the data of a set of G tasks. The `xor` of M bytes from each of the G tasks will result in M bytes for the redundancy code. This M bytes have to be divided among the G tasks. This method increases the checkpoint time, but reduces the memory requirements. An extension of this protocol has shown how it is possible to tolerate the concurrent failure of a high number of nodes in the system [28].

A version of checkpoint/restart that does not rely on coordinated checkpoint is named *communication induced checkpoint* (CIC). The spirit of CIC is to allow each task to checkpoint at any time and enforce some additional checkpoints at message reception. Thus, if a task receives a message from another task that has taken more checkpoints than the receiver, the system forces the receiver to take a checkpoint before delivering the message. Although CIC has an elegant theory to prove certain properties of the global checkpoint, in practice it has been shown to have a high overhead due to the additional checkpoints it induces [29].

Checkpoint/restart continues to be the preferred method for providing fault tolerance in HPC with multiple implementations. A popular library is Berkeley Lab Checkpoint Restart (BLCR) that provides system-level checkpoint for Linux clusters [30]. The Scalable Checkpoint Restart (SCR) library offers a model with multiple levels for storing the checkpoint, from main memory, flash memory, local disks and network file system [31].

The fundamental drawback of checkpoint/restart is that it suffers from a high cost during recovery. If a single node fails on a large scale system with hundreds of thousands of nodes, then all tasks have to roll back and redo the work just because few tasks failed. This

scheme will not scale if failure rates are high, because the system will spend most of the time recovering from failures and making no progress in the execution. We have addressed this problem by accelerating the recovery using an alternative method that will be discussed below. Other authors have pointed out that checkpoint/restart also requires coordinated checkpoint and that may saturate the network file system if state is stored in stable storage [32].

2.4 Message-Logging

In order to avoid all tasks in the system having to roll back in case of a failure, an additional mechanism to checkpoint/restart should be employed to keep track of the communication among the tasks. Each task will keep a copy of every message it sends. After a node fails, only that node is rolled back and starts recovering. The messages sent to tasks on the failed node must be resent and messages should be delivered in the same order to guarantee that all tasks reach a consistent state with the rest of the system. Figure 2.3 presents the same scenario as in figure 2.2 but this time using message-logging. One of the advantages of message-logging is that it does not require coordinated checkpoint. However, coordinated checkpoint simplifies the garbage collection stage in the protocol. The same messages as in figure 2.2 are exchanged until node X fails. Once the runtime detects the failure, it only rolls back that particular node. The rest of the system has to resend all the messages to tasks A and B for them to reach a consistent state with the rest of the tasks. Notice that messages m_1 and m_2 have to be processed in exactly the same order as they were before the crash. Otherwise, the system could reach an inconsistent state.

A fundamental concern in message-logging relates to non-determinism. Since only the crashed tasks are rolled back in case of a failure, information about every non-deterministic event has to be stored to assure the recovery is consistent. The piece-wise deterministic assumption (PWD) will then guarantee that message-logging achieves a correct recovery [33]. The PWD assumption states that storing all the outcome of potentially non-deterministic events is enough to provide a consistent recovery. In general, message reception is non-deterministic, so every time a message is received, certain information, called a *determinant*, has to be safely stored. In general, a determinant is composed of four entries $\langle sender, receiver, ssn, rsn \rangle$. The first two elements correspond to the unique identifiers of sender and receiver tasks. The *sender sequence number* (ssn) represents a unique number per each pair of $\langle sender, receiver \rangle$ identifying the message. The *receive sequence number* (rsn) represents the order in which the message is to be processed at the receiver. Both ssn

and rsn are used during recovery to reach a consistent state.

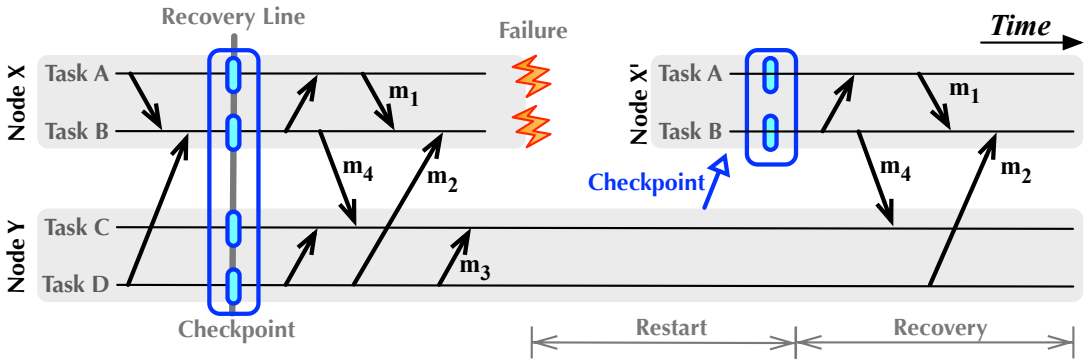
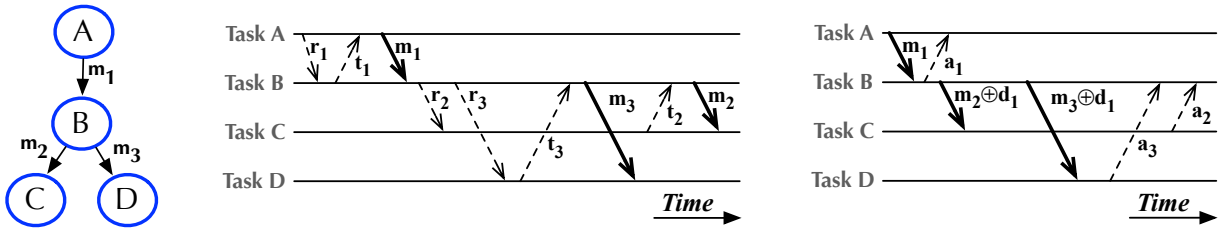


Figure 2.3: Message-Logging with coordinated checkpoint. The same example as in Figure 2.2 is presented, but this time using message-logging. Only tasks in node X are forced to roll back. Messages are re-sent by other nodes and determinants help to ensure reception order is the same as before the crash.

There are different message-logging protocols, differing in the way they deal with determinants. A broad classification has three major families: pessimistic, optimistic and causal [34]. Figure 2.4 shows an example in which four tasks participate in a broadcast from task A. For simplicity, we will assume each task runs on its own node. The spanning tree for the broadcast is presented in Figure 2.4(a). In the pessimistic approach, determinants have to be safely stored at the sender task before the message is delivered to the application. Figure 2.4(b) presents how the protocol works. In order to send message m_1, the sender sends a request r_1 to receive a ticket t_1 for that message. In this case, the ticket corresponds to the rsn of message m_1. The same rule applies for all messages in the execution. In the optimistic variant (not depicted in the figure), the request is avoided and the ticket is returned upon reception of the message. This scheme may provoke cascading rollbacks if failures cause determinants to be lost. It is optimistic in the sense that failures are expected to happen at those points in time where all the information for recovery can be retrieved. The causal approach is depicted in figure 2.4(c). The spirit of causal message-logging is to propagate determinants in the causal path of the messages. When message m_1 is received at B, then determinant d_1 is generated, but it will only by piggybacked in the next outgoing messages. An acknowledgment is required from the receiver of determinants to ensure that particular determinant is safely stored. The acknowledgment a_1 ensures determinants piggybacked on m_1 are safely stored on B. The same rule applies to all determinants generated. A project called Manetho [35] was one of the first to incorporate causal message-logging. A comparison of different message-logging protocols can be found elsewhere [36, 37].



(a) Scenario. (b) Pessimistic approach. (c) Causal approach.

Figure 2.4: Message logging protocols. Using a broadcast spanning tree as a scenario, pessimistic and causal message-logging are contrasted. The causal variant incurs less latency overhead, but it increases bandwidth consumption.

Figure 2.4 presents the most basic case where determinants are only stored in one single place. In the pessimistic version, the determinant of a message is stored at the sender. In the causal variant, the determinant of a message is stored, at least, in the destination of the next outgoing message (if any). This means the system cannot recover from the crash of multiple nodes if there is at least a pair of nodes for which one of the nodes stores determinants of the other. Determinants are crucial for recovery and the lost of at least one of them prevents a correct recovery. The general case guarantees that each determinant is saved either in stable storage or in k places. Thus, if a failure involves $k-1$ nodes, then it is still possible to recover the determinants. Although tolerating up to k multiple node failures provides a more reliable protocol, we argue below that in HPC this is not necessary.

There are several options for where messages should be logged. For instance, messages can be saved on reliable storage at the receiver node. If a node fails, then messages received by tasks on that node are retrieved from disk and delivered again. Another approach is known as *sender-based message-logging* [38]. In this case, messages are stored in the memory of the sender. The failure of a node requires the senders to retrieve messages from the memory log and resend them. The original implementation of this protocol used pessimistic message-logging that tolerates the failure of only one node. If both sender and receiver failed simultaneously, then recovery was compromised. If causal message-logging is used with sender-based message-logging, then it is still possible to survive multiple node crashes in some cases.

Recently, there has been some research on creating hierarchical protocols, where the set of tasks is divided into groups and different protocols apply to communication between groups and within the group. The goals of this type of protocols include to reduce the overhead of a global coordination for checkpoint/restart and to decrease the amount of memory reserved for the message log [39–43].

Although MPI does not include a standard mechanism to handle failures, there have been various libraries implementing message-logging for MPI applications. The MPICH-V project [44] provided various protocols for fault tolerance [32, 45], including pessimistic [46] and causal variants [47]. The FT-MPI project [48] incorporates a version of pessimistic message-logging.

An interesting observation about HPC applications is that a high percentage of them show a deterministic behavior in their communication [49]. Programs in HPC follow, most of the time, a regular pattern to compute and to exchange data. A *send-deterministic* application is one that always sends the same sequence of messages in any valid execution. In other words, regardless of the reception order of messages, tasks necessarily send out exactly the same messages. Send-deterministic applications, also called *linear order* programs in other contexts [50], are appealing for simulation, since they impose less restrictions for the execution of the basic blocks that make the application. An even more restrictive property for an application is to be *deterministic* in which case, both send and receive sequences are always the same.

Communication determinism can be used to develop new message-logging protocols. One of them was implemented in MPICH2 [51], a popular implementation of MPI. The key observation of this algorithm is that it is possible to avoid storing most of the determinants. A protocol based on this property [51] uses uncoordinated checkpoint and a few extra concepts, necessary for the correctness of the approach. Each task will checkpoint in an uncoordinated fashion, but it will keep track of the checkpoint interval, called an *epoch* in this method. For every message sent, a response is always expected from the receiver. That response will notify the sender whether or not the sender has to log the message. The protocol only logs messages that cross epochs from an earlier epoch to a later one. Messages in the same epoch are not logged, since they will be recreated in case of a failure.

2.4.1 Comparison of Pessimistic and Causal Message-Logging

Message-logging protocols require determinants to provide a consistent recovery. The different flavors of message-logging differ in the way determinants are saved. However, the particular mechanisms to ensure that determinants survive a crash may have markedly different performance penalizations.

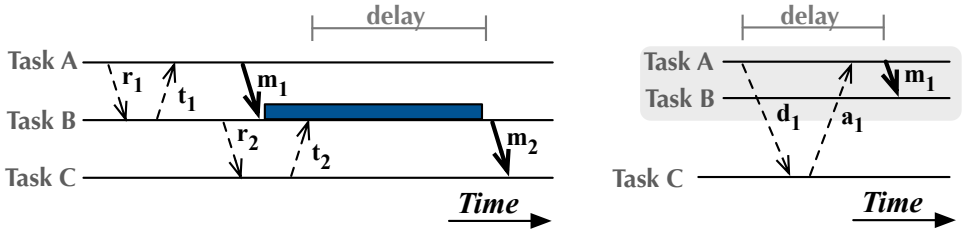
The most popular implementation of messages-logging is the pessimistic approach described above [52]. There are a few implementations of this protocol in HPC libraries [46, 53, 54]. The pessimistic variant of message-logging has the advantage that it is relatively

easy to understand, debug and garbage collect. However, it has several disadvantages for our computational model:

- *High cost on collective communication operations.* Since each message adds extra latency, in collective communication operations implemented through a spanning tree, each level of the spanning tree increments the total time to complete the operation. The final accumulation of latency may be substantial if the collective operations are a bottleneck in the application.

- *Interference.* On a remote message (sent to a task on a different node), before the receiver node is able to deliver the message to the target task, there is an extra trip through the network. That delay in delivering a message may provoke an unintended effect of interference. Figure 2.5(a) shows this situation. The delay occurs because m_2 could have been delivered when r_2 was received, but due to the extra latency and the fact that the sender is busy executing a non-preemptive application code block, message m_2 gets delayed. We have observed this phenomenon causes certain applications to exhibit an *alternate* execution, where two sets of tasks on different nodes do not overlap their execution.

- *Extra cost for local message.* Even when a local message (between tasks on the same node) does not even hit the network, pessimistic message-logging adds a remote message to store the determinant. Figure 2.5(b) shows an example of this case. Both tasks A and B reside on node X. Message m_1 is local, but it still requires a remote notification to store the determinant.



(a) Remote message. (b) Local message.

Figure 2.5: Latency overhead scenarios in pessimistic message-logging.

A way to see the causal message-logging protocol is as an optimization of the pessimistic message-logging protocol. In the causal protocol, we move from storing the determinants at the sender to store them (possibly) at the receivers. A determinant created on a node

might not be replicated, because that depends on whether the node sends a message after it is created. As an optimization, causal message-logging gets rid of the extra network roundtrip per message. That way, collectives perform better and there is no risk of inducing interference in the application since message sends are not delayed. Finally, local messages do not require a remote acknowledgment, since determinants are accumulated at the node level. In conclusion, causal message-logging does not have any of the limitations of the pessimistic approach listed above.

The disadvantage of the causal approach comes in two different places. One is during garbage collection, i.e., the removal of unneeded messages from the log. If an object has stored the effect of a message m into a checkpoint, then message m is not required any more. Garbage collecting is rather straightforward with pessimistic message-logging, but becomes more burdensome with causal message-logging. In the pessimistic case, after an object checkpoints, it sends the largest ticket number processed so far to all other objects that have sent messages to it. Each sender will remove from its message log all messages having a smaller ticket number. In the case of causal message-logging, all determinants must be sent to the senders. However, since garbage collection runs asynchronously with the application, it does not have a major impact on performance. One possible optimization of causal message-logging protocols is to use coordinated checkpoint. Even though checkpoint may be either coordinated or not in message-logging, the coordinated variant makes it easier to garbage collect, since at every checkpoint all data structures and the message log are flushed.

The second drawback of causal message-logging is that during recovery messages and determinants come from different places and the recovering object has to sort them out. The performance penalty for this is not significant but it adds more complexity to the protocol.

2.5 Parallel Recovery

Message-logging features *local rollback*, the ability to only rollback one node in case of a failure. The vast majority of the system does not need to roll back and hence, may stay idle (consuming less energy), make progress on their own or help in recovery. This last option has been explored in the context of a particular computational model, called *migratable objects*.

We assume a parallel application is composed of a set of objects Γ. Each object $\alpha \in \Gamma$ is responsible for carrying out a portion of the computation and holds a fraction of the data. The memory in one object is private and the only way to share information is by

asynchronous method invocation. This means, an object α can call a remote method on another object β. The asynchrony arises from the fact that calling a remote method is in general a non-blocking operation.

The architecture on which the application runs is formed by a set of *processing elements* (PEs), denoted by Σ. In modern architectures a PE may correspond to a core. The set of PEs is connected through a reliable network that does not guarantee FIFO order in its channels. There is a runtime system that orchestrates the execution of an application by assigning objects to PEs, schedules what method has to execute on a particular PE and moves objects around to dynamically adapt to the runtime conditions. To serialize an object, the runtime system relies on the programmer to write a marshaling method for each object. This permits the runtime system to save the state of any object at certain points in the execution where the programmer agreed the object could be moved or checkpointed.

There are several advantages in having user-level checkpoint. First, the programmer may determine at what points in the execution the state of the object is minimum (or small enough) to be saved. Second, it is portable across different architectures. Third, user-level checkpoint allows the program to be run on a different number of PEs than the initial number of PEs used.

This model has been implemented by the Charm++ runtime system [55]. The programmer of a Charm++ application decomposes the computation into *chares* or objects that will react to method invocations by other chares. The number of objects does not need to match the number of physical cores, but usually there are many more objects than cores for the runtime system to have room to overlap computation with communication and to adapt to load imbalances in the system. Thus, we say the programmer in Charm++ *overdecomposes* the application. The ratio between the number of objects and the number of PEs is called the *virtualization ratio*.

The Message Passing Interface (MPI) also fits our model. Each rank in MPI can be conceived as an object that reacts to the reception of messages. However, MPI makes the model more rigid, since it has blocking operations and requires channels to be FIFO. An extension to Charm++, called Adaptive MPI (AMPI) [56] permits MPI applications to run on top of the Charm++ runtime and get the benefits of migratable objects (overlap of communication and computation, load balance, fault tolerance, and more). We use Charm++ as the substrate for the fault-tolerance research described in this dissertation.

The main advantage of using message-logging in the migratabale-objects model comes from the ability to implement *parallel recovery*, a mechanism the accelerates the recovery of the failed PE, reducing to a fraction the time required to redo the work lost due to a failure [5]. Figure 2.10 presents the main characteristics of parallel recovery. The figure

depicts an example of how this scheme works. Let us assume we have a system with just four PEs. There are four objects running on PE B, represented by colored circles. After PE B fails, the runtime system will find a replacement from a pool of spare PEs. We denote the replacement by B' and this PE will take over all the responsibilities that PE B had. The buddy of PE B' is the same as PE B (in this case A) and will provide it with the latest checkpoint. If virtualization ratio is higher than 1, then the checkpoint will consist of multiple objects. In this example, virtualization ratio is 4. Before starting recovery, B' may distribute its objects to other PEs in order to speed up recovery. If the other PEs are idle waiting for B' to catch up, then they may help B' to recover. In this fashion, we can expect to reduce recovery to a fraction of the time (a potential 75% reduction in our case). Notice that PEs A, C and D receive one object each and thus objects are recovered in parallel.

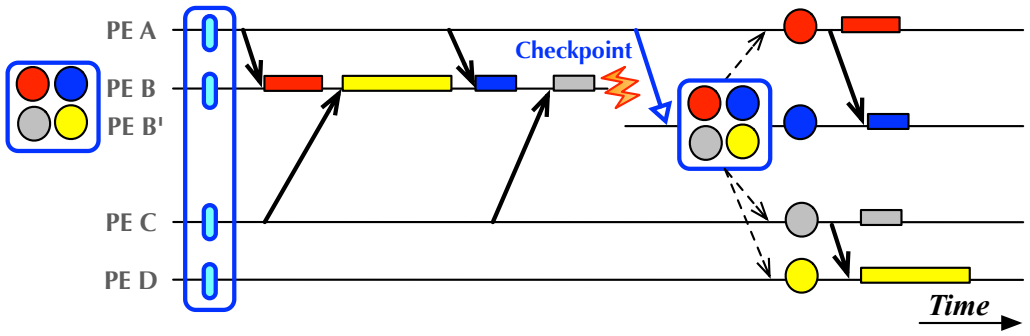


Figure 2.6: Parallel recovery in message-logging.

2.6 Simple Causal Message-Logging

Section 2.4 described the three major disadvantages of pessimistic message-logging. Namely, higher cost of collective communication operations, increased risk of synchronized alternate execution and unnecessary remote control messages. In this section we propose a version of the causal approach which we call *simple causal message-logging* [6]. This protocol is an adaptation of family-based message-logging [57] for the migratable-objects model.

The *simple* part comes from the fact that a determinant needs to be stored in at least one other node than the one it was created on. That contrasts with the traditional implementation of the causal approach that may tolerate up to k concurrent failures. Literature regarding the piggyback of determinants has shown the high cost of tolerating up to k concurrent failures [58]. If we were to tolerate up to k concurrent failures, we would have to

replicate the determinant in at least $k+1$ different nodes. Thus, a determinant that is piggybacked on a message also carries a *time-to-live* (TTL) value that is decremented every time it gets stored in a node. When the TTL value reaches zero, the determinant stops being piggybacked. Besides the number of replicas of a determinant, the number of checkpoints of each PE would need to be incremented to $k+1$. The aggregated cost of these two extensions would be too onerous to bear. Therefore, the simple causal message-logging protocol guarantees that at least one copy of each determinant will survive, i.e., $k = 1$. Literature on failures in HPC systems show that a high percentage of failures only affect a single computational element [31, 59].

The protocol is designed to work with the migratable-objects model of Section 2.5. Thus, parallel recovery can be incorporated in the strategy. This protocol will be extended throughout the rest of the dissertation to include several other considerations to decrease performance and memory overheads in message-logging.

2.6.1 Algorithmic Description

The simple causal message-logging protocol is implemented at the object level. Consequently, each object manages the list of send sequence numbers and the receive sequence of messages. However, messages and determinants are logged at the PE level. Upon reception, every message generates a determinant $\langle sender, receiver, ssn, rsn \rangle$. The protocol is designed to work in tandem with parallel recovery. However, we will only present the description for traditional recovery. An extension to support parallel recovery is presented in Chapter 3. This protocol is subject to the following list of restrictions. It assumes checkpoint is globally synchronized. Load balancing is allowed as long it is immediately followed by a checkpoint call. The protocol tolerates the failure of only one PE per checkpoint period. It may tolerate the concurrent failure of several PEs, as long as all determinants can be recovered. In the following description the *local* qualifier is used for intra-PE entities, whereas the *remote* qualifier is applied to inter-PE entities.

The data structures at the object level are the following:

- `ssnTable`: associates the latest sender sequence number (ssn) for every other object. The method *getSsn* in an object receives an object ID and returns the current ssn.
- `rsnTable`: maps a receive sequence number (rsn) for every combination $\langle sender, ssn \rangle$ of sender and sender sequence number. The method *getRsn* receives the tuple $\langle sender, ssn \rangle$ and returns the corresponding rsn.

The data structures at the PE level that serve all the objects on that PE are the following:

- `msgLog`: stores remote messages sent from objects on that PE.
- `detLog`: stores remote determinants coming from objects on other PEs.
- `detList`: accumulates the list of local determinants that have not been acknowledged. Once a message leaves the PE, it will piggyback the whole collection of determinants on this list.
- `IncarnationNumber`: a number reflecting the incarnation number of the PE. Every time the PE fails, it will increase its incarnation number. This counter is used to discard messages coming from old incarnations.

The message envelope includes the following fields:

- `sender`: the ID of the sender object.
- `receiver`: the ID of the receiver object.
- `ssn`: the sender sequence number between *sender* and *receiver*.
- `dets`: list of determinants piggybacked on the payload. This list of determinants must be safely stored at the PE receiving the message.
- `incarnation`: refers to the incarnation number of the sending PE.

Algorithm 1 SEND(α, msg, β): object α sends msg to object β

1: $msg.sender \leftarrow \alpha$
2: $msg.receiver \leftarrow \beta$
3: $msg.ssn \leftarrow \alpha.getSsn(\beta)$
4: $msg.dets \leftarrow$ `detList` ▷ Piggybacking determinants
5: $msg.incarnation \leftarrow$ `IncarnationNumber`
6: **if** α.PE $\neq \beta$.PE **then**
7: `msgLog.add`(msg) ▷ Storing remote message
8: **end if**
9: `NetworkSend`(msg)

Algorithms 1 and 2 present the procedures for sending and receiving a message, respectively. When object α sends a message msg to object β, the system ensures all the necessary information is added to the message envelope, including the tuple $\langle sender, receiver, ssn \rangle$. The simple causal message-logging is a sender-based protocol. Therefore, the sender logs all

Algorithm 2 RECEIVE(α, msg, β): object β receives msg from object α

```
1: num ← msg.incarnation
2: if OldIncarnation(num) then
3:     DiscardOld(msg)                          ▷ Ignoring old message
4: end if
5: rsn ← β.getRsn(α, msg.ssn)
6: if β.beyond(rsn) then
7:     DiscardDuplicate(msg)                    ▷ Ignoring repeated message
8:     return
9: end if
10: detLog.add(msg.dets)
11: NetworkSendAck(msg.dets)
12: detList.add(⟨α, β, msg.ssn, rsn⟩)
13: Process(msg)
```

the remote messages. The local messages are not stored because they will be lost in case of a failure. At the receiver side, old and duplicate message detection is the first step performed. If the receiving object has already processed that message, it is safe to discard it. Most likely, the message comes from a recovering object. The method *beyond* in an object checks if the object has made progress beyond a particular rsn. If the message has to be delivered, the whole determinant is generated and added to the list of determinants to be acknowledged. The function `Process` may buffer the message if it is not the next message in the sequence. It might happen this is an early message in recovery and must be processed later.

Algorithm 3 ACKNOWLEDGE($dets$): received at PE A

```
1: detList.remove(dets)
```

Algorithm 4 CHECKPOINT(): called at PE A

```
1: ckptMsg ← {}
2: msgLog.clean()
3: detLog.clean()
4: for all objects α do
5:     ckptMsg.add(α.state)
6:     NetworkSend(ckptMsg)
7: end for
```

Algorithms 3, 4 and 5 present the miscellaneous functions of acknowledging determinants, checkpointing and restarting, correspondingly. Once determinants have been acknowledged, they are removed from the list of determinants and not piggybacked anymore. A single determinant may be copied multiple times, depending on the order of messages sent and

Algorithm 5 RESTART(A): received at every PE except A

```
1: for all objects α in A do
2:     Send all determinants of α in detLog
3:     Send all messages bound to α in msgLog
4: end for
```

acknowledge messages received at the sender. The checkpoint mechanism is supposed to be globally coordinated, thus both message and determinant logs can be cleaned at that point. Finally, the restart method is called on every PE other than the one failed, A. The fundamental task for every PE is to forward all the messages and determinants logged for PE A.

2.6.2 Formal Proof of Correctness

Lemma 2.1. *All required determinants are successfully retrieved during recovery.*

Proof Sketch. If a particular object α generated a determinant d at PE A and that determinant was piggybacked and received at some other PE B, then it will be provided by B to A for recovery. It is possible (and valid) to lose some determinants if they did not affect the rest of the system. For instance, if determinant d is piggybacked on message m from A to B and m arrives after the failure notification on B, then m is going to be discarded, because its incarnation number would not match the incarnation number for A at B. In that case, it is possible to lose determinant d because it never affected the rest of the system. This may provoke messages to be received in a different order during the recovery of A, but it would still be a correct execution of the program. □

Lemma 2.2. *All required messages are successfully replayed during recovery.*

Proof Sketch. Note that all remote messages are logged at the sender. Thus, if PE A crashes, all messages bound to A will be replayed again by the senders. If the messages are local, then they will be regenerated by the PWD assumption on the program. □

Lemma 2.3. *There are no orphan objects.*

Proof Sketch. By contradiction. Imagine object β at PE B received a message m from object α in PE A. During the recovery of PE A and all its objects, including α, all determinants and messages are available. Given the PWD assumption and the application of all the available determinants, α will again send message m to β. This is a contradiction, therefore there are no orphan objects. □

Theorem 2.4. *The recovery process in simple causal message-logging is correct.*

Proof Sketch. By Lemmas 2.1, 2.2 all determinants and messages are available for recovery. Additionally, Lemma 2.3 guarantees there is no orphan object. Consequently, the recovery in simple causal message-logging is correct. □

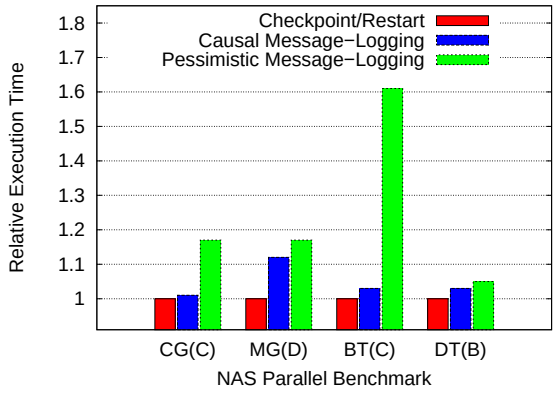
2.7 Experimental Results

Several fault-tolerance algorithms discussed in this chapter have been implemented in the Charm++ runtime system. First, the double local-checkpoint mechanism described in Section 2.3 has two variants. The double in-memory version saves the two checkpoints in the main memory of two different PEs. Its secondary storage counterpart, the double in-disk version dumps the checkpoints to the local disk of two different PEs. Second, the simple causal and simple pessimistic message-logging protocols are implemented at the object level. This means, each object holds a registry of all the messages it has sent to all other objects. Although this bookkeeping is maintained by each object, there are structures at the PE level that log determinants from other PEs. The PE is the unit of failure in this implementation.

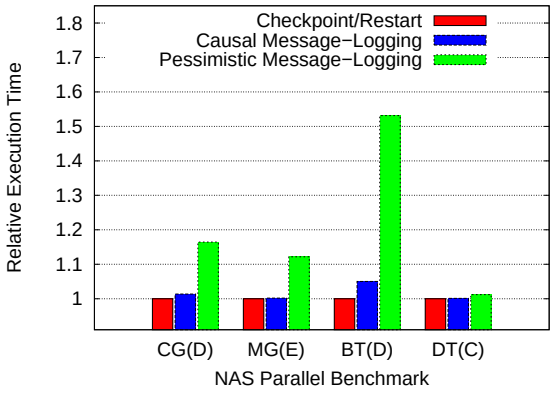
2.7.1 Performance

We present a comparative evaluation between the simple version of the causal and pessimistic approach for message-logging. Since causal message-logging ameliorates most of the drawbacks of pessimistic message-logging, we show the improvement on different benchmarks. Figure 2.7 presents the results of comparing performance of the two protocols with 4 different NAS Parallel Benchmarks (NPB) on Abe supercomputer. Figure 2.7(a) shows the overhead in total execution time relative to checkpoint/restart. There are no checkpoints taken in this experiment. It only shows the overhead during the forward path. In general, causal message-logging shows much lower overhead for all the benchmarks. In particular, the pessimistic approach is more sensitive to communication-intensive programs (for instance, NPB-BT). Figure 2.7(b) shows the results for the same set of programs on 1,024 cores. Causal message-logging shows overall a maximum latency overhead of 5% compared to checkpoint/restart. Pessimistic is way above that margin and latency penalty may rise up to 53% in the case of NPB-BT benchmark.

An important performance concern for message-logging relates to collective communication operations. In order to obtain an idea of this overhead, we designed a collective-intensive



(a) Overhead of message-logging protocols with 256 cores on Abe.

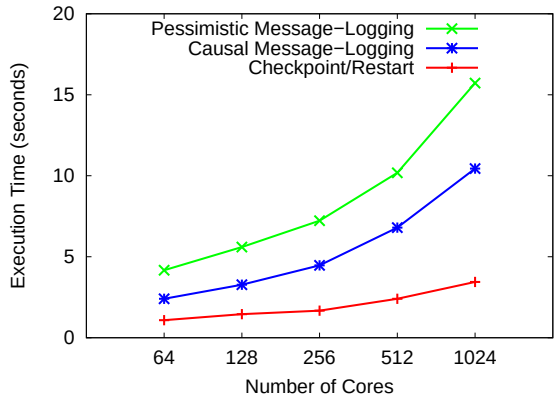


(b) Scale results with 1,024 cores on Abe.

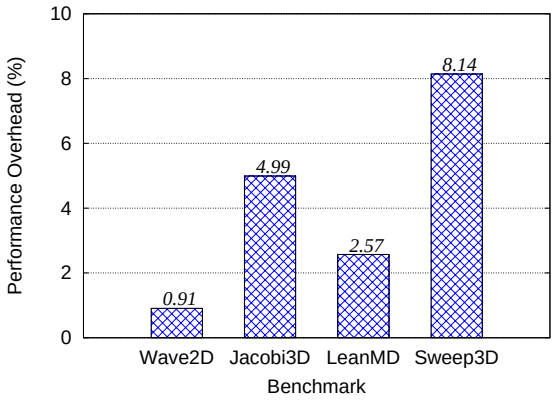
Figure 2.7: Performance overhead of message-logging protocols. Pessimistic message-logging incurs higher overhead than causal message-logging. The penalization of pessimistic is higher with NPB-BT, a communication-intensive benchmark. On the other hand, causal message-logging scales better.

benchmark. It consists in a program that iteratively performs a broadcast followed by a reduction over a set of objects. There is no computation in the benchmark. Thus, it represents an extreme case of a communication-bound program. The implementation of the two collective operations is through a spanning tree that covers all the PEs in the system. Compared to the pessimistic approach, causal message-logging does much better, but it still shows a large overhead when the number of PEs reaches 1,024. Figure 2.8(a) shows the results on Abe supercomputer. The performance overhead of causal message-logging varies from program to program. Figure 2.8(b) presents the execution-time overhead in different applications running on 1,024 cores of Ranger. The spectrum of performance overhead ranges from 0.91% to 8.14%. There are several variables that determine how high the overhead is. Extremely relevant variables are the communication characteristics and the computation/communication ratio of the application. An application that frequently sends messages will require lots of determinants to be generated and handled. This is the case of Sweep3D. Conversely, if the application features a high amount of computation, the communication overhead can be hidden to a certain degree. This is the case with Wave2D and LeanMD. Jacobi3D stands in the middle with a moderate amount of computation but with a well connected communication graph that increases message-logging overhead.

To understand better the limits in scalability of causal message-logging, we show in Figure 2.9 the relative performance overhead of the causal protocol compared to checkpoint/restart. Again, only the forward path penalization is considered. This test used Ja-



(a) Performance overhead of message-logging protocols in an extreme communication-bound scenario.

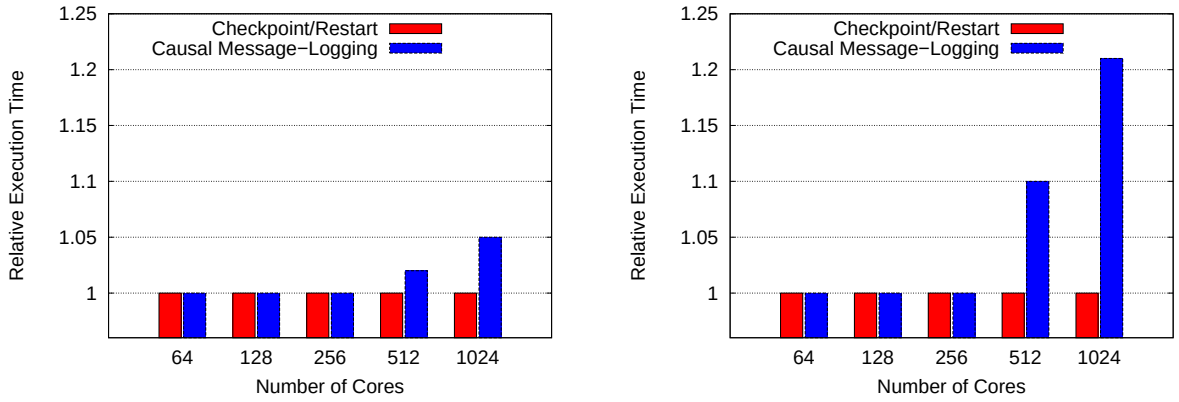


(b) Performance overhead of causal message-logging on different benchmarks.

Figure 2.8: Performance overhead of simple causal message-logging. The particular features of different applications have a different impact on the performance penalization of the protocol.

cobi3D on Abe supercomputer. Figure 2.9(a) presents the weak scale results. The overhead stays below the 5% mark throughout the whole spectrum. However, as the number of cores increases, so does the overhead. The reason for this is that there is a reduction after each iteration of the stencil code and the more cores, the higher the relative contribution of the reduction to the execution time. The strong scale experiment is shown in Figure 2.9(b). The story is different. In this case, the overhead keeps increasing as more cores are added. The results verify the intuition that communication bound applications show higher overhead for message-logging. As more core are added, the relative cost of communication increases in a strong scale setting, elevating the overhead to a value above 20%.

Figure 2.10 shows an experiment about the speedup in recovery using causal message-logging and parallel recovery. We present the results for Jacobi3D with 256 PEs on Ranger supercomputer. We made one of the PEs fail by using `sigkill` to abruptly kill the process running on that PE. All the objects running on that particular PE are immediately lost. The runtime system is equipped with a failure detector and an automatic failure restart that performs all the necessary steps to restore the state of the failed PE. There are 32 objects running per each PE. This virtualization ratio gives us room to use up to 32 PEs to recover in parallel. However, we only present results with maximum 8 PEs helping recovery. Figure 2.10(a) compare the progress rate of checkpoint/restart versus causal message-logging with parallel recovery. The shaded area in the plot represents the time spent on recovery. Checkpoint/restart requires more than 32 seconds for recovery, while causal message-logging



(a) Weak-scale experiment.

(b) Strong-scale experiment.

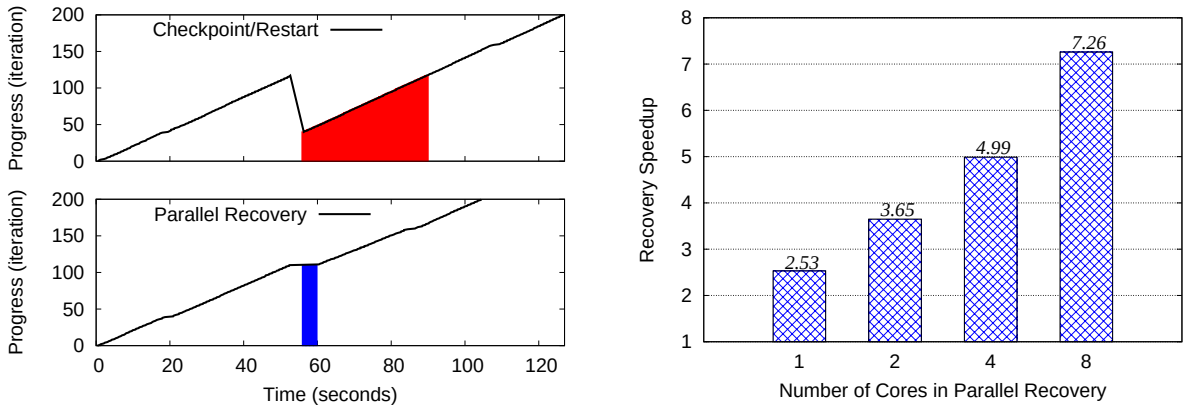
Figure 2.9: Overhead in scaling causal message-logging. The weak scale experiment shows causal message-logging scales well. However, the strong scale experiment suggest the communication overhead starts dominating at the right extreme of the scale.

less than 4 seconds. The plot in Figure 2.10 presents different levels of parallelism during recovery. It shows the speedup in recovery compared to the progress rate during the forward path. It may seem surprising to have superlinear speedup in Figure 2.10 when using just 1 PE to recover. The reason for that behavior is due to the fact that with message-logging there is no delay in receiving most of the messages. A normal execution of the application (what occurs during recovery with checkpoint/restart) will sometimes make objects wait for a message before they can start computation. With message-logging, those messages are already available during recovery and there is no wait. Adding more PEs to the recovery increases speedup. There are, however, diminishing returns when many PEs are added, because then communication among those PEs has to be considered.

2.7.2 Energy Consumption

One of the advantages of message-logging lies precisely on its ability to perform a local rollback. Avoiding a global rollback should translate in potentially a huge reduction in energy consumption during recovery. We examine this advantage of message-logging combined with parallel recovery. In fact, for our experiments with the Energy Cluster, we consider checkpoint/restart, message-logging and parallel recovery as levels in a hierarchy of protocols. The base is coordinated checkpoint/restart that is extended by message-logging, which in turns is augmented with parallel recovery.

Figure 2.11 shows the different energy levels that appears during the execution of Jacobi3D



(a) Progress rate in fault-tolerance protocols. Shaded areas represent recovery time.

(b) Parallel recovery with causal message-logging. Recovery time can be substantially reduced.

Figure 2.10: Evaluation of parallel recovery. Compared to checkpoint/restart, parallel recovery requires only a fraction of the time recover. The more PEs involved in recovery, the faster it gets.

on the Energy Cluster. We present the power draw of one node with a power reading frequency of 1 second. The program executes 200 iterations in total and checkpoints at iteration 50 and 150. This figure only shows the forward path, but it is clear that during checkpoint (double in-disk variant), the power goes down to almost the idle power. More precisely, the average idle power is 47 W, while the average checkpoint power is 51 W. The power raises to 106 W during the execution of the program. A similar experiment but using double in-memory checkpoint showed the same pattern in the power levels.

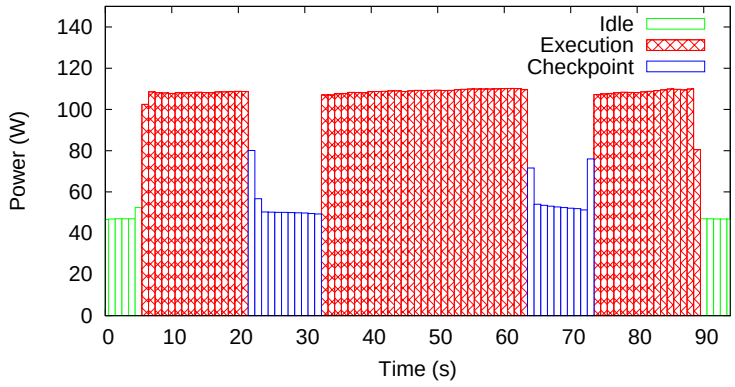
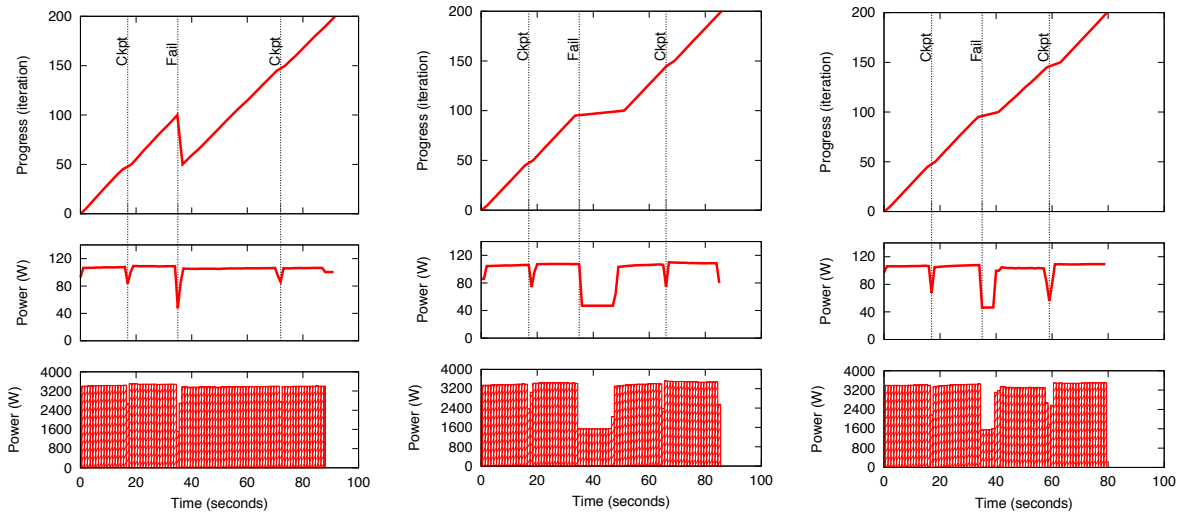


Figure 2.11: Power levels during checkpoint/restart. At checkpoint time, the power draw goes down to almost the idle power level. During execution, the power draw reaches a higher level. The maximum power draw depends on the application and how intensely it uses the computational resources.

A comparative evaluation of the fault-tolerance protocols is presented in Figure 2.12. We used the causal variant of message-logging. The top row of the figure shows the progress rate of the Jacobi3D program running the same configuration as above. However, this time a failure is inserted at second 35 in all cases. In the progress rate we observe a slight improvement of message-logging. This is due to the fact that message-logging recovers the work with a network with almost no latency. Therefore, the probability of interference is small and the recovery is faster. Even when message-logging has a penalization of 5%, it manages to complete the total number of iterations faster than checkpoint/restart. Parallel recovery, reduces the recovery time to a fraction and is the faster of all three protocols. In this case, parallel recovery uses 8 PEs to recover from the failure of one PE. The total speedup is 7.3, a value close to 8, the maximum recovery speedup expected.

The second and third rows of Figure 2.12 present the power draw of one node and the power draw of the whole system. The shaded are behind the curve of the bottom row should represent the energy consumed during the execution. It is clear that checkpoint/restart maintains the power level almost constant across the execution. Message-logging reduces power during recovery. Parallel recovery reduces power in recovery and in addition reduces the time to recover the work lost. In total, checkpoint/restart consumes 299 kJ, message-logging 255 kJ (85% of checkpoint/restart) and parallel recovery 203 kJ (68% of checkpoint/restart).



(a) Checkpoint/restart. (b) Message-logging. (c) Parallel recovery.

Figure 2.12: Energy profile of different fault-tolerance methods. Message-logging is able to substantially decrease the energy consumed during recovery. In addition, parallel recovery manages to reduce the recovery time to a fraction.

2.8 Discussion

The migratable-objects model provides a natural substrate to build fault tolerance mechanisms. Thanks to the load balancing infrastructure, the checkpoint mechanisms are straightforward to implement. Additionally, parallel recovery can be naturally incorporated. Additional mechanisms for resilience in HPC have been developed using the migratable objects model. An important example is proactive fault tolerance [60, 61], where a failure predictor is used to *avoid* failures through preventive migration. Upon reception of a warning, a PE evacuates all its objects to other PEs, making unnecessary any rollback in case of a failure.

The causal variant of message-logging manages to reduce the performance overhead compared to the pessimistic version. It does so by removing the synchronization nature of determinant storing in the pessimistic approach. Causal message-logging is more asynchronous and only stores the information when it is required. The general lesson is that message-logging protocols should not synchronize the execution of the application, neither during forward path nor during recovery. Otherwise, the potential benefits of message-logging may be offset by the high cost in performance.

Parallel recovery is a fundamental tool in advancing message-logging as a promising fault-tolerance alternative. Not only is it able to reduce the total execution time, but it also reduces the energy consumption.

The experiment in Figure 2.12 showed how the considerations in rollback-recovery change when energy is the function to minimize. The execution of an application goes through different power levels, being the checkpoint level considerably close to the idle power. The direct conclusion of this fact is that checkpoint is *cheaper* than execution in terms of energy consumption. Thus, in order to decrease the total energy consumed of an application on a faulty machine, it may be worthwhile to increase the checkpoint frequency. That way, the amount of work to recover is smaller and less expensive in energy terms. Having more checkpoints than the optimal number for a minimal execution time may hurt performance, but it may definitively decrease total energy. The traditional thinking of *minimize execution time to minimize energy* is definitively not true, at least on a faulty environment.

2.9 Related Work

The idea of message-logging was initially applied to a fault-tolerant system in the context of on-line transaction processing environments [62]. The main idea of this effort concentrated on providing software tolerance of single hardware failures for message-based communication

systems. Each *primary* process would have one or more *backup* processes that were capable of continuing execution if the primary process failed. Global synchronization points would serve as checkpoints for the processes in the system. Therefore, messages sent since the last synchronization point had to be stored in order to be replayed to the backup process after a crash. The backup process was supposed to read the messages in the exact same order as the primary had read them. To this effect the system used a replication mechanism where each primary process would be mirrored by a backup process. A message sent to a primary process has to be sent to the backup too. The backup process would receive the messages but not process them. That way, in case of a crash, the backup process would take over the position of the primary and would replay the messages in its own log to catch up with the rest of the system. Atomicity in the delivery of the messages was ensured by the hardware. Also, counters would be used to suppress duplicate messages.

Fundamentally, migrating a task and checkpointing a task are very similar. Both functionalities require the serialization of the tasks. This parallel between task migration and task checkpointing was drawn in the MPI model with a tool called CoCheck [63]. Within the same framework, CoCheck provides disk checkpoint and dynamic migration of MPI ranks. CoCheck implements an algorithm that finds *global consistent states* [20]. A global state of a system is formed by the state of each task plus all messages that were in transit when the snapshot of the system was taken. In a consistent global state, if a receive of a message is part of the global state, then the send of such a message is part of the state. Conversely, if the send of a message is part of the state, but the receive is not, then the message must be stored as part of the checkpoint. CoCheck maintains a mapping of MPI ranks to IP addresses in a network and that mapping changes when a migration is enforced. The task migration in CoCheck is synchronous with the execution of the system. This means before CoCheck can migrate an MPI rank, it has to ensure that all the communicating ranks hold back all messages. Once the rank has been successfully migrated to its new location, the communication with that rank resumes. Migration time is usually measured in a handful of seconds. CoCheck relies on system-level checkpoint.

Process-level live migration has also been applied to MPI applications [64]. The idea in these projects is to combine health monitoring of nodes with live migration to form a proactive fault tolerance mechanism. A migration of an MPI rank is *live* because it occurs concurrent with the execution of the application. Upon the reception of a warning about an impending failure, the system starts migrating a process by shipping the whole memory footprint of the process to the destination. Given that the MPI rank may execute during migration, the set of dirty memory pages have to be sent before the migration process is complete. Once this is done, the system enforces a consistent state in which all in-flight

messages are stored and all processes stop while the migrating task completes the migration. After the MPI rank is finally settled on the new location, the communication channels are reestablished and the computation can continue. This scheme is based on BLCR [30] and it performs system-level checkpoint. The migration time obtained was in the order of seconds.

A comparative study of checkpoint versus migration [26] introduced an analytical model to understand which factors affect performance. This study provides several future scenarios with plausible values for the parameters of the model. It argues that migration is more beneficial in the short term and will eventually be as powerful as checkpoint as we move toward larger systems. This model assumes a perfect failure predictor. A different model that incorporates both proactive migration and checkpoint is FT-Pro [65]. It uses a stochastic model to adaptively schedule checkpoints and migrate processors when impending failures are detected.

Perhaps the most intuitive way to deal with failures is to provide redundancy in the computation. Imagine each task t has a copy t' performing exactly the same computation. If the node on which t is running fails, then its copy t' may take over its place and continue with the execution. The advantage of this method is that there is no need to store any checkpoint and to roll back to any previous state, since a task and its copy have the same state at any point in time. An implementation of this idea in Message Passing Interface (MPI) has shown the benefits of the approach if failure rates are extremely high [66, 67]. Double modular redundancy makes it possible to recover from hard errors and detect soft errors. Triple modular redundancy could detect and correct soft errors.

The drawback of this method is that it incurs a high cost. In the best case, the resources have to be duplicated, exhausting any allocation on a machine twice as fast. Moreover, in order to keep a task consistent with its copy, additional verification is necessary. For example, before delivering a message to a task the runtime system should verify that both the task and the copy have received the message. This will add certain overhead to the forward path.

We believe that full replication of all the tasks in the system may become impractical in exascale. In fact, using replication will bound the efficiency of the system to 50%, even for an application that scales perfectly all the way to millions of nodes. It is to be seen if *partial* replication of the system, where only a subset of the tasks are replicated, is promising for some scenarios. At any rate, we will not consider replication as a major contender to provide fault tolerance to HPC applications. The rest of this document will be devoted to rollback-recovery mechanisms.

Parallel recovery achieves acceleration during recovery by spreading out the objects on the failed PE to multiple other PEs. The same effect can be obtained with other parallel

programming models. For instance, task parallelism naturally allows the tasks to migrate from one processor to another. Work stealing computations guarantee that tasks will migrate during computation. A data-driven fault-tolerance approach for this type of computations allows recovery in parallel [68]. The authors propose the use of a marker-based mechanism that enforces idempotent data structures. A structure is said idempotent if the execution of the same operation does not alter the final result. An example of this occurs with the *put* operation on a memory region. However, non-idempotent operations must be handled in a special way. Therefore, a marker exists per each task and each data region. This marker identifies update operations from the execution of a task. If the task fails in the middle of a computation, the recreated tasks will attempt to perform the same set of operations. Markers help to prevent multiple inconsistent updates. In some sense, the markers play the role of determinants, avoiding duplicate operations. The parallelism during recovery comes once a crash is detected and the task subtree is recreated. Since during recovery, many processors may be idle, they will be able to help in executing the recovering tasks.

CHAPTER 3

Fast Message-Logging

Programming languages are a fundamental tool to help humans communicate with computers. It is not surprising to find a plethora of programming languages. After all, they all are a natural extension of our human need of developing languages and interact with our environment. There are more than $6,000$ natural languages known and more than 600 notable programming languages. These artificial languages to program machines come in many different flavors, ranging from a wide scope of expressiveness and some with highly sophisticated properties. There is usually a tradeoff between the freedom with which programs can be written and the safety of a particular programming language.

One example of this compromise appears in type systems. Languages in the *Lisp* family have usually used dynamic typing, which is less strict than many statically types languages. Hence, symbols in programs written in Lisp get dynamically a type according to the value they hold at certain point in the computation. A symbol that represents a string at the beginning of the program may transition to a number in the middle of the computation and end up as a list. This flexibility permits the user to write code without the burden of declaring the types of each symbol. It also helps in reusing symbols for different parts of the computation where they may have the same meaning but different type. On the other hand, programming languages from the *C* tradition have relied on a strong type system that requires programmers to make the type of each variable *explicit*. Although it is more cumbersome to write programs in this fashion, it avoids hard-to-track bugs that may appear as a result of a liberal type mechanism. The discipline of declaring types also helps the memory allocator to efficiently pack data and optimize data transmission.

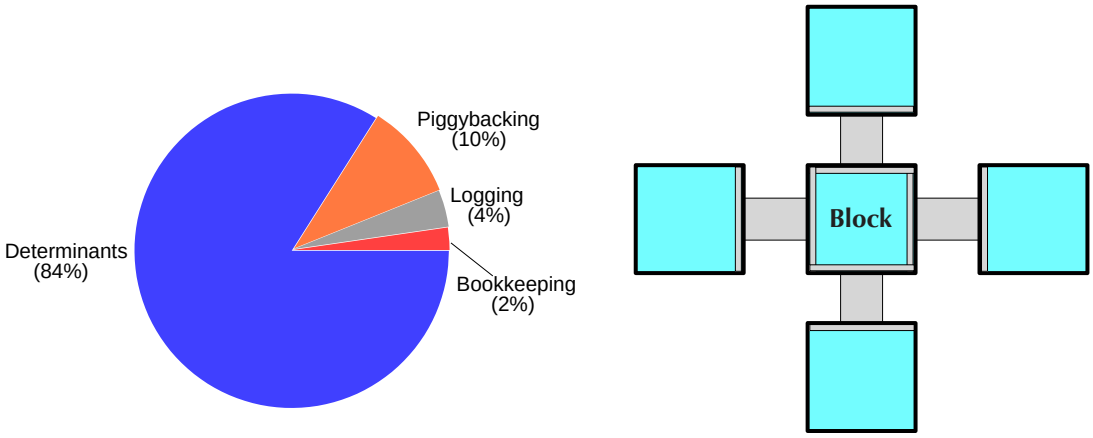
Not only is type systems a difference between programs written in Lisp and C, but also the two different paradigms these two languages come from. In the functional programming paradigm, which has Lisp as an archetypical example, the programmer focuses on *what* data

is required and what transformations are needed to perform a computation. The usual control flow mechanism is recursion and the primary manipulation unit is a function. There is little focus on the state of the system. Conversely, in the imperative programming paradigm represented by C, the programmer focuses on *how* the computation should be carried out. The flow control mechanisms include loops, conditionals and particularly variable assignments. In this paradigm, the state of the program is fundamental. A computation is seen as a transition of states from start to end. Although the functional paradigm enjoys cleaner expressions of the programs, it has struggled to provide the same performance as its imperative counterpart. By making more explicit how computation should be performed, the programmer can give a key insight on how to decrease execution time.

This is the main reason the HPC community has mostly used imperative languages. Furthermore, highly scalable codes in HPC usually follow a method that makes additional information explicit. Two big paradigms for parallel codes are shared memory and message-passing. The former provides the notion of a common set of variables all tasks have access to. The runtime system is in charge on finding the actual location of a variable and handling the concurrent accesses to those variables. The latter paradigm forces the programmer to specify *where* the variables will reside. Each task has its own private memory and the only way to update values and share information is through messages. The message-passing paradigm dominates scalability.

In this chapter we explore a scripting language that makes the control flow explicit. This is a language extension to Charm++ that provides certain structures and tame the relative flexibility in which messages can be processed at their destination in the migratable-objects model. These extra constructs in the language are referred as SDAG or *structured dagger*. Using programs written in SDAG, we aim to reduce the number of determinants generated in the program and reduce the total execution-time overhead of message-logging.

Determinants play a major role in the performance penalization of message-logging. Figure 3.1(a) presents the results of an experiment that reported the different components of the slowdown imposed by message-logging. Using $1,024$ cores on Stampede and the LULESH benchmark, we examine the four sources of performance loss for the causal message-logging protocol. *i*) *Bookkeeping* refers to the mechanism that assigns sender and receiver sequence numbers to the different messages. It also checks for duplicate messages upon reception of every message. Its relative contribution to the total slowdown is little over 2%. *ii*) *Logging* represents the cost of storing the messages in main memory and all the indirect effects of this. The cost of logging messages is about 4%. *iii*) *Piggybacking* overhead is derived from increasing the envelope size of each message to piggyback the sequence numbers, sender, and receiver of a message. The cost of this overhead goes up to 10%. *iv*) *Determinants*



(a) Contribution of each factor to message-logging performance penalty.

(b) Communication structure in LULESH.

Figure 3.1: Performance cost of determinants in LULESH. The main source of the performance penalty of message-logging with LULESH comes from determinants. The communication structure of LULESH, however, suggests there is a way to avoid all determinants.

represents the contribution of creating, storing, sending, and acknowledging determinants. It is the dominant contributor of performance overhead with 84%.

Figure 3.1(b) shows the big opportunity SDAG represents to reduce the alarming cost of determinants in Figure 3.1(a). The program LULESH comes from a big family of codes collectively referred to as *stencils*. These programs work on a multidimensional grid by applying an operation to each element. The usual way to distribute the data among tasks is by splitting the grid into *blocks*. In Figure 3.1(b) we observe a two-dimensional grid and a block with all its neighbors. As the computation progresses the blocks will exchange the border elements with each neighbor in every iteration before proceeding to apply the transformation of its own elements of the grid. SDAG provides a mechanism to express this type of computation explicitly, but more importantly, in a very simple way. Since the migratable-objects model does not provide any guarantee in the order of messages from the same sender, then messages from different iterations can get intermingled. SDAG offers a way to tell the runtime system that the particular computation method must be executed when certain messages have arrived. Besides, a *reference number* is used to separate messages from different iterations.

This is a list of the focal points in this chapter:

- A description of a particular kind of programs and high level programming language constructs that exposes the determinism in communication is presented (§ 3.1).

- The design of *fast message-logging*, a protocol that removes all determinants in this type of programs (§ 3.2).
- A comparative evaluation between simple causal message-logging and fast message-logging is offered (§ 3.3).

3.1 Removing Determinants in Parallel Programs

We will use the migratable-objects model described in Section 2.5. The underlying machine is formed by a set Σ of PEs. We assume the network is reliable but does not ensure FIFO ordering in the delivery of messages between any pair of PEs. The application is decomposed into a set Γ of objects. We assume there is no shared memory in the program and the only mechanism to exchange information is via message passing. In particular, the objects of the application are *reactive* and execute a method upon the reception of a message. A similar paradigm is Active Messages [69]. This asynchronous mechanism provides a message-driven execution of the program. All message sends are asynchronous, even the contribution to reductions.

In this model, each message has a *type*, determined by the particular method that gets triggered when it is received. Thus, it is possible to distinguish between two messages based on their type. Furthermore, messages of the same type can also be differentiated by the particular combination of sender object and receiver object. Finally, each message may carry a *tag* (the reference number in SDAG) that is used to decide whether to process a message at reception. The tag can be used to further separate two otherwise identical messages. The combination of type, sender, receiver, and tag is an essential component of a message-logging infrastructure.

One of the salient features of the migratable-objects model is the ability to dynamically relocate objects. Initially, the runtime system distributes the objects across the set of PEs. As the execution progresses, objects may be shuffled around to optimize performance, energy efficiency, fault tolerance, or any metric the runtime system attempts to optimize. In order to migrate, every object must implement a serialization interface that allows the runtime system to pack the state of the object and ship it to its next host. There is also a contract between the runtime system and the programmer about when it is legal to move the objects. For the purpose of this chapter, we will assume the objects can only migrate at global synchronization points in the application. These places are clearly identified by the programmer. The serialization infrastructure is also used to checkpoint the objects. In this model, a checkpoint

is viewed as a migration to some storage in a PE (main memory, local SSD, local disk, etc).

The migratable-objects model is able to express a wide variety of parallel programs. In particular, it is very well suited for a class of programs named as *stencil codes*. These programs are iterative kernels that update elements on a grid in a very structured way. Partial differential equations (PDEs) are a good source for this type of codes. Usually, to numerically solve a PDE, a discretized version of the space is required. The space can thus be represented by a grid or mesh. Other types of stencil codes are used in image processing, computational fluid dynamics, and other kinds of computer simulations.

The nature of stencil codes consists of applying an operation to all the points in the grid until some convergence criteria is met or after certain number of iterations have been completed. In a parallel implementation of this type of codes, the whole grid is split into *blocks*. Each processing element holds a subset of the blocks. The computation proceed by iteratively exchanging some values between neighboring blocks, applying an operation over the elements in the blocks and following to the next step. Most of the time, the values exchanged between blocks correspond to the neighboring elements of each block. The communication is very structured and does not change during the execution. The name *stencil* actually comes from the fixed pattern in which message exchange takes place.

A traditional example of a stencil code is a Jacobi or Gauss-Seidel kernel over a two-dimensional space. Figure 3.1(b) represents the structure of this particular code. A rectangular grid is split into blocks, over which a relaxation code will be applied. In each iteration, every element in a block requires the values of the neighboring positions to compute its own value for the next iteration. In a block, the internal elements have all that information available. However, for the elements on the extremes of the block, some of the values belong to a different block. We refer to these extreme values as *ghost* values. The communication pattern in Figure 3.1(b) shows a block and its four neighbors with which it will exchange the ghost values. This program formulated in the migratable-objects model is shown in Figure 3.2.

Two types of objects are shown: `Main` and `Block`. The former orchestrates the execution of the total number of iterations in the program. It initially broadcasts the message `start` to all blocks (line 5). The latter represents each block and handles exchanging messages between all the blocks. Each iteration starts by sending the ghost elements to the neighbors (line 15). Then, each block must keep track of how many ghost-element messages it has received. Once the counter has reached the total number of neighbors, the block proceeds to apply the computation to its elements. At the end of every iteration (line 23), all the set of blocks contribute to a reduction that returns the control to `Main`. The cycle starts again until the total number of iterations is completed. Note that the reduction after each

```
1  class Main{
2        Collection<Block> blocks;
3        method main(){
4              iteration = 0;
5              blocks.start();
6        }
7        method reduction(){
8              iteration++;
9              if(iteration <= TOTAL_ITERATIONS)
10                   blocks.start();
11       }
12 }
13 class Block{
14       method start(){
15             sendGhostElems();
16       }
17       method ghostElems(msg){
18             copyElems(msg);
19             counter++;
20             if(counter == neighbors){
21                   counter = 0;
22                   compute();
23                   contribute(Main::reduction);
24             }
25       }
26 }
```

Figure 3.2: Program structure of a two-dimensional stencil code. Each block exchanges the ghost elements with its neighbors in each step. There is an asynchronous barrier after each iteration.

iteration is inevitable in this model. Since the channels are not FIFO in delivering the messages, then it is possible for a couple of messages between neighboring blocks to go out-of-order. Therefore, a synchronization must be used to avoid such scenario. The reduction effectively separates messages from consecutive iterations.

The very nature of the migratable-objects model offers a lot of flexibility in the way the parallel program executes. It does, however, introduce concerns regarding the order in which messages are going to be received. The `counter` in Figure 3.2 reflects the palliative effort in the program to allow concurrency but avoid erroneous receptions. The same effect can be achieved through a high-level script language that expresses the control dependencies between certain types of events. Additionally, this script language must retain the advantages of the reactive characteristic of objects in the program. To illustrate the way a high-level description would work with the same example as in Figure 3.2, we show the new version of the code in Figure 3.3.

The high-level script in Figure 3.3 features various grammatical constructs that alleviate

the issues a programmer faces when writing code in the migratable-objects model. The main difference between the two versions of the code resides in the fact that the control mechanism is moved away from the `Main` object. The only responsibility of the `Main` object is to spawn the start of the program (line 4). The number of iterations is controlled by the `Block` objects (line 9). Each iteration will consist in sending the ghost elements to the neighboring blocks, followed by the reception of messages and the computation code. The first grammatical construction is the `overlap` region that allows the execution of its enclosing statements in any order. If the statements are all the same, it may be specified as a parameter. For instance, the `overlap` construct in Figure 3.3 (line 11) has `neighbors` as parameter, meaning it allows the reception of the `ghostElems` messages in any order. This clearly expresses the structure of the code, that requires the ghost data from all the neighbors before performing the computation. The second grammatical construct is the `when` statement that specifies a message type and a tag (line 12). In the example the message type corresponds to the transmission of ghost elements and the tag matches the iteration number. Using tagging removes the need of a synchronization call after every iteration, because it separates messages from different iterations with otherwise equal type, sender and receiver.

The code in Figure 3.3 makes explicit the messages that must be received before the computation can take place. It defines the control dependencies in the program. Given that message receptions are specified in the code, this high-level description promotes a *receiver centric* view of the program. However, it still retains the flexibility of the model by allowing different reception orderings via the `overlap` construct. Permitting different sequences of message receptions may be a source of non-determinism. However, if the behavior of the program is the same, regardless of the reception order of messages within an `overlap` region, then we say the statements in the region *commute* and any ordering in the reception of those messages is always correct. Note that different sequences of message receptions may lead to a different order of messages sent. However, a different order in the sending of messages is natural in the system model. The receiver will have to guarantee that messages are actually processed in the right order.

One implementation of the high-level scripting language presented above is called *Structured Dagger*(SDAG) [70]. This scripting language allows the Charm++ programmers to make explicit some data and control dependencies in the code.

Expressing more clearly the control and data dependencies in the program permits not only eliminating artificial synchronization calls, but effectively removing determinants. The reason of existence of determinants is to guarantee a consistent recovery. Therefore, determinants ensure messages are received in the same order during recovery as they were before the failure. Additionally, the combination of $\langle sender, receiver, ssn \rangle$ is used in discarding

```
1  class Main{
2        Collection<Block> blocks;
3        method main(){
4              blocks.start();
5        }
6  }
7  class Block{
8        method start(){
9              for(iteration=1; iteration<=TOTAL_ITERATIONS; iteration++){
10                   sendGhostElems();
11                   overlap[neighbors]{
12                         when ghostElems[iteration](msg) {copyElems(msg);}
13                   }
14                   compute();
15             }
16       }
17 }
```

Figure 3.3: High-level script for program in Figure 3.2. The synchronization reduction after each iteration is removed. To handle message reordering, iteration numbers tag each message.

duplicate messages. In the stencil code for the two-dimensional stencil of Figure 3.1(b), it is possible to avoid the generation of determinants if a high-level script is used. Figure 3.3 shows that a `Block` would receive the four messages from its neighbors in every iteration before computing and sending out the messages for the next iteration. If a block α would be recovering, then the high-level structure of the code would order all the messages being resent from the other objects. No determinants are required to guarantee a successful recovery. The other objects should, nevertheless, discard duplicate messages.

Using the stencil code as an example, we provide a list of conditions for the total elimination of determinants in a program expressed in a high-level language:

1. **Unique messages.** It should be possible to uniquely identify each message. Besides the combination of $\langle sender, receiver \rangle$, each messages should be tagged with a $msgID$ that will tell apart otherwise identical messages. The $msgID$ may be a composition of message type and iteration number, for instance. That particular combination would make messages unique in stencil codes.

2. **Commutative overlap regions.** The statements in `overlap` regions must commute.

3. **Explicit causal ordering.** The program must make explicit the causal order between two messages.

In addition, if determinants disappear from the message-logging layer, it must be guaranteed that all internal structures in the runtime system are still correct. This includes all the data structures for load balancing, checkpointing, collective communication operations, etc.

3.2 Fast Message-Logging Protocol

Using the insight from the previous section and the background work of Chapter 2, we present a new breed of message-logging protocols. We name it *fast message-logging* because it focuses on accelerating the three sources of overhead in a resilience solution presented in Figure 1.2. This is brief justification about why it is fast message-logging:

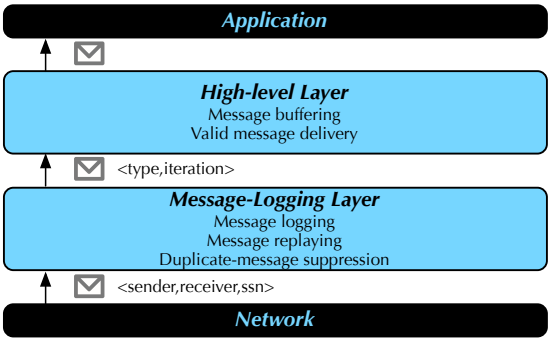
Fast forward-path By removing determinants from an execution, it reduces the slowdown of message-logging. According to Figure 3.1(a) determinants are the main source of overhead, so eliminating them should bring the performance overhead to a minimum.

Fast checkpoint It uses local checkpoint to avoid checkpoint-time congestion in the file system. This reduces the robustness of the system, but just by a tiny margin, given that most failure in HPC systems only involve a single node [59].

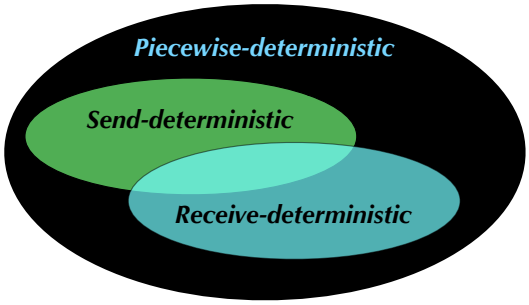
Fast recovery It uses parallel recovery to accelerate the recovery of the failed components.

The fast message-logging only generates message identifiers and does not create determinants. At send time, each message is labeled with $\langle sender, receiver, msgID \rangle$. This information will be used to eventually ignore messages if they are repeated. It relies on the high-level scripting infrastructure to buffer early messages and to deliver them in a correct order for the program. This way, there is a clear separation of concerns with respect to the functions that must be executed during recovery. Figure 3.4(a) show the way this protocol achieves a separation of concerns between the layers in the software stack. The bottom layer stands for the message-logging protocol that is in charge of reacting to a failure. This mainly represents performing two tasks. The first is to replay the messages to the failed objects. The second task is to suppress duplicates during recovery based on the tuple $\langle sender, receiver, msgID \rangle$. The top layer is the high-level language infrastructure that guarantees the consistency in the state of the failed objects by delivering the messages in the correct order.

We call the type of programs that comply with all the conditions to remove all the determinants is called *receive deterministic*. Even when receives and sends may not be deterministic, the state of the objects will nevertheless be the same. Figure 3.4(b) shows a Venn diagram with the relationships between piece-wise deterministic, send-deterministic and receive-deterministic programs.



(a) Separation of concerns with the fast message-logging protocol.



(b) Relationships between piecewise, send and receive determinism.

Figure 3.4: Fast message-logging protocol. The functionalities of the protocol are split with the high-level scripting infrastructure. The type of programs that can run with this protocol overlap send-determinism and require piece-wise determinism.

3.2.1 Algorithmic Description

The fast message-logging algorithm assigns a message identifier $msgID$ to each message. There are various sources for this identifier. If the application is send-deterministic, the protocol may assign a sender sequence number (ssn) to each message based on the combination $\langle sender, receiver \rangle$. If the application is a receive-deterministic stencil, the $msgID$ can be the concatenation of iteration and message type. Otherwise the message type and the tag associated with that message will form the identifier for the message.

There are a handful of major data structures that keep the protocol correct. The structure `idTable` returns the $msgID$ for each message and combination of $\langle sender, msg, receiver \rangle$. For each of the cases explained above, this structure will return a unique identification for each message. The structure `dupTable` determines whether a message is a duplicate or not. Again, depending on the properties of the application, this structure can be optimized to improve performance. The structure `msgLog` stores all messages sent between the PEs. Finally, a couple of lists keep track of objects that have been distributed to other PEs for parallel recovery. If an object α resides in a PE A that crashes, α might be sent to other PE B for recovery. In that case, we refer to α as an *emigrant* from the perspective of A and as an *immigrant* from the perspective of B. The sets `listImmigrants` and `listEmigrants` store the list of objects in each category, respectively.

The algorithms 6 and 7 describe the process for sending and receiving a message, correspondingly. At the sender side, messages must carry the combination $\langle sender, receiver, id \rangle$. All messages are stored in the message log. The reception of a message includes verifying the messages is not a duplicate. Once this is ensured, the message is passed to the layers

above to be correctly processed. This may include buffering the message, forwarding the message to other PE or delivering the message to the application.

Algorithm 6 SEND(α, msg, β): object α sends msg to object β

```
1: id ← idTable.getID(α, msg, β)
2: msg.id ← id
3: msg.sender ← α
4: msg.receiver ← β
5: msg.incarnation ← IncarnationNumber
6: if α.PE ≠ β.PE then
7:     msgLog.add(msg)                          ▷ Storing remote message
8: end if
9: NetworkSend(msg)
```

Algorithm 7 RECEIVE(α, msg, β): object β receives msg from object α

```
1: num ← msg.incarnation
2: if OldIncarnation(num) then
3:     DiscardOld(msg)                          ▷ Ignoring old message
4: end if
5: flag ← dupTable.getFlag(α, β, msg.id)
6: if flag then
7:     DiscardDuplicate(msg)                    ▷ Ignoring repeated message
8:     return
9: end if
10: Process(msg)                                ▷ Forward to high-level layer
```

Fast message-logging relies on globally coordinated synchronized checkpoint. The programmer uses global synchronization points in the application to trigger the checkpoint calls. Algorithm 8 presents the steps included in the checkpoint process. First, all immigrant objects are send back to their original PEs. These objects may have been migrated to a PE for parallel recovery purposes. Next, a PE waits for all its emigrant objects to arrive. The message log is cleaned up then and a new checkpoint message is built with the state of all the objects.

Once a failure has been detected, the runtime system notifies the rest of the PEs about the crash of one PE. Let us assume PE A fails, thus Algorithm 9 shows the steps after each PE receives the failure notification. It merely consists in replaying the messages in `msgLog` bound to objects in PE A. At the same time, PE A follows the recovery procedure, that includes Algorithm 10 to distribute all its objects to as many PEs are involved in parallel recovery. The set $\{A_1, A_2, ..., A_P\}$ stands for the set of other P PEs helping the recovery of A.

Algorithm 8 CHECKPOINT(): called at PE A

1: Send all objects α in `listImmigrants`
2: Wait for all objects α in `listEmigrants`
3: $ckptMsg \leftarrow \{\}$
4: `msgLog.clean()`
5: **for all** objects α **do**
6: $\quad ckptMsg.add(\alpha.state)$
7: $\quad$ `NetworkSend`($ckptMsg$)
8: **end for**

Algorithm 9 RESTART(A): received at every PE except for A

1: **for all** objects α in A **do**
2: $\quad$ Send all messages bound to α in `msgLog`
3: **end for**

Algorithm 10 RECOVERY(): called at PE A

1: **for all** objects α in A **do**
2: $\quad$ Distribute α to a PE in $\{A_1, A_2, ..., A_P\}$
3: $\quad$ Add α to `listEmigrants`
4: **end for**

3.2.2 Formal Proof of Correctness

Lemma 3.1. *All necessary messages for recovery are available.*

Proof Sketch. Let us assume PE A crashes. All remote messages sent to objects in A have to be available at their sender PE. During restart, those messages will be replayed form the message logs. Since we assume PWD applications, all the local messages will be regenerated after the causally dependent messages are received and the necessary computation takes place. Note that in the case of parallel recovery, an object that was distributed to a different PE will get its messages thanks to the forwarding mechanism in the high-level layer. □

Lemma 3.2. *All replayed messages are received in the same order as before the failure or in an equivalent order.*

Proof Sketch. During the recovery of PE A, all necessary messages will be resent again. Duplicate messages are discarded by the message-logging layer using the `dupTable` data structure and the combination $\langle sender, receiver, id \rangle$. Since messages can be uniquely identified, then the high-level layer will deliver them in the same order as before the crash or in an order that is consistent with the state of the rest of the application. □

Lemma 3.3. *There are no orphan objects.*

Proof Sketch. By contradiction. Let us assume object β is an orphan. It other words, its state depends on a message m that does not get resend during recovery. The original sender of message m was object α, which used to live on the failed PE A. Given that object α recieves all the messages it received before the crash and those messages are delivered in the same order (or an equivalent one), α will necessarily send the same messages because of the PWD assumption. Albeit not in the same order, message m must eventually arrive at β. □

Theorem 3.4. *The recovery process in fast message-logging is correct.*

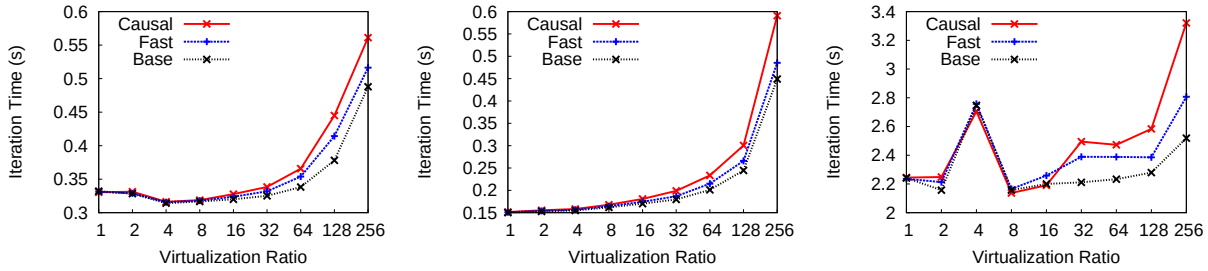
Proof Sketch. After lemmas 3.1,3.2 and 3.3, all messages are sent again, they are processed in the same order or in an equivalent consistent order and there are no orphan objects. Therefore, the recovery of a PE is correct. □

3.3 Experimental Results

In order to understand the performance penalization imposed by the fast message-logging protocol, we examined three stencil codes: Wave2D, Jacobi3D and LULESH. These programs were implemented in SDAG to decrease execution time (since barriers between iterations are not needed anymore) and allow the possibility of removing determinants.

We first examine the effect of virtualization ratio on each program. Recall from Chapter 2 that virtualization ratio stands for the average number of objects per PE. For this experiment, each PE is a core. Figure 3.5 presents the results on $1,024$ cores of Intrepid. Each data point reflects the average of 5 repetitions of the same experiment. Wave2D in Figure 3.5(a) seems to manifest that Wave2D benefits from virtualization. In fact, the performance of the program stays within a 5% difference up to 32 objects per core. A similar behavior occurs in Jacobi3D in Figure 3.5(b), except in this case the program is always slightly slowed down by virtualization. Again, the average iteration time stays within a 10% margin up to 32 objects per core. Finally, Figure 3.5(c) accepts a higher virtualization ratio without a significant performance degradation. Even 128 objects per core stays within a 3% margin. Having a high virtualization ratio is beneficial for applications in view of the eminent thermal variation of future systems. With more objects per core, it is possible to obtain a better load balance in case some of the PEs have to be slowed down to reduce their temperature.

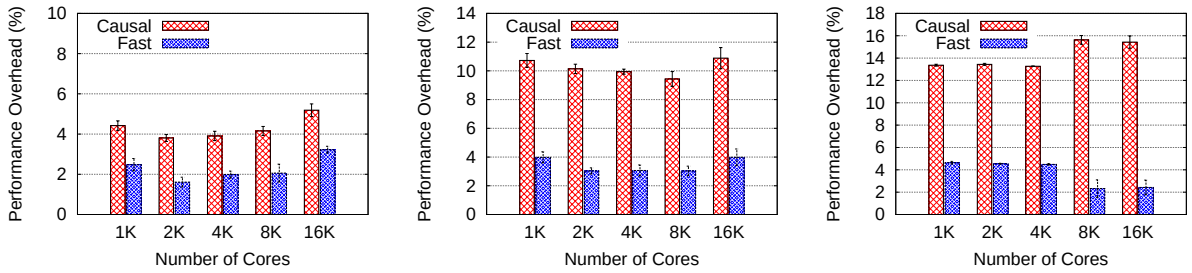
Using a virtualization ratio of 32 for Wave2D and Jacobi3D and 128 for LULESH, we ran 5 times each program and compared the results between fast message-logging and causal message-logging. The results are presented in Figure 3.6 and offer the relative performance overhead when compared with the base Charm++. The figure shows a weak-scale experiment



(a) Wave2D. (b) Jacobi3D. (c) LULESH.

Figure 3.5: Effect of virtualization ratio on performance. Stencil codes admit a high virtualization ratio without sacrificing a significant portion of its performance.

on Intrepid from 1K to 16K cores. For Wave2D, Figure 3.6(a) shows that fast message-logging is able to halve the performance all across the spectrum. Figure 3.6(b) tells about a more beneficial scenario for the fast protocol with Jacobi3D. The most dramatic difference appear with LULESH. Figure 3.6(c) shows the big difference determinants can make in message-logging. As the program scales the difference between the fast and causal variants increases to the point where the overhead of fast message-logging is around 15% of the overhead of causal.

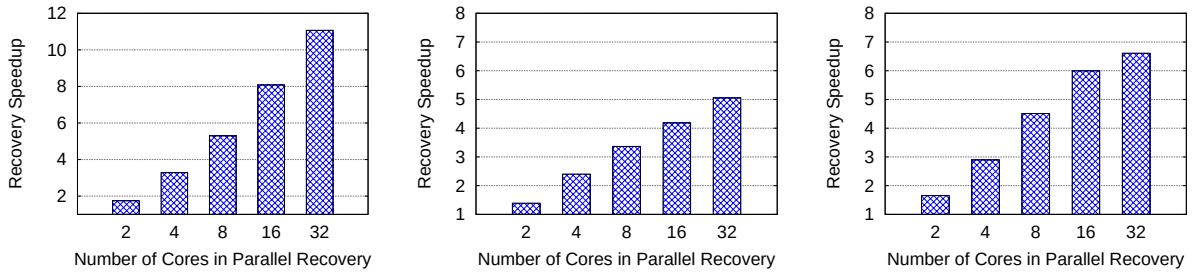


(a) Wave2D. (b) Jacobi3D. (c) LULESH.

Figure 3.6: Performance overhead of fast message-logging. It approximately reduces performance overhead to a half when compared with causal message-logging.

An important feature of the fast message-logging protocol is it ability to work in conjunction with parallel recovery. Chapter 2 introduced parallel recovery. The more PEs help in recovery, the faster it is expected the failed PE will catch up with the rest of the system. There are, however, a couple of considerations to keep in mind. First, the number of PEs helping in recovery cannot exceed the virtualization ratio. Second, it is possible to have diminishing returns with the addition of more PEs. This latter effect results stems from the fact that more PEs involve sending more remote messages and potentially hitting network bottlenecks. Figure 3.7 shows for the 3 applications the speedup in recovery when the num-

ber of PEs helping ranges from 2 to 32. Wave2D offers the best scenario for parallel recovery. This is a result of its relatively simple communication characteristics. Therefore, spreading the objects to more PEs results in a greater speedup. Both Jacobi3D and LULESH present moderate speedup levels during recovery.

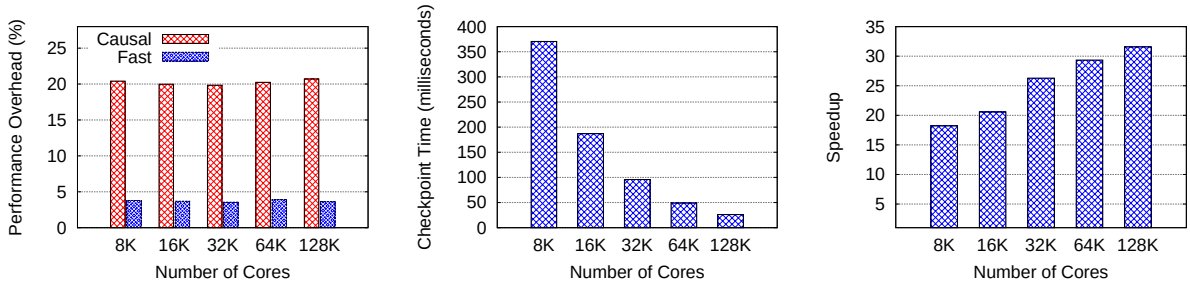


(a) Wave2D. (b) Jacobi3D. (c) LULESH.

Figure 3.7: Parallel recovery in fast message-logging. The more cores are used to recover, the faster the recovery.

Figure 3.8 offers an overall demonstration of the advantages of using fast message-logging. This scenario corresponds to a large-scale run where the number of cores varies from 8K to 128K on Intrepid. Additionally, it represents a strong-scale test, that stresses even more the message-logging protocol. Figure 3.8(a) shows the overhead in the forward path can always be kept low. Whereas causal message-logging has an overhead that goes up to approximately 20%, fast message-logging has an overhead lower than 4%. Checkpoint time is measured in milliseconds. Figure 3.8(b) offers the checkpoint time as the program is scaled. Based on the runtime-level checkpoint and in-memory checkpoint, the dump of the state of an application is fast. Finally, the speedup over checkpoint/restart is reported in Figure 3.8(c). For this case, the program runs for a two checkpoint periods, with a failure injected in the second one. The speedup reported in the figure corresponds to the total execution time of fast message-logging versus checkpoint/restart.

Table 3.1 presents statistics about the number of messages and determinants in different programs. This data was collected on Intrepid, using 1,024 cores and with the same configuration as in Figure 3.6 for each program. The causal message-logging protocol was used to collect the data. The table shows the number of instances per iteration, averaged across all cores. We see the number of remote messages varies widely between Wave2D and LULESH. This can be justified by the fact that LULESH has a more complex communication graph (neighbors in 3 dimensions) and the configuration of LULESH has a higher virtualization ratio (128 compared to 32). More messages is proportionally related to the number of determinants generated. In Table 3.1 there are more determinants than messages, explained by



(a) Performance Overhead. (b) Checkpoint Time. (c) Speedup.

Figure 3.8: Large strong-scale experiment with LULESH. Fast message-logging keeps a low performance overhead, fast checkpoint and fast recovery, compared to checkpoint/restart.

the fact that local messages generate determinants too. The number of piggybacked determinants also grows as the number of messages. The ratio of determinants piggybacked over determinants generated provide an idea on the number of copies each determinant has in the system. Although causal message-logging only requires one copy of each determinant to be stored safely, usually several more copies are logged in the system. Finally, the last row in Table 3.1 reports the average number of determinants piggybacked per message. This quantity directly dictates the performance overhead of causal message-logging. Not surprisingly, the higher the number of determinants piggybacked per message, the higher the performance overhead (supported by the results in Figure 3.6).

	Program		
	Wave2D	Jacobi3D	LULESH
Remote Messages	72.90	141.10	3181.85
Determinants Generated	144.40	214.80	4295.55
Determinants Piggybacked	317.59	870.78	32411.52
Determinants per Message	4.36	6.17	10.19

Table 3.1: Number of determinants in different programs. Average statistics on messages and determinants per iteration.

3.4 Discussion

Collective communication operations are useful programming devices for large-scale applications. Message-logging protocols should allow a seamless inclusion of this type of operations in a parallel program. Although the problem was not explored in this chapter, collective operations should not represent a major challenge for the fast message-logging protocol. If

the collective operation is synchronous, it will enforce an ordering of the reception order, guaranteeing that recovery will respect that order. If the collective is asynchronous, it will require an identification number. Using this unique number, the system can differentiate between contributing messages for particular collective operations. This means that collective calls can be uniquely identified in any case.

A further issue related to collective operations lies in the way the contribution from the different tasks is accumulated. More specifically, floating-point arithmetic is not associative. Therefore, in principle, the same set of operations should be repeated to produce the same contribution message. Note however that the contribution messages for a reduction, for instance, will nevertheless be ignored by the receiver. Thus, the way results are accumulated in a collective call is irrelevant. All that matters is the state of the different tasks and the fact they need to be kept consistent.

Despite the fact that most failure bring down one single node at a time [31, 59], tolerating multiple concurrent node failures is a positive feature. It increases the robustness of the system and it may be adopted in environments where this type of failures occur more frequently. The fast message-logging protocol is able to tolerate any arbitrary number of concurrent node failures. Given that it does not require determinants and the high level language enforces the reception order, any number of nodes can simultaneously fail (provided they are still able to recover their checkpoint) and resume execution.

3.5 Related Work

The seminal work on send determinism [49, 51, 71] provided a clear insight on the futility of creating determinants for all message receptions. The protocol presented in the send-determinism literature depends on FIFO channels for it to properly work. We remove that assumption to use the asynchronous execution model of Charm++. However, to tame the excessive flexibility in the order of message reception, we relied on high level programming language constructs. Additionally, a major difference in the send-determinism protocol and fast message-logging appears during recovery. The send-determinism protocol requires to replay the causally-dependent messages in a synchronized fashion. In other words, the senders of messages can not send the whole set of messages to the recovering node as soon as they are notified about the restart. They must wait to receive the causally related messages to emit the next message. This hampers the ability of message-logging to achieve a faster recovery. By using a reception control mechanism, fast message-logging is able to receive all messages at once and completely sort them in a valid program order. Thus, during recovery

it is possible to achieve near-zero latency. The evaluation of send-determinism used up to 256 processors.

A new design of the message-logging layer for Open MPI [53] revealed that vast amount of determinants that are not necessary to guarantee a safe recovery. By interposing a message-logging substrate between the application and the network layer, this new design is able to create matchings of events posted by the application and arrival events coming from the network. Matchings may be deterministic if the expected sender and the actual sender of the message are the same. Use of wildcards will create non-deterministic matches. By logging only non-deterministic matches, this design is able to dramatically reduce the number of determinants.

The large scale simulator *BigSim* [50] used parallel discrete event simulation (PDES) to make predictions on the performance of scientific codes for supercomputers. Since BigSim is based on POSE (a framework for PDES), it would allow speculative simulation of different threads of events. In that regard, programs that allow only one possible execution sequence would find a very efficient simulation. In BigSim, *linear order parallel programs* are a special kind of codes for which messages are processed in exactly one order.

CHAPTER 4

Performance and Energy Models

> Essentially, all models are wrong, but some are useful
>
> George E.P. Box

Understanding the laws that govern the universe has been a constant quest in science. The result of that quest has brought several theories of how things came to be. The Victorians, for instance, believed the whole universe was filled with ether. This medium was able to carry light and objects moving through ether would generate ether wind. Later on, experimental evidence denied the existence of ether and the special theory of relativity defined spacetime, a single entity that represents the flexibility of time and space. In that theory, there was a cosmological constant that would provide the illusion of a static and eternal universe. However, more recent empirical evidence and theoretical breakthroughs have given rise to the big bang theory, which states the universe had a beginning and it is dynamic. All these theories of the universe are models to facilitate the comprehension of our physical reality.

A model is a conceptual device that represents reality in a way that makes different phenomena easier to understand. From that definition, a good model has to be *realistic* and *simple*. The first characteristic is fundamental for the model to have any applicability. The second characteristic is what makes a model convenient. If a model were as complex as reality, it would not make a particular phenomenon easier to study. The real power of a model comes from the ability to abstract the unimportant details of reality and consider those fundamental variables that contribute the most to the effect under study. Simplicity does not necessarily means dullness. A simple model can be powerful if it is able to provide two additional features. It ought to be *insightful* if it can reveal the hidden connections of the different components and what can be expected from the interplay of those components.

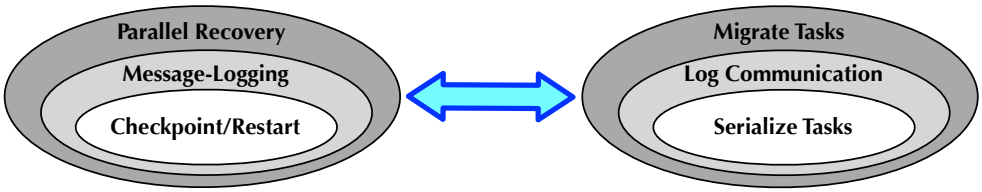


Figure 4.1: Hierarchical organization of protocols. Checkpoint/restart is the base case that allows tasks to be serialized. Message-logging can be seen as an extension to that base case where communication is logged. Furthermore, parallel recovery extends message-logging by allowing tasks to migrate.

Additionally, a good model is also *predictive* if the results can be extrapolated to different conditions.

In particular, for fault-tolerance in HPC, models should be able to consider the most relevant parameters of an execution and predict results at different scalability levels. Rollback-recovery techniques are usually modeled through the following equation [18, 19]:

$$T = T_{Solve} + T_{Checkpoint} + T_{Recover} + T_{Restart} \tag{4.1}$$

where T_{Solve} stands for the computation work to solve a problem, $T_{Checkpoint}$ is the checkpoint overhead measured as the time spent on dumping the state of the system, $T_{Recover}$ is the time spent on recovering from failures, and $T_{Restart}$ accounts for the time required to restart from failures. This latter quantity includes all time spent on failure detection, making reconnections and launching a new process. Equation 4.1 will be the base for developing specialized models for the different variants of rollback-recovery protocols examined in this dissertation. The models presented in this chapter are based on a weak-scale setup, where the amount of total useful work remains the same regardless of the number of components used.

We will present three different models for checkpoint/restart, message-logging and parallel recovery, respectively. These three protocols can be seen as an incremental sequence of protocols. Figure 4.1 presents a hierarchical view of the protocols. The first and most basic protocol is a blocking coordinated checkpoint/restart mechanism that only requires tasks to be serializable. In continuation of checkpoint/restart, message-logging is seen as a natural extension, where checkpoint is still blocking and coordinated, and messages are logged at the sender. Additionally, information about message reception ordering is maintained. Finally, parallel recovery is understood as an extension to message-logging, where tasks can be migrated after a crash to accelerate recovery.

In this model, failures are assumed to be exponentially distributed. This means, the interarrival time between failures is modeled through a random variable with exponential distribution. Although, other distributions have been found to model better interarrival failures in supercomputers [72], the exponential distribution significantly simplifies the model.

This chapter highlights the following contributions:

- An analytical model to predict the performance for message-logging protocols and parallel recovery at large scale (§4.2).
- An analytical model to predict the energy consumption for rollback-recovery protocols at large scale (§4.3).
- Large-scale projections on the benefits of message-logging and parallel recovery for both performance and energy consumption (§4.4).
- A simulation-based set of projections of message-logging protocols at very high failure rates. The results show that parallel recovery is able to have a checkpoint period longer than the mean-time-between-failures (§4.5).

4.1 Parameters

In order to capture the most relevant phenomena of rollback-recovery protocols in the performance and energy-consumption models, we use the parameters listed in Table 4.1. They can be divided in roughly 4 categories (seen as segments in the table). The first category corresponds to system-specific data. The second category stands for application-specific data. The third accounts for application-specific data regarding message-logging. Finally, the last category collects system-specific data about energy consumption. Let us examine these parameters closely.

Parameters M and S are interrelated. The size of the machine will define how reliable the whole system is. In general, the higher the value of S, the lower the value of M. In fact, these two values are related through the mean-time-between-failures of a socket, M_S. The actual equation relating M and S is $M = \frac{M_S}{S}$. Each application will have an optimal value of V. In fact, this value may change according to the scale of the run. The other values for rollback-recovery come from the original formulation of the performance model [19]. It is assumed the application has to perform W time units of work without any interruption. The application takes δ time units to checkpoint and restarts in R. The performance model computes the optimum value of τ that minimizes total execution time T. It is clear that the

Table 4.1: Parameters of performance and energy consumption models.

Parameter	Description
M_S	Mean-time-to-interrupt of each socket
M	Mean-time-to-interrupt of the system
S	Total number of sockets in the system
V	Optimal virtualization ratio
W	Time to solution with V
δ	Checkpoint time
τ	Optimum checkpoint period
R	Restart time
T	Total execution time
μ	Message-logging slowdown
ϕ	Message-logging recovery speedup
P	Available parallelism during recovery
σ	Parallel recovery speedup
λ	Parallel recovery slowdown
H	Max power of each socket
L	Base power of each socket
E	Total energy consumption

value for the checkpoint period τ creates a tradeoff. If τ is small, the checkpoint overhead will be high, but the rework time will be small. Conversely, if τ is large, the checkpoint overhead will be small, but at a cost of a more expensive recovery. Therefore, finding an optimum value for τ is essential in decreasing the total execution time.

Figure 4.2 presents an example of an execution under the assumptions of this model. It shows a system with 4 PEs, taking periodic checkpoints. The checkpoint duration is δ and the checkpoint period is τ. A failure on PE C will force the system to rollback to the most current checkpoint and restart from there. PE C' replaces PE C. The failure occurs when the checkpoint period has executed t time units out of τ time units in a checkpoint period. The cost of restart is R and then the system proceeds to compute again for t units to recover the work lost.

Message-logging changes the progress rate of the application at several levels. First of all, it incurs overhead during the forward path. This is represented by μ. But, during recovery, it may accelerate the pace by a factor of ϕ because the application may not encounter interference for the recovery of the failed PE. Additionally, if parallel recovery is used, the available parallelism P during recovery will dictate how much speed up is feasible during recovery. More specifically, $P \leq V$ and it is very likely that the speedup during recovery will

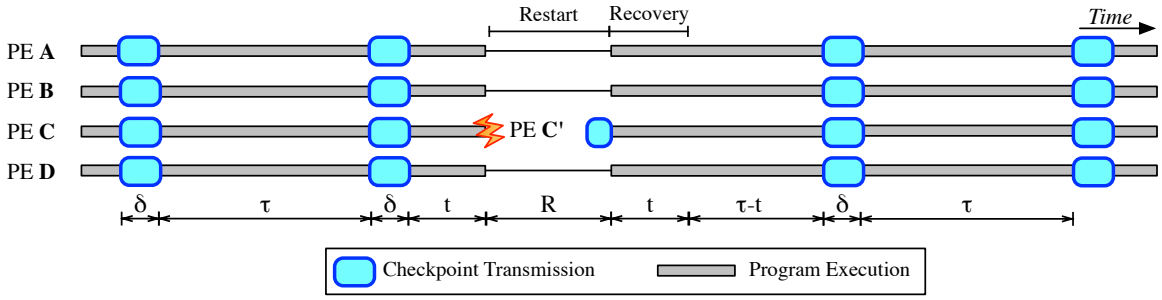


Figure 4.2: Execution model example. The system takes periodic checkpoints and rolls back to the most recent checkpoint in case of a failure.

be bound by P. The value of σ stores the actual speedup during recovery and λ represents the slowdown. We must remember that parallel recovery will induce a load imbalance for a portion of the checkpoint period after recovery is complete. In Figure 4.2 , using parallel recovery would mean that the t time units that must be recovered will be executed with σ speedup. Also, the rest of the interval, made of $\tau - t$ time units will execute with a slowdown of λ.

Finally, the values of L and H represent the power levels at which each socket operates for both idle and dynamic power. The goal of the energy-consumption model will be to minimize the value of the total energy consumed E.

4.2 Performance Model

The ability to predict performance behavior in HPC is instrumental. The main motivation behind parallelism is precisely to speed up an execution. Therefore, the performance model will use the parameters in table 4.1 and minimize T using equation 4.1. We will derive a different equation for T using each fault-tolerance protocol. Therefore, we will distinguish each T with a subscript, having T_C, T_M, T_P representing checkpoint/restart, message-logging and parallel recovery, respectively.

4.2.1 First Order Approximation

As an introductory academic exercise, we will develop an imprecise but handy model. We will call this a first-order model in accordance with the literature [19]. This model has a goal to find the optimum value of τ to minimize T for message-logging with parallel recovery. We

reformulate equation 4.1 in the following way:

$$T_P = W\mu + \left(\frac{W\mu}{\tau} - 1\right)\delta + \frac{W\mu}{\tau}\left(\frac{\tau+\delta}{M}\right)\left(\frac{\tau+\delta}{2P}\right) + \frac{W\mu}{\tau}\left(\frac{\tau+\delta}{M}\right)R \qquad (4.2)$$

where the four components match one-to-one those of equation 4.1. T_{Solve} will be equal to $W\mu$ because the total useful work has to be extended to account for the slowdown of message-logging. $T_{Checkpoint}$ should be equal to the total number of checkpoints multiplied by the checkpoint duration δ. The total number of checkpoints in the execution can be approximated by $\left(\frac{W\mu}{\tau} - 1\right)$. Since this first-order approximation assumes the number of faults is determined by the useful work (and not by the total execution time), for the next two components we use $\frac{W\mu}{\tau}\left(\frac{\tau+\delta}{M}\right)$ as an approximation of the total number of failures, following a conventional model [19]. Thus, $T_{Recover}$ is equal to the number of crashes multiplied by the average work to be recovered in a crash. This latter quantity is approximated by $\left(\frac{\tau+\delta}{2}\right)$. Note that we add a factor P to represent the parallel recovery of that portion of the execution. Finally, $T_{Restart}$ just multiplies the number of failures by R.

To optimize T_P, we find the minimum of a continuous function by solving the equation $\partial T = 0$. It follows that the optimum value for τ is:

$$\begin{aligned} \frac{\partial T}{\partial \tau} &= -\frac{W\mu\delta}{\tau^2} + \frac{W\mu}{M}\left(\frac{1}{2P} - \frac{\delta^2}{2P\tau^2} - \frac{\delta R}{\tau^2}\right) = 0 \\ 2\delta MP &= \tau^2 - \delta^2 - 2\delta RP \\ \tau &= \sqrt{2\delta P(M+R)} \end{aligned} \qquad (4.3)$$

This short formula relates τ to four other parameters to which it is proportional: δ, M, P, R. A reduction of any value in those parameters will reduce the value of τ. In particular, increasing the level of available parallelism during recovery P will increase τ and reduce the checkpoint frequency. This means, the system is able to afford a higher checkpoint period because recovering from a crash is relatively cheaper.

4.2.2 Analytical Model

In this section we will remove an important assumption that the first-order model makes. Basically, in computing the total execution time, it was assumed that errors cannot occur neither during restart nor during recovery. This assumption is obviously advantageous for techniques with a high recover cost. To incorporate this concern into Equation 4.1, we modify the previous definition of $T_{Recovery}$ and $T_{Restart}$.

The number of expected failures is now calculated as $\frac{T}{M}$ for checkpoint/restart. We make the assumption that, on average, a failure will land in the middle of a checkpoint period. Thus, the amount of work to be redone is actually $\frac{\tau+\delta}{2}$. The final expression for T is:

$$T_C = W + \left(\frac{W}{\tau} - 1\right)\delta + \frac{T_C}{M}\left(\frac{\tau+\delta}{2}\right) + \frac{T_C}{M}R \tag{4.4}$$

In message-logging we must account for the overhead associated with the protocol. This slowdown is represented by μ. Additionally, since recovery in message-logging enjoys a negligible latency and a reduced contention, recovery can be accelerated by ϕ. However, this speedup does not apply to the recovery of checkpoint. The complete checkpoint interval is given by $\tau + \delta$. The probability of a failure landing in the first τ units is given by $\frac{\tau}{\tau+\delta}$. On average, the amount of work to be recovered if the failure lands in that segment is $\frac{\tau}{2}$. The probability of a failure falling in the δ segment is $\frac{\delta}{\tau+\delta}$. The amount of work to be recovered, on average, for that case is $\tau + \frac{\delta}{2}$. The acceleration factor ϕ only applies to the τ segment. Thus, we have the following expression for the execution time in message-logging:

$$T_M = W\mu + \left(\frac{W\mu}{\tau} - 1\right)\delta + \frac{T_M}{M}\left(\frac{\tau}{\tau+\delta}\cdot\frac{\tau}{2\phi} + \frac{\delta}{\tau+\delta}\left(\frac{\tau}{\phi}+\frac{\delta}{2}\right)\right) + \frac{T_M}{M}R \tag{4.5}$$

Parallel recovery has an additional constraint. If a failure occurs t time units after the latest checkpoint (as in Figur 4.2), the first t time units are accelerated by a factor σ due to the recovery of the tasks in parallel. Nevertheless, the rest of the segment, having length $\tau - t$, will be executed with a slowdown of λ. A similar probability analysis as in message-logging leads us to express the execution time of parallel recovery as:

$$T_P = W\mu + \left(\frac{W\mu}{\tau} - 1\right)\delta + \frac{T_P}{M}\left(\frac{\tau}{\tau+\delta}\left(\frac{\tau}{2\sigma} + \frac{\tau}{2}(\lambda-1)\right) + \frac{\delta}{\tau+\delta}\left(\frac{\tau}{\sigma}+\frac{\delta}{2}\right)\right) + \frac{T_P}{M}R \tag{4.6}$$

4.3 Energy Model

Although minimizing execution time has been the most important goal in HPC, reducing energy consumption will likely become equally important as the size of machines grows and consequently the energy bills. It is estimated that minor reductions in energy consumption can save millions of dollars per year in supercomputing facilities [73].

An extension to the execution time model presented above makes it possible to project energy consumption for systems with different characteristics and under different failure

scenarios. The basic formula for energy is directly derived from Equation 4.1:

$$E = E_{Solve} + E_{Checkpoint} + E_{Recover} + E_{Restart} \tag{4.7}$$

where $E, E_{Solve}, E_{Checkpoint}, E_{Recover}$ and $E_{Restart}$ have an analogous meaning to their execution time counterpart.

The fundamental assumption of the energy model is that there are two power levels at which PEs operate. When a PE is executing an application, its power draw is H. Otherwise, its power draw is L. Since most of the power draw of a computational node comes from the processor, we assume that during checkpoint a PE operates at power L. This statement is not too optimistic in view of the energy consumption results of Chapter 2. Again, we will denote E_C, E_M, E_P the energy consumed by checkpoint/restart, message-logging and parallel recovery, respectively.

4.3.1 First Order Approximation

Similar to Equation 4.2, the equation that defines the total energy consumed in the execution of an application that uses message-logging with parallel recovery is given by:

$$E_P = W\mu H + \left(\frac{W\mu}{\tau} - 1\right)\delta L + \frac{W\mu}{\tau}\left(\frac{\tau+\delta}{M}\right)\left(\frac{\tau+\delta}{2P}\right)H + \frac{W\mu}{\tau}\left(\frac{\tau+\delta}{M}\right)RL \tag{4.8}$$

where we assume that PEs draw H watts of power while executing (making progress or recovering) and L watts of power during checkpoint and restart.

In order to minimize the energy consumed by the execution of an application, we proceed to compute the derivative of E_P with respect to τ and find a solution to the equation:

$$\begin{aligned}
\frac{\partial E}{\partial \tau} &= -\frac{W\mu\delta}{\tau^2}H + \frac{W\mu}{M}\left(\frac{1}{2P} - \frac{\delta^2}{2P\tau^2} - \frac{\delta R}{\tau^2}\right) = 0 \\
2\delta MP &= \tau^2 - \delta^2 - 2\delta RP \\
\tau &= \sqrt{\frac{L}{H}} \cdot \sqrt{2\delta P(M+R)}
\end{aligned} \tag{4.9}$$

The difference in the values of τ for execution time and energy (equations 4.3 and 4.9) is the additional factor $\sqrt{\frac{L}{H}}$ in the value of τ that minimizes energy. In other words, a higher difference between L and H implies a higher difference in the optimum value of τ for execution time and energy.

4.3.2 Analytical Model

Proceeding in an analogous way to the execution time case, we develop more precise formulations for the total energy consumed in the execution of an application on a system with S PEs. As explained above, we assume PEs may execute at two levels of power, H or L. The energy consumed by checkpoint/restart can be expressed as:

$$E_C = WSH + \left(\frac{W}{\tau} - 1\right)\delta SL + \frac{T_C}{M}\Omega_C + \frac{T_C}{M}RSL \tag{4.10}$$

where $\Omega_C = \frac{\tau}{\tau+\delta} \cdot \frac{\tau}{2}SH + \frac{\delta}{\tau+\delta}(\tau SH + \frac{\delta}{2}SL)$.

Similarly, energy consumption for message-logging is described by the following equation:

$$E_M = W\mu SH + \left(\frac{W\mu}{\tau} - 1\right)\delta SL + \frac{T_M}{M}\Omega_M + \frac{T_M}{M}RSL \tag{4.11}$$

where $\Omega_M = \frac{\tau}{\tau+\delta} \cdot \frac{\tau}{2\phi}\left(H + (S-1)L\right) + \frac{\delta}{\tau+\delta}(\frac{\tau}{\phi}(H + (S-1)L) + \frac{\delta}{2}SL)$.

Finally, energy consumption for parallel recovery is defined as follows:

$$E_P = W\mu SH + \left(\frac{W\mu}{\tau} - 1\right)\delta SL + \frac{T_P}{M}\Omega_P + \frac{T_P}{M}RSL \tag{4.12}$$

where $\Omega_P = \frac{\tau}{\tau+\delta}\left(\frac{\tau}{2\sigma}\left(PH + (S-P)L\right) + \frac{\tau}{2}(\lambda-1)SH\right) + \frac{\delta}{\tau+\delta}\left(\frac{\tau}{\sigma}\left(PH + (S-P)L\right) + \frac{\delta}{2}SL\right)$.

An important observation about the energy equation is its dependence on T and τ. This dependence creates two possible alternatives for obtaining the total energy consumed. Since T only depends on τ, the first alternative is to look for the optimum value of τ for T, denoted by τ^T and then use that value in the equation for E. The second option is to expand the expression for T in the energy equation and find the optimum value that minimizes E, denoted by τ^E.

4.4 Large-Scale Projections

The real power of the analytical model lies in predicting performance for future systems in particular and for different environments in general. We will present a large-scale prediction of the performance of the different fault tolerance protocols presented in this chapter. In order to do that, we chose the parameters of the analytical model using reasonable values expected at exascale [1, 2, 74]. Table 4.2 lists the baseline values for the parameters. We chose an MTBF per socket of 10 years and a checkpoint time of 3 minutes for a workload

of one day. The MTBF of the system, denoted by M will linearly depend on the number of sockets. An exascale machine is expected to have more than $200,000$ sockets. In this case, we will examine a system size S ranging from 16K to 1M sockets. The restart time is assumed to be half a minute. The rest of the parameters were chosen from the results obtained in Chapter 2.

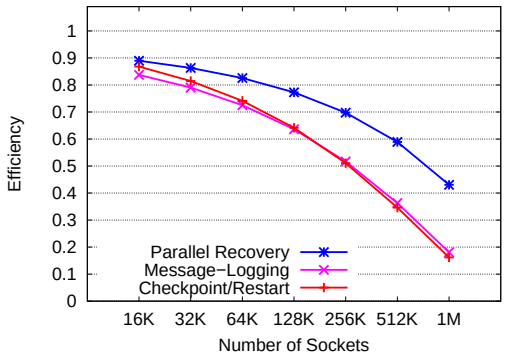
Table 4.2: Baseline values of parameters in the model.

Parameter	W	M_{Socket}	δ	R	μ	ϕ	σ	λ	H	L
Value	24h	10 years	180s	30s	1.05	1.2	8	$\frac{9}{8}$	100W	40W

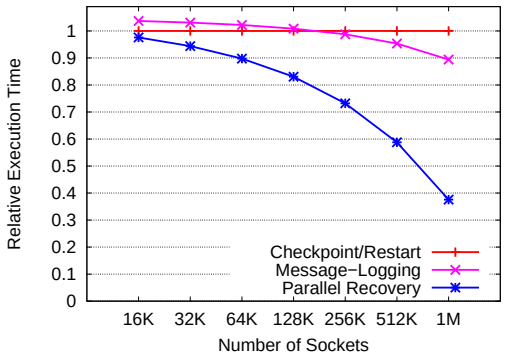
One of the major concerns at exascale is the overall utilization of a system. Today, some large systems spend more than 20% of their total computing capacity on to failures and recoveries [75]. It is believed that utilization may drop to extremely low values if rollback-recovery techniques do not improve substantially. For instance, a checkpoint time of 30 minutes will definitively render an exascale machine unusable. Two ways to address this important challenge is to decrease the checkpointing overhead by using double-local checkpoint and to accelerate recovery through a message-logging mechanism. We will compare the three fault tolerance schemes by computing their *efficiency* in a system. Efficiency is defined as $\frac{W}{T}$.

Figure 4.3 presents a comparison of the fault-tolerance protocols according to their efficiency and relative execution time. The efficiency of a system with a number of sockets ranging from 16K to 1M can be seen in Figure 4.3(a). Message-logging starts with a worse efficiency than checkpoint restart, but a crossover occurs before 256K sockets. Parallel recovery offers a better efficiency overall and provides a 20% difference after more than 256K sockets. This improvement in efficiency can be explained directly by the total execution time of a workload of $W = 24$h, shown in Figure 4.3(b). The values have been normalized with respect to checkpoint/restart execution time. Parallel recovery always offers a faster execution time. Parallel recovery executes twice as fast compared to checkpoint/restart at very large scale. Message-logging fetches up to a 10% reduction in execution time.

In terms of energy consumed, message-logging and parallel recovery consistently perform better than checkpoint/restart. Figure 4.4 shows the relative energy consumption for both τ^T and τ^E. Recall that τ^T minimizes execution time. The energy performance of different fault tolerance strategies for τ^T is shown in Figure 4.4(a). Both message-logging and parallel recovery perform much better than checkpoint/restart. At large scale, message-logging decreases energy consumption by more than 30% and parallel recovery more than 50%. Although these results are similar to Figure 4.3(b) for parallel recovery, they are much different



(a) Efficiency of fault-tolerance protocols at large scale. In a machine with more than 256K sockets, parallel recovery improves efficiency for more than 20%.

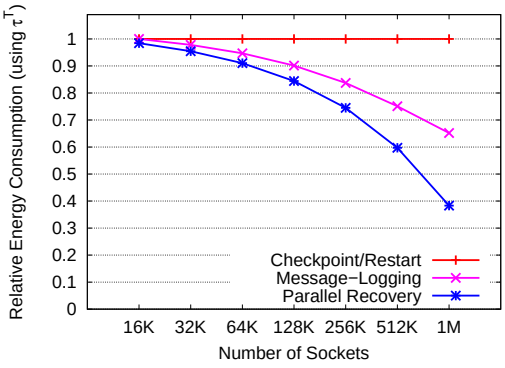


(b) Relative execution time. Compared with checkpoint/restart, both message-logging and parallel recovery decrease the total execution time at exascale.

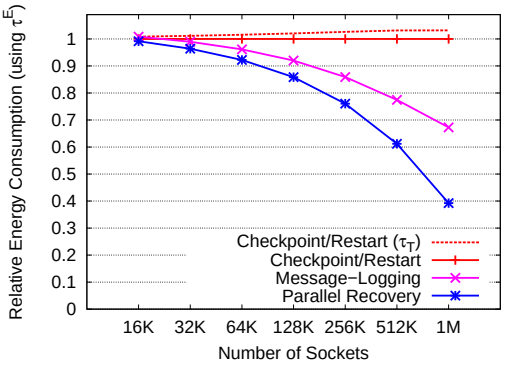
Figure 4.3: Comparison of performance of fault-tolerance methods at large scale. An exascale machine can improve its efficiency and decrease the total execution time of applications by using message-logging and parallel recovery. Parallel recovery may significantly improve efficiency and execute twice as fast compared to checkpoint/restart at very large scale.

for message-logging. The advantage of message-logging comes from its ability to minimize the amount of work to redo after a crash. That alone saves a significant amount of energy, particularly in systems where failures are common. Figure 4.4(b) shows the results for τ^E. They seem similar to Figure 4.4(a). The most important difference comes from the lower end of the scale for message-logging, where it performs worse than checkpoint/restart. At such failure rate, message-logging has a high performance overhead in the forward path that affects its energy consumption. Energy consumption when using τ^E is marginally lower than using τ^T. The difference increases with the size of the system but is never higher than 3%.

The benefits of parallel recovery in both execution time and energy come from the ability to accelerate recovery after a crash. This directly affects the checkpoint frequency. In order to appreciate this effect, Figure 4.5 shows the value of the checkpoint period τ of the different fault tolerance protocols. Figure 4.5(a) presents τ^T, the checkpoint period to minimize the total execution time. As the system grows, the ratio of $\frac{\tau}{M}$ increases. Since the formula relating τ to M is roughly a square root, a smaller M implies a smaller τ, all other things being equal. The system requires frequent checkpoints to handle effectively the growing incidence of failures, but the checkpoint frequency can not be decreased at the same speed as the failure rate. For both checkpoint/restart and message-logging, τ^T converges to a value close to $\frac{M}{2}$. However, parallel recovery manages to checkpoint less often. In



(a) Energy consumption using τ^T. Both message-logging and parallel recovery perform better than checkpoint/restart all along the range.

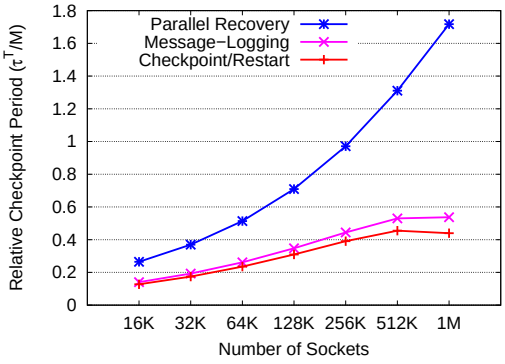


(b) Energy consumption using τ^E. Message-logging provides a lower energy consumption for most of the interval. It only has a higher energy consumption at the start, presumably because its higher execution time.

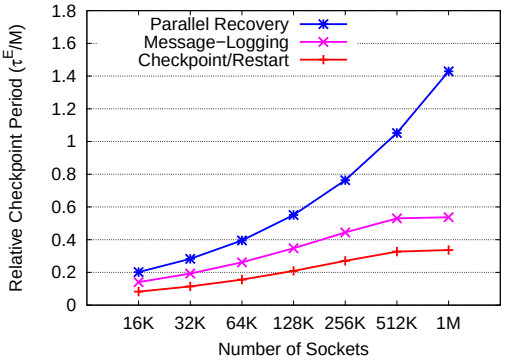
Figure 4.4: Comparison of energy consumption of fault-tolerance methods. Message-logging and parallel recovery offer an energy efficient solution as systems scale. Message-logging can save more than 30%, while parallel recovery more than 50%. Using τ^T, message-logging does not always run faster than checkpoint/restart, but it always uses less energy.

fact, at very large scale, parallel recovery checkpoints less often than the failure rate. This somehow counterintuitive statement can be explained by considering σ, the speedup in recovery. Since recovery runs much faster than execution, it pays off to checkpoint seldom and have more work to recover in an accelerated fashion. Figure 4.5(b) shows the equivalent relative checkpoint period for τ^E. The trend is very similar, but all the values of the ratio $\frac{\tau}{M}$ are smaller. It is because checkpointing is cheaper than execution in energy terms. The results form Chapter 2 support this claim. At checkpoint time, the power draw reduces to a value close to the base power. Thus, if energy is to be minimized, it makes more sense to checkpoint more often, extending the execution time, but saving energy.

An analytical model offers the invaluable opportunity of exploring different configurations. The value of the different parameters were taken from a baseline set that collects expected results with empirical results. However, each parameter also has a spectrum that is worth exploring. We investigate the impact of two different parameters, M_S and P. Figure 4.6 shows the effect of those two factors. Using checkpoint/restart as a base case, Figure 4.6(a) shows the effect of changing M_S (the mean-time-between-failures per socket). The higher the failure rate per socket, the more beneficial parallel recovery is. In fact, if $M_S = 5$ years, the model predicts checkpoint/restart will not be able to cope with the failure frequency at



(a) Relative checkpoint period using τ^T. When execution time is to be minimized, the checkpoint period of checkpoint/restart and message-logging converges to a half the failure rate. Parallel recovery manages to checkpoint much less often, due to its acceleration during recovery.



(b) Relative checkpoint period using τ^E. A similar trend to τ^T, but the checkpoint frequency is higher. This is due to the fact that checkpoint is relatively cheap in energy terms compared with execution.

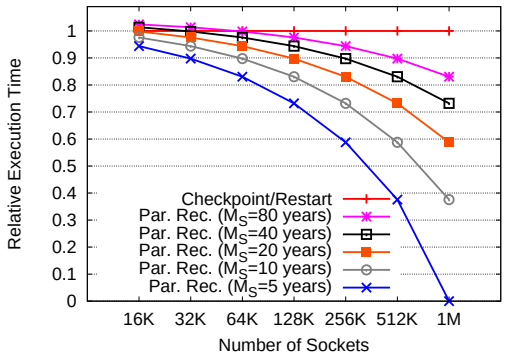
Figure 4.5: Comparison of the checkpoint period of different protocols. Compared to the mean-time-between-failures of the system (M), parallel recovery manages to checkpoint less often than the failure rate.

1M sockets. Figure 4.6(b) presents the benefits of a higher availability of parallelism during recovery. Assuming $\sigma = P$ and $\lambda = \frac{P+1}{P}$, a higher parallelism leads to a higher reduction in execution time compared to checkpoint/restart. Interestingly, the benefit saturates at $P = 16$. A higher value of parallelism only provides diminishing returns. This observation implies that an ever increasing level of parallelism is not required to scale parallel recovery to higher system sizes.

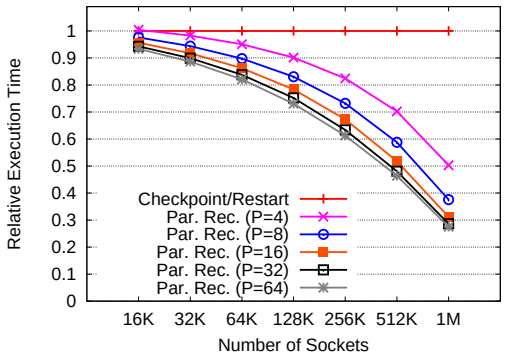
4.5 Simulation

One of the limitations of the analytical model resides in its ability to predict performance in scenarios with an extremely high failure rate. Since the failure point in the analytical model is an approximation, chances are that having frequent failures will make optimistic predictions. In reality, a high failure rate implies that the majority of failures occur in the first half of the checkpoint period, reducing the amount of work to be recovered in parallel. To verify the potential of the analytical model and determine its accuracy, we will present a simulator that executes both checkpoint/restart and parallel recovery.

Since the protocols are based on synchronous checkpoint, we divide the total execution of



(a) Effect of different values of M_S. The higher the failure rate, the more relative benefits of parallel recovery with respect to checkpoint/restart.



(b) Effect of different parallelism availability during recovery. The more parallelism available, the higher the speedup and the more the benefits of parallel recovery.

Figure 4.6: Exploration of the analytical model. Understanding the effect of different parameters in the model and its overall benefit is fundamental in deciding what factors should be explored when designing fault tolerance mechanisms.

an application into *periods*. These periods correspond to the number of checkpoint periods determined by τ. Figure 4.7 shows the state diagram used by the simulator and a portion of the execution of a program. The diagram shows the transitions for both checkpoint/restart and parallel recovery. Following is a list of the different states in the diagram:

- State **E**, *Execution*: it corresponds to the normal execution of the program at its natural progress rate. Only a failure or a checkpoint call can move the system away from this state.
- State **C**, *Checkpoint*: the program is dumping the state to a safe place. This involves sending the checkpoint across the network to the checkpoint buddy. The application does not make any progress in this state. The duration of this state is determined by δ, the checkpoint latency.
- State **R**, *Restart*: the system is restarting from a failure. The protocol sets up the system to continue execution during this stage. It includes the transmission of the checkpoint to the failed component. The latency of this state is defined by R.
- State **P**, *Parallel Recovery*: the tasks are distributed and recovered in parallel using several PEs. During this stage only the tasks that failed are assumed to be executing.

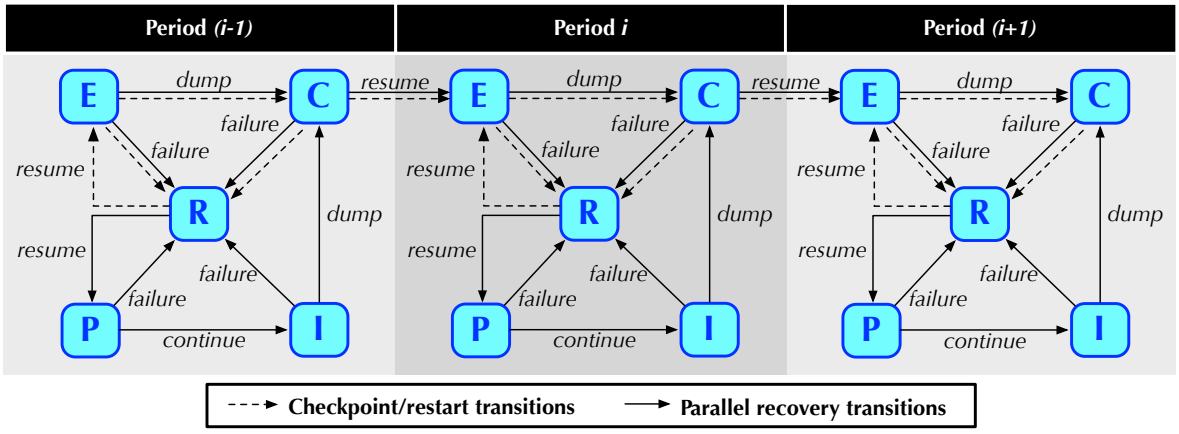


Figure 4.7: Simulation of fault tolerance methods. The state diagram presents the different states in which the application can be during an execution.

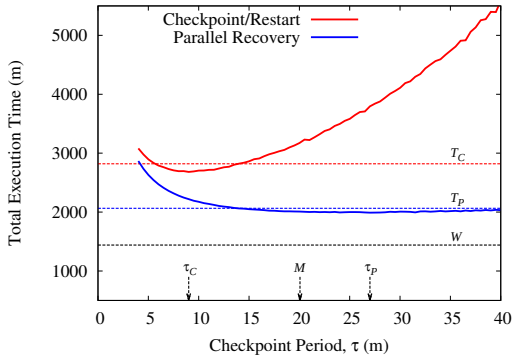
The rest of the system is waiting for these tasks to catch up. This state performs an accelerated execution of the program defined by σ.

- State **I**, *Imbalanced Execution*: as soon as parallel recovery finishes, the tasks do not return to their original PE, but they stay in their host PE until the next checkpoint call is reached. At that precise point, they return to their original PE and perform the checkpoint. The program is assumed to be executing at a lower progress rate (defined by λ) in this state.

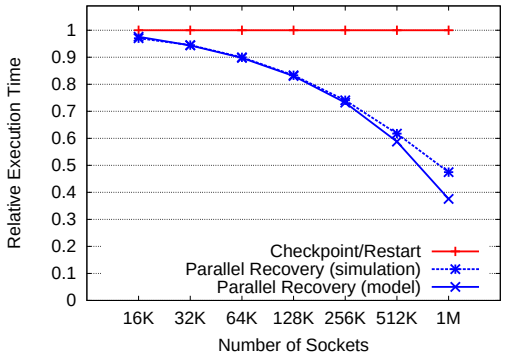
Checkpoint/restart only uses states **E**, **C** and **R**. A failure will immediately transition from any state to **R**. However, checkpoint/restart has no notion of recovery. Once the system is in state **E**, it assumes it is executing normally. Parallel recovery introduces two additional states to the diagram. Once restart is finished, the system moves to the **P** state, where accelerated recovery occurs. Once this phase is over, the system moves to state **I** that has an imbalance in the load. It is the result of having moved some tasks to other PEs for recovery. Once this stage is over and the next checkpoint call is made, the system transitions to state **C**.

The simulator uses the same parameters as in Table 4.1 with the values from Table 4.2. It proceeds by executing a program that transitions through the states of Figure 4.7. It generates a sequence of exponentially distributed inter-failure times. Those failures will cause the simulator to transition to states like **R**, **P** and **I**, depending on the particular fault tolerance protocol it is being used. Since every run represents a random sample, we repeat each simulation 500 times and show the average results.

Figure 4.8 presents the results of matching the simulation results to the analytical model predictions. The impact of the checkpoint period on execution time is shown in Figure 4.8(a). For a system size of 256K sockets, along with baseline values for all other parameters, the simulator shows that the optimal checkpoint period for checkpoint/restart is much smaller than the optimal checkpoint period for parallel recovery. More accurately, the simulation revealed that $\tau_C = 9.01$ minutes, whereas $\tau_P = 27.01$ minutes. The value of M for this case is $M = 20.06$ minutes. The values for T_C and T_P predicted by the analytical model are shown in the figure. The minimum value for the execution time obtained by the simulator is always within a 5% error margin, matching parallel recovery more closely than checkpoint/restart. Figure 4.8(b) shows the relative execution time for a system ranging from 256K to 1M sockets. The prediction in execution time reduction matches very well to the simulation results. The exception occurs at extremely high failure rates, where the the prediction differs from the simulation results and predicts a higher benefit.



(a) Effect of checkpoint period in total execution time. The minimum of checkpoint/restart is reached at a much smaller value than parallel recovery.



(b) The model prediction results match very well the simulation results. The only prediction a little off is at extremely high failure rates, where the analytical model predicts higher benefits.

Figure 4.8: Simulation results of fault tolerance protocols. Results are predicted accurately by the model, except when failure rate is extremely high. At that point, the prediction of the model seems to be optimistic.

4.6 Discussion

One of the inevitable consequences of rollback-recovery strategies can be seen in Figure 4.3(a). The predicted efficiency of all the protocols drop as the system grows in size. Since a larger

system brings a higher failure rate, it is natural to see a plunge in the overall utilization of the system. Techniques that reduce the cost of recovery, like parallel recovery, extend the applicability of rollback-recovery techniques. However, it is clear that rollback-recovery will not scale indefinitely. New ideas on how to cope with extremely high failure rates are needed to make systems at scale useful. One option is to decrease the checkpoint latency by allowing checkpoint to run concurrently with the application. An exploration of this idea can be found elsewhere [76]. Alternatively, techniques that do not require rollback may become an important candidate in solving the challenge of extremely high failure rates. Replication is one of those possibilities [2], but it sacrifices at least half the system to provide fault tolerance. Another possibility is to avoid the replication of tasks, but to frequently send the state of a tasks in a message. This may not be viable for all applications, but it certainly is a good option for molecular dynamics. The state of a task consists of only a set of particles. The coordinates of those particles are sent to other nodes in every iteration to compute the interaction between particles. Thus, effectively the state of a task is being transmitted continuously along the execution. Storing certain messages would be equivalent to storing the state of a task. Therefore, no checkpoint is required, but the complexity in recovery is higher.

Figure 4.8(b) shows that the analytical model fails to accurately predict performance for extremely high failure rates. This is a consequence of the simplifying assumptions built in the model. For instance, we assume the total work lost in a failure to be half the checkpoint interval $\frac{\tau+\delta}{2}$ on average. This assumption becomes hard to satisfy at very high failure rates, where failures will most likely hit the system at the beginning of the checkpoint interval. A more accurate description of the model is required to make effective predictions for this scenario.

Equation 4.9 sheds some light about a relevant factor in determining the tradeoff between execution time and energy. In that equation, the optimum checkpoint period differs from its time-based counterpart in a $\sqrt{\frac{L}{H}}$ factor. A smaller ratio between idle and maximum power leads to a smaller checkpoint period. As machines become more power efficient, the idle power seems to be reducing compared to the maximum power [77]. This means that in order to optimize energy, the checkpoint period will keep decreasing, because checkpoint will become relatively cheaper than executing. Thus, the projected values for τ^T and τ^E will diverge. The net effect of this phenomenon is that saving energy will have every time a higher impact in total execution time. The small differences found in Figure 4.4 will no longer be common.

Parallel recovery manages to improve both the execution time and the energy consumption in scenarios where failures are frequent. This property satisfies the most important request

of the programmers (faster execution) and one fundamental request of administrators of supercomputing centers (energy efficiency).

4.7 Related Work

The first attempt to provide the HPC community with a formula to compute the optimum checkpoint interval comes from Young [18]. In his paper, he devised an expression for the total execution time based on the checkpoint frequency. After a couple of standard manipulation steps of the formula, he came up with the traditional $\tau = \sqrt{2\delta M}$.

That formula and the overall derivation procedure was extended by Daly [19, 78]. Daly develops a sequence of ever more complex (but more accurate) models to compute τ in an incremental fashion. First, the *first-order* model corresponds to Young's formula, extended with the restart time: $\tau = \sqrt{2\delta(M + R)}$. Second, the *modified* model solves a limitation of the first-order approximation, which is its poor predictive power to deal with small values of M. Thus, the formula for the optimum checkpoint period becomes $\tau = \sqrt{2\delta(M + R)} - \delta$. Third, the *complete* model improves the previous models in two ways. It does not approximate the rework time as a half of the checkpoint interval $\tau + \delta$, because in a high failure rate scenario failures are more likely to occur at the beginning of the interval. Also, this last model contemplates the possibility of a failure hitting the system during restart and the next checkpoint interval.

The Scalable Checkpoint/Restart library (SCR) has an underlying performance model based on a Markov model [31]. The SCR library can checkpoint to multiple levels. Each level increases the checkpoint latency but improves the reliability at the same time. The first level consists of RAM disks that can only tolerate a fraction of all the failures in the system. The second level incorporates partner nodes that store the checkpoint and are able to handle more types of failures. Finally, the third level corresponds to the file system, which may tolerate almost any type of failure but at a higher cost in performance. The performance model in SCR defines L checkpoint levels and associates a checkpoint duration and a probability of handling a failure to each level. This model computes how often SCR should checkpoint in each level to optimize the total execution time.

An early version of the performance and energy models in this chapter appeared in a previous publication [77]. We have extended those formulations by modeling the checkpoint interval in a different way. This change allows us to be more accurate in the predictions for exascale. Additionally, we validated the model predictions with simulation results.

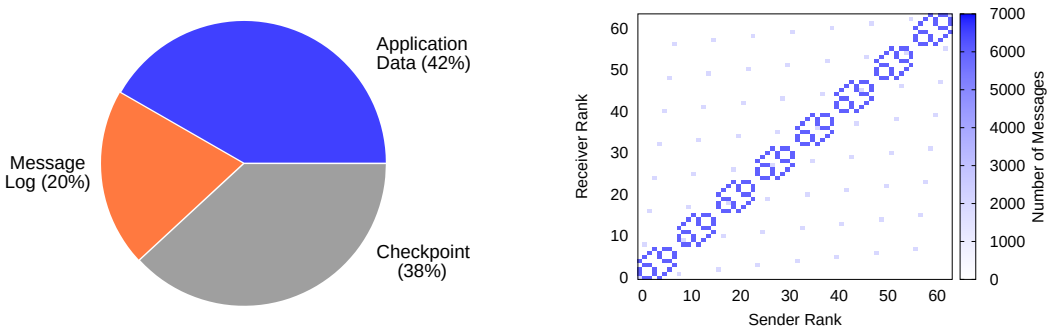
CHAPTER 5

Team-based Message-Logging

Message-logging protocols are a promising alternative to provide fault tolerance in HPC applications at large scale. Chapter 3 showed how the performance overhead of message-logging can be reduced by exploiting the static communication properties in parallel programs. A projection on the dramatic reduction of message-logging in execution time and energy consumption was presented in Chapter 4. However, one fundamental challenge of message-logging is the increase in memory overhead. Since messages are stored in memory, the size of these messages and the frequency of communication may drastically increase the memory footprint of the whole application, ruling out message-logging as an effective resilience solution.

This chapter offers a general solution to reduce the memory overhead of message-logging. It stems from an observation of multiple parallel applications and the programming patterns used in those codes. It is natural to find groups of highly connected tasks in parallel programs. We call this groups *teams* of tasks and develop a more memory-efficient message-logging protocol for applications that exhibit clusters in their communication graph. Other strategies to decrease the memory footprint of message-logging can be found in following chapters. Chapters 6 and A present additional application-specific strategies to reduce the size of the message log.

Depending on the communication characteristics of an application, memory consumption may become a major obstacle in adopting message-logging. Imagine an application that sends large messages with a high frequency. This particular application will make message-logging quickly exhaust the available memory, forcing the operating system to swap out memory pages and slowing down the execution. We analyzed the memory overhead created by certain applications when using message-logging and observed how critical this problem might become. Figure 5.1 shows the memory footprint and the communication patter of



(a) Contribution of different factors to memory footprint. The message log may represent a significant memory overhead.

(b) Communication graph in NPB-CG class B. There are clear clusters of tasks that encircle most of the messages.

Figure 5.1: Characteristics of NPB-CG benchmark class B on 64 PEs. The memory overhead of message-logging can be onerous, but the communication graph shows that most messages are exchanged inside groups of tasks.

NPB-CG benchmark when running on 64 PEs. Figure 5.1(a) displays the breakdown of all the memory footprint of the application when using message-logging. The application data consumes 42%. The checkpoint size uses 38%, a little less than the data size. Checkpoint size may not be the same as data size, because the application may use temporary data structures that are not required to be checkpointed. What is alarming is the relative size of the message log. With 20% of the total memory consumed by the program, it represents a non-trivial amount of memory. Even worse, the size of the message log depends on the checkpoint period. Following the notation in Chapter 4, if the checkpoint period τ is sufficiently large, then the relative size of the message log may exceed the size of the checkpoint, making it a more memory expensive approach than double in-memory checkpoint/restart [25]. In some cases, the amount of memory used to store messages may surpass the size of the physical memory.

The other side of the story is presented in Figure 5.1(b). Although this program requires a lot of memory to store messages, its communication structure offers an opportunity. The communication graph shown in the figure reveals the presence of groups of tasks that have a higher connection is terms of the number of messages. More specifically, across the main diagonal, we see 8 strongly connected groups. If we did not log messages between groups, but only across groups, we could save a substantial amount of memory. Not only is the communication graph highly clustered, but also very sparse. And this is another important observation, because a high percentage of the total memory required to store messages in the

application can be reduced by forming communication groups. The tradeoff of this approach is that communication groups will behave like teams. If one of the team members fails and needs to recover, the rest of the team will rollback along the failed member.

It does not come as a surprise that many applications show a structured communication pattern. The reason behind this topology is that programmers usually follow programming patterns to put together their application. That provides well structured graphs that can be analyzed with relative ease. Exploiting this structure is key in addressing message-logging challenges. The team-based message-logging strategy reduces memory overhead by applying clustering techniques to the communication graph on an application.

Clustering is a very useful tool in data mining. Finding clustered sets of entities is a fundamental principle that has applications from phylogeny creation in molecular biology to fraud detection in electronic transactions. There are many different methods to find clusters in a data collection. Some of those methods require the number k of clusters, while other methods function without that input. What is always required in a clustering mechanism is the idea of *distance* or its inverse *similarity*. This function associates a score to every pair of entities in the data collection. In our case, the similarity function corresponds to the communication volume exchanged between two tasks.

By grouping tasks and only logging inter-team messages, we reduce memory consumption, but we rollback more tasks. This tradeoff will be a constant in this chapter. Chapters 6 and A offer a different kind of tradeoff, where no more tasks are rolled back when one of them fails, but an increased complexity in the code is necessary to handle a failure.

This is a list of the highlights of this chapter:

- A collection of different applications and their clustering structure is presented (§ 5.1).
- A traditional message-logging protocol is extended to add the notion of communication teams (§ 5.2). We demonstrate this extension offers a correct recovery and a tradeoff between memory overhead and recovery effort.
- A team-based load balancing framework is presented (§ 5.3). We showed how a runtime can dynamically form teams to minimize memory overhead.
- An implementation and experimental results of the protocols in this chapter are offered (§ 5.4).

5.1 Mining for Communication Clusters

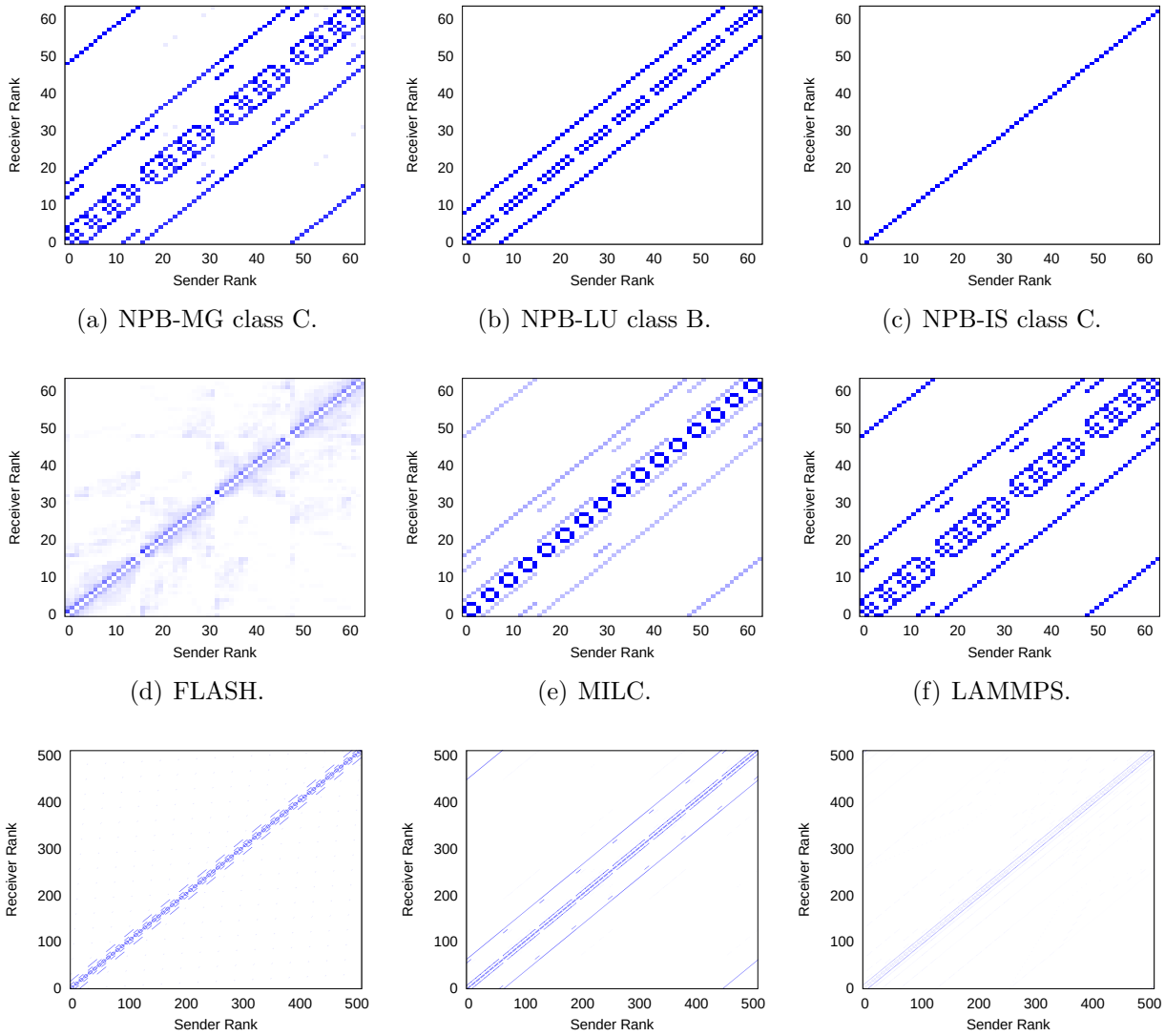
The first step in understanding the applicability of the team-based approach is to analyze different parallel programs and examine their communication graphs. We surveyed several benchmarks and applications to see whether clusters arise in different codes. The initial intuition was that the traditional programming schemes would generate clusters in the communication graph of programs.

The communication pattern of an application is the result of the programming pattern employed to code the program. The links in the graph are determined by the initial data and functional decomposition into tasks. For instance, in a stencil program in 3D, the communication pattern is regular. Each tasks will contact its 6 neighbors in 3D and create a predictable communication structure. Moreover, as the 3D stencil scales the communication pattern will remain the same.

Figure 5.2 presents a collection of communication graphs for different programs. It presents the number of messages exchanged between sender and receiver rank. Since messages are almost all the same size, the number of messages and the communication volume are correlated. The top row contains three other NPB benchmarks on 64 PEs. Figure 5.2(a) represents NPB-MG class C benchmark. Most of the communication concentrates near the main diagonal, but there is some non-trivial amount of messages that are far away from the main diagonal. In any case, a high volume of communication near the main diagonal suggests a clustering of consecutive ranks. Dividing the ranks into 4 groups would naturally capture a great deal of messages within the groups. Tighter clusters appear in Figure 5.2(b) for the NPB-LU class B program. In this case, most of the communication concentrates near the main diagonal and 8 clusters emerge at simple sight. The most extreme case of concentration of communication appears in Figure 5.2(c) for the NPB-IS class C benchmark, where the message exchange pattern only involves the next rank.

The second row in Figure 5.2 shows real life scientific applications running on 64 PEs. Figures 5.2(d), 5.2(e) and 5.2(f) represent FLASH, MILC and LAMMPS, respectively. They show very different stories. On the left extreme, FLASH presents a modest concentration of communication near the main diagonal, but it appears that a lot of communication is dispersed throughout the whole matrix. MILC has a more organized structure. In fact, it shows highly concentration of messages in 16 different clusters that are located along the main diagonal. These clusters resemble the ones in Figure 5.1(b). Interestingly, LAMMPS presents the exact same communication pattern as NPB-MG with minor differences in the concentration of messages away from the main diagonal.

The bottom row in Figure 5.2 scales some of the programs to 512 PEs. The first two



(a) NPB-MG class C. (b) NPB-LU class B. (c) NPB-IS class C.

(d) FLASH. (e) MILC. (f) LAMMPS.

(g) NPB-CG class D. (h) NPB-MG class D. (i) GTC.

Figure 5.2: Communication graphs of several parallel programs. There is usually a clear clustering structure of the tasks, which causes most of the communication to be enclosed within the clusters.

programs, NPB-CG class D and NPB-MG class D are shown in Figures 5.2(g) and 5.2(h), respectively. We see that in both cases, the communication pattern remains fundamentally the same as its smaller counterparts, except that it is now stretched to a larger system. Figure 5.2(i) shows GTC and its communication graph that features a high density of messages close to the main diagonal with clusters similar to those in Figure 5.2(g) but with diagonals carrying more communication.

Many applications amenable to the team-based approach because they naturally contain

clusters of tasks. The next big question to answer is how to automatically find such clusters. Section 5.3 will explore more deeply this issue, but we will introduce a series of important insights about the size of the teams. Intuitively, the larger the teams, the more communication is enclosed by them. This is in general true, but we must remember that having teams too large may overturn the advantage of having teams in the first place. Thus, a sweet spot in the team size and number of teams is certainly desirable.

Table 5.1 shows a list of all the applications in Figure 5.1(b) and Figure 5.2 and the fraction of communication (measured as number of messages) that needs to be logged as the team size increases. The teams were formed by joining consecutive ranks into a team. For instance, if the team size is t, then ranks 0 to $t-1$ will form the first team, ranks t to $2t-1$ will form the second, and so on. From the data in the table, it is clear that bigger teams reduce the amount of communication that has to be logged. The effect is radically different for different applications. The NPB-CG benchmark finds a sweet spot in teams of size 8, where it has to only log 8% of the total number of messages. Doubling the team size in NPB-CG does not fetch any significant advantage. The NPB-MG benchmark tells a different story. In this case, the benefits of larger teams seem to increase every time at a good rate. The same is true for NPB-LU. A very regular case is that one of NPB-IS where doubling the team size roughly halves the ratio of communication that moves across teams.

The full-fledged applications FLASH, MILC and LAMMPS provide a similar scenario in terms of the team size effect. They all still retain more than 25% of the communication inter-team even when the team size is 16. The large scale programs in Table 5.1 show that for the same benchmarks, as we scale the team size must scale as well to keep the same ratio of inter-team communication.

Table 5.1: Edge cut or fraction of total communication that crosses team boundaries.

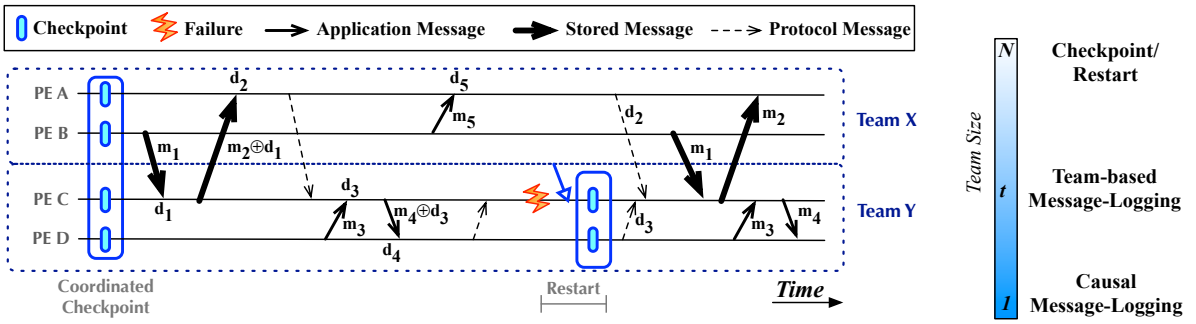
	Program									
Team Size	NPB-CG class C	NPB-MG class C	NPB-LU class B	NPB-IS class C	FLASH	MILC	LAMMPS	NPB-CG class D	NPB-MG class D	GTC
2	0.69	0.83	0.71	0.49	0.83	0.75	0.83	0.80	0.83	0.88
4	0.38	0.66	0.57	0.23	0.64	0.50	0.66	0.62	0.75	0.79
8	0.08	0.50	0.50	0.11	0.45	0.37	0.50	0.43	0.66	0.72
16	0.07	0.33	0.21	0.04	0.25	0.25	0.33	0.24	0.50	0.45
32	0.05	0.17	0.07	0.01	0.12	0.12	0.17	0.06	0.42	0.28

In view of this abundant opportunity for clustering, we embarked on a mission to gather more communication graphs and to find a good way to cluster them. A collection of different parallel programs and their clustering structure, along with a clustering algorithm, can be found elsewhere [79].

5.2 Message-Logging Protocol

We leverage the locality in communication of many HPC applications by designing a message-logging protocol that trades off a reduction in memory overhead for an increase in the number of PEs that roll back after a failure. The protocol divides the system into teams of t PEs each and avoids logging messages internal to a team. Only messages crossing team boundaries will be stored. After the failure of one PE, all its team members roll back along the failed PE. For simplicity, we will only present a team-based version of a causal message-logging protocol. However, we are confident the same idea can be applied to many other protocols.

Figure 5.3 presents an illustration of team-based message-logging. An example execution appears in Figure 5.3(a) where a system with 4 PEs is divided into two teams. Team X contains PEs A and B and team Y groups PEs C and D. The execution starts with a global coordinated checkpoint. Although this is not a strict requirement for the protocol, we will assume global checkpoints across the system. This is a safe assumption considering that many HPC applications contain global synchronization points, where the checkpoint calls could be made. Messages m_1 and m_2 are inter-team and as such are logged. These two messages generate a determinant as soon as they are received, d_1 and d_2, respectively. Message m_2 carries the determinant d_1 as part of the causal protocol. Messages m_3 and m_4 are intra-team and are not logged, because they will be reproduced during recovery. The same is true for message m_5.



(a) Sample execution with team-based message-logging.

(b) Spectrum of protocols.

Figure 5.3: Team-based message-logging protocol. Only messages crossing team boundaries are stored, but determinants are generated for all messages. If one team member fails, the rest of the team rolls back along.

Figure 5.3(a) presents the case where PE C fails. Note that both PEs C and D roll back to their latest checkpoint. The system will ask all other PEs to send any determinants they may have for PE C and to re-send the messages to all team members. Determinants d_2 and

d_3 are provided by external and internal team members to C. Message m_1 gets re-sent from the log of PE B. However, message m_3 is re-sent as part of the recovery of PE D. In fact, message m_3 represents the tradeoff in team-based message-logging. Since m_3 is not logged, it must be regenerated by rolling back its sender, PE D. The rest of the execution proceeds normally with the observation that message m_2 is a duplicate and gets ignored at PE A.

One way to understand team-based message-logging in terms of the memory overhead of the message log is presented in Figure 5.3(b). Imagine a spectrum of fault tolerance protocols according to the amount of communication they log and how the team size is related to that. For instance, if the team size is equal to the total number of PEs in the system, N, then there are no messages being logged, because there is only one team and all messages are intra-team. At the other extreme, when the team size is 1, then every message between PEs gets logged. In this case, there are N teams and all the external messages are inter-team. Finally, the team-based approach offers a middle ground between the two extremes, where the team size t will make the system log some messages.

5.2.1 Algorithmic Description

We assume an execution model equivalent to the one presented in Chapter 2 for migratable objects. Thus, a system Σ with S PEs runs an application with a set Γ containing G objects. The objects are placed onto the set of PEs by the runtime system. Any object may be moved to a different PE during execution. However, for the sake of simplicity, we assume objects do not migrate. Extending the algorithms below to work with migration is feasible, but it may come at a non-negligible expense in complexity. Each PE then holds a set of objects that are *local* to that PE. All other objects in the system are called *remote* from the point of view of that PE. We will present the necessary algorithms from the perspective of a PE sending or receiving messages for objects it contains.

There is a handful of fundamental data structures to guarantee the consistent recovery of the protocol. Each PE holds a `ssnTable` that stores the mapping of send sequence numbers (ssn) for every pair of objects $\langle sender, receiver \rangle$. Conversely, there is also an `rsnTable` which maps for every pair of objects and a ssn a unique receive sequence number (rsn). Recall from Chapter 2 that the union of those four values $\langle sender, receiver, ssn, rsn \rangle$ form a determinant. Each PE will store the determinants it produces in the `rsnTable`. Additionally, since all the determinants must be safely stored in a PE different form the origin, a list of unacknowledged determinants is held in each PE. This list is called `detList` and will expand and shrink during execution. The determinants coming from different PEs

are stored in `detLog`. This data structure will be used to send the determinants to a crashed PE. Finally, `msgLog` will store the content of the messages sent to other teams. Thus, this is a sender-based message-logging scheme.

Algorithm 11 shows the procedure to send a message from a local object α to object β (local or remote). Only inter-team messages are logged, but every single message gets its corresponding *ssn*. The team of an object is the team of its enclosing PE. The receive counterpart of the protocol is shown in Algorithm 12, where local object β receives a message from object α (local or remote). Every received message gets an *rsn* to form the whole determinant. Thus, the formation of a determinant occurs in two stages. The sender provides the *ssn* and it is not until the receiver assings the *rsn* that the determinant is complete.

To discard duplicate messages during recovery, each object stores the current *progress* state in terms of the most recent *rsn* processed. Thus, if the object is *beyond* an *rsn*, we tag the message as duplicate and ignore it. Note that the function `Process` will perform any buffering of messages that are not ready to be delivered.

Algorithm 11 SEND(α, msg, β): object α sends msg to object β

```
1: msg.sender ← α
2: msg.receiver ← β
3: msg.ssn ← α.getSsn(β)
4: msg.dets ← detList                          ▷ Piggybacking determinants
5: msg.incarnation ← IncarnationNumber
6: if α.team ≠ β.team then
7:     msgLog.add(msg)                         ▷ Storing only inter-team messages
8: end if
9: NetworkSend(msg)
```

Algorithm 13 describes the process to update `detList` with the set of determinants that have just been safely stored in other PE. Since the protocol assumes globally coordinated checkpoints, at checkpoint time all relevant data structures are cleaned up and the checkpoint is sent to the *partner* PE. Algorithm 14 describes the checkpoint procedure. Finally, once a failure has been detected and the restart of PE A has been triggered, all other PEs are notified. Algorithm 15 offers the perspective of a PE that gets the restart message. To help PE A to recover, the first step is to send all the determinants belonging to objects in A. Then, messages bound to objects in A are sent along with messages to objects in the same team as A. Note that determinants of objects in the same team as A but not in A are not forwarded. The reason is that those determinants exist in their origin processor. If B belongs to the same team as A and B rolls back along with A, it will not need its own determinants to be re-sent, because those determinants already exist in B.

Algorithm 12 RECEIVE(α, msg, β): object β receives msg from object α

```
1: num ← msg.incarnation
2: if OldIncarnation(num) then
3:     DiscardOld(msg)                          ▷ Ignoring old message
4: end if
5: rsn ← β.getRsn(α, msg.ssn)
6: if β.beyond(rsn) then
7:     DiscardDuplicate(msg)                    ▷ Ignoring repeated message
8:     return
9: end if
10: detLog.add(msg.dets)
11: NetworkSendAck(msg.dets)
12: detList.add(⟨α, β, ssn, rsn⟩)
13: Process(msg)
```

Algorithm 13 ACKNOWLEDGE($dets$): received at PE A

```
1: detList.remove(dets)
```

Algorithm 14 CHECKPOINT(): called at PE A

```
1: ckptMsg ← {}
2: detLog.clean()
3: msgLog.clean()
4: for all objects α do
5:     ckptMsg.add(α.state)
6:     NetworkSend(ckptMsg)
7: end for
```

Algorithm 15 RESTART(A): received at every PE except A

```
1: for all objects α in A do
2:     Send all determinants of α in detLog
3:     Send all messages bound to α in msgLog
4: end for
5: for all PEs B in the same team as A do
6:     for all objects β in B do
7:         Send all messages bound to β in msgLog
8:     end for
9: end for
```

The restart procedure for A is omitted for brevity. After PE A crashes, the runtime system will use a spare PE to replace A and recreate all the objects in the lost PE. The checkpoint buddy of A will provide the latest checkpoint to A. Then, the runtime system will make the RESTART(A) call in every other PE.

5.2.2 Formal Proof of Correctness

We will prove that the team-based message-logging protocol recovers correctly from the failure of one PE. We will constructively prove that the protocol retrieves all necessary determinants and all necessary messages during recovery. Additionally, there are no orphan objects and a global consistent state is reached.

Lemma 5.1. *All required determinants are successfully retrieved during recovery.*

Proof Sketch. Let us suppose PE A fails and during recovery object α in A collects all its determinants. Since the process to generate, piggyback and collect determinants remains the same as in the regular causal message-logging protocol, then all determinants for α are successfully collected. If a determinant was generated by α but was never piggybacked in any outbound message from A, then it is impossible to retrieve. However, that determinant is not necessary for a consistent recovery, because it never affected the rest of the system. An object β in PE B belonging to the same team as A will successfully retrieve all its determinants because B clearly has them all, as B never failed and its data structures still persist. □

Lemma 5.2. *All required messages are successfully replayed during recovery.*

Proof Sketch. Let us assume object α is recovering in PE A. If message m was sent to α before the crash, it will be sent again during recovery. There are 3 possible cases. First, message m may have been an inter-team message in which case it will be stored in the message log of some PE and replayed after restart. Second, it may have been an intra-team message. Thus, message m was never logged and can not be replayed. However, the sender of message m must be recovering along with α and given the PWD assumption, it will eventually send m. Third, message m may have been a local message. If this is the case, then m will be generated by the same token as the previous case. □

Lemma 5.3. *There are no orphan objects.*

Proof Sketch. By contradiction. Let us assume there is an orphan object γ. This object must have received at least one message that was not re-sent during recovery. Let us call m one of those messages. The sender of m did not send m during recovery, but it received all necessary determinants and messages according to Lemmas 5.1 and 5.2. Thus, according to the PWD assumption, all the causally related events before message m must have occurred and m must have been sent. This is a contradiction, then there can not be neither such a message m nor such an orphan object γ. □

Theorem 5.4. *The recovery process in team-based message-logging is correct.*

Proof Sketch. By Lemmas 5.1 and 5.2 all determinants and messages are retrieved during recovery. That guarantees all the necessary information for a recovery is available. Finally, the recovery is consistent by Lemma 5.3. □

5.3 Team-based Load Balancing

The team-based message-logging protocol provides a promising method to decrease the memory overhead of the message log. The number of teams k provides a tradeoff between the memory overhead reduction and the additional recovery cost. Given a user-defined value for k, there are at least two important classifications for the type of teams to be formed. First, the teams can be either *random* or *structured* if the communication graph of the application is taken into consideration when forming the teams. Second, the groups can be either *static* or *dynamic* if they are allowed to change during execution.

Random team formation provides nevertheless a moderate benefit. If messages were sent to random targets, using k teams, we should expect having a reduction of $1/k$ in the total memory used. This is because there is a chance of $1/k$ that a particular message is sent to a target in the same team and does not require logging. However, as figure 5.1(b) illustrates, many HPC applications have a well defined communication structure that can be exploited to aggressively reduce the memory overhead. Thus, we will prefer structured teams to further improve the impact of the team-based philosophy.

Static structured teams are able to leverage the divide-and-conquer approach of teams for message-logging. However, dynamic structured teams provide at least two major advantages. In the first place, dynamic teams are *automatic*. As such, there is no need to profile the application to get the structure of the teams. This provides a great advantage when the same application is used at a different scale or with a different problem size. Second, dynamic teams may capture the communication changes of an application during execution. Imagine a weather modeling application that is simulating a storm over a small geographical region. As the storm makes its way through the region, the communication volume between the different objects that represent subregions in the space will change. To better capture that pattern, dynamic teams will adapt accordingly.

In order to obtain dynamic structured teams to use as the basis for the team-based approach, we build upon the notion of a load balancing framework. The fundamental reason to use the load balancer is that a change in communication will probably be correlated with a change in the load of the different PEs in the system. Thus, the two aspects, teams and load,

should be modified together. We assume the runtime system keeps track of all the activity of the objects in the system, including the computation they perform and the communication among them. Using that information, the runtime system can build an *object graph*, where nodes in the graph are objects and links determine how many bytes are exchanged between objects. A load balancer receives as a parameter the object graph and the number of PEs. As an output, the load balancer returns a mapping between objects and PEs. Although the main goal of a load balancer is to improve performance, additional objectives can be attached to it. Applications in several fields suffer from load imbalance, including weather forecast [80], molecular dynamics [81] and cosmology [82].

A dynamic and structured formation of teams can be obtained by extending the load balancing framework of a runtime system [83]. The basic idea is depicted in figure 5.4. It is a multilevel process, where the two goals are attained: create structured teams and balance the load. At the left end of the figure the object graph is depicted. Darker nodes stand for objects with more computation. The first step uses a graph partitioning strategy to create teams with roughly the same combined load, but with a small *edge cut*. This means, the communication flowing between teams is reduced as much as possible. This way, most of the messages are retained inside teams and they do not need to be saved. We used a graph partitioning library to implement this step [84, 85]. The second step of the load balancer takes each team and distributes its objects into a subset of PEs. Since the load balancer is called periodically, a different mapping of objects to teams may be obtained and we have a dynamic team composition throughout the execution.

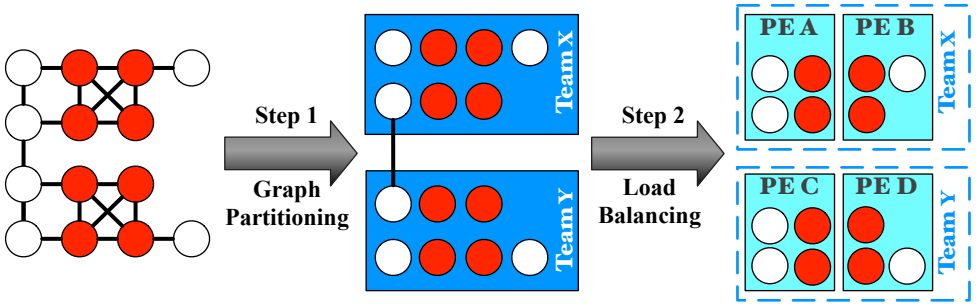


Figure 5.4: Multilevel load-balancing framework for team formation. The first step uses a graph partitioning tool to obtain teams with similar total load but with a small edge cut between them. The second step refines the load distribution among the PEs of each team.

Finally, the team-based load balancing framework (called TeamLB) provides a powerful insight: minimizing memory overhead in message-logging is equivalent to graph partitioning.

5.4 Experimental Results

We implemented the ideas of this chapter in the Charm++ runtime system [55]. The team-based message-logging protocol in Section 5.2 is implemented [86] at the object level in Charm++. This means, the runtime system keeps track of all messages and determinants a particular object has generated. That way, if an object migrates from one PE to another, all relevant information is transmitted along with the object. We also extended the load balancing framework in Charm++ to incorporate the multilevel load balancer of Section 5.3. The implementation [83] features an interface to use any graph partitioning tool.

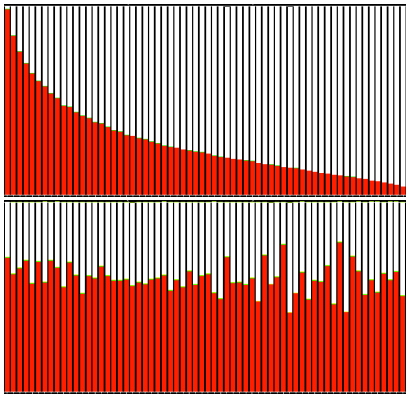
Results with the team-based message-logging protocol showed how much memory overhead can be reduced. Table 5.2 presents experimental results of three different applications running on Abe supercomputer. The protocol decreases in 80% the memory overhead for NPB-CG. Note that this program is communication bound. However, Figure 5.2(g) shows that locality in communication is high in NPB-CG. The case of NPB-MG is a little different because there is more dispersion in the communication in this case. Nevertheless, the memory overhead in cut down by 47%. These two applications show a similar decrease in the memory overhead as predicted in Table 5.1. The small discrepancy comes from the fact that Table 5.1 considered the number of messages to make the estimate. The results presented in Table 5.2 used the number of bytes as the communication graph. The two quantities are tightly related in these benchmarks, but are not totally equivalent. Finally, the last column in Table 5.2 shows a 7-point stencil and a reduction of 63% in memory consumption.

Table 5.2: Memory overhead of team-based message-logging.

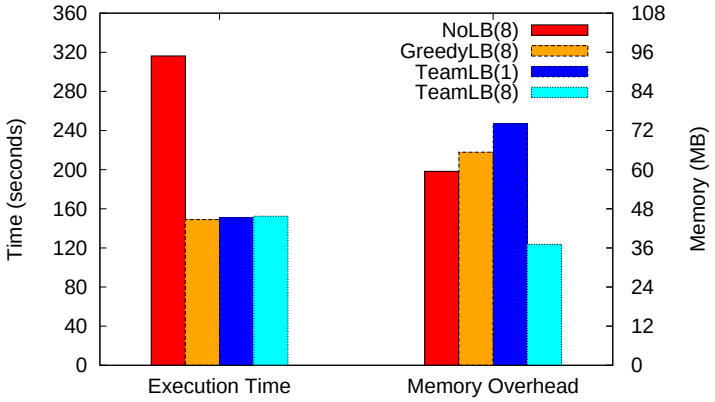
	Program		
	NPB-CG class D	NPB-MG class D	Jacobi3D
Number of PEs	512	512	256
Team size = 1 (Y)	420.11 MB	13.18 MB	195.84 MB
Team size = 16 (X)	83.85 MB	6.97 MB	73.13 MB
Fraction (X/Y)	0.2	0.53	0.37

An illustrative experiment on the load balancing scheme is presented in Figure 5.5. On the left end, we can appreciate the impact of a load balancer on 64 cores of Steele supercomputer when running the multizone version of NPB-BT. The top plot of Figure 5.5(a) shows the utilization of each of the 64 cores when no load balancer is used. The bottom plot presents the utilization on each core when TeamLB is used. The difference is dramatic and average utilization can go from 27% to 59%. Figure 5.5(b) shows the performance results of the team-based load balancer. The left side of the figure shows the execution time. We ran class B on 64 PEs and with 256 ranks on Steele. We present a comparison between three different

load balancers: *NoLB* which does not balance the load but creates random teams, *GreedyLB* balances the load and generates random teams and *TeamLB* that creates structured teams and balances the load. The number in parenthesis indicates the size of the team. By using a load balancer, we are able to halve the execution time of the benchmark. The overhead of *TeamLB* over *GreedyLB* is below 2%. But, the gains of using *TeamLB* in memory required for the message log are evident on the right part of the figure. Compared to *GreedyLB*, *TeamLB* uses only 56% of the memory.



(a) Effect of load balancing in NPB-BT multizone.

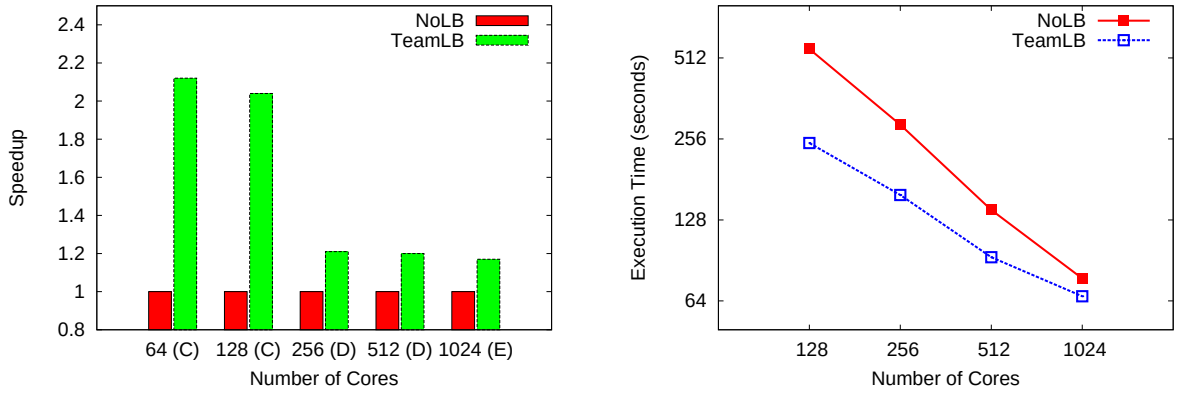


(b) Performance of TeamLB in terms of execution time of the application and memory overhead.

Figure 5.5: Evaluation of TeamLB with NPB-BT multizone. TeamLB can solve the load imbalance of the application. Compared to a traditional load balancer, it almost performs as well, incurring minimum overhead. However, the teams generated by TeamLB considerably reduce the memory overhead.

The scalability of TeamLB was tested on Steele supercomputer up to 1,024 cores. Figure 5.6 presents the results of scaling tests with two different applications. Figure 5.6(a) presents the weak-scale tests using NPB-BT multizone with different classes (specified by the letter in parenthesis next to the core count). At the lower end, the use of TeamLB reduces the execution time to less than half. At the high end the reduction is lower and settles in a speedup of 20%. The NoLB option provides a baseline case where no load balancer is used. Figure 5.6(b) confirms the scalability of TeamLB with a strong-scale test. Mol3D was run with APOA1 dataset that contains around 92,000 atoms. The scalability of this benchmark is almost linear in both cases with or without load balancing. However, execution time is halved when TeamLB is used at the lower end of the scale. The benefits continue throughout the spectrum of cores. The speedup is 16% at the higher end.

To test the dynamic team formation feature of TeamLB, we used a synthetic benchmark called LBTest. This customizable program allows us to change a wide variety of features,



(a) Effect of TeamLB when scaling NPB-BT multizone.

(b) Effect of TeamLB in a strong-scale test with Mol3D.

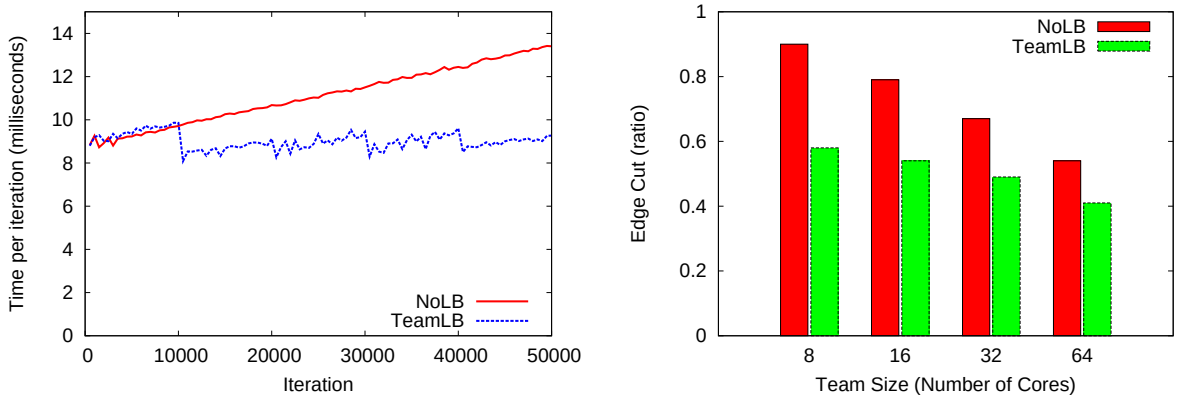
Figure 5.6: Scale tests for TeamLB. In both weak-scale and strong-scale, TeamLB is able to provide high benefits, cutting into half the execution time at the lower end of the spectrum.

from the communication topology to the granularity of computation. Figure 5.7(a) shows the result on 256 cores of Steele supercomputer when LBTest ran for 50,000 iterations. In each iteration every object exchanges a 1KB message with all its neighbors (in this case a 3D torus topology). To simulate computation every object computes for an interval of t time units (the range of t goes from 100 to 1,200). There are 4,096 objects in total and each starts with a value of t that is equal to the middle point of the scale. The load imbalance will appear as the value of t in every objects drifts to a random extreme. The load balancer was applied every 10,000 iterations and the figure shows how TeamLB was able to bring down the iteration time after load imbalance would decrease the time per iteration of the program.

Figure 5.7(b) presents the result of running Mol3D on 256 cores of Steele supercomputer with different team sizes. Note that NoLB creates random teams of size equal to TeamLB. However, the consideration of communication patterns in the application makes TeamLB outperform NoLB by a margin higher than 20% on the low end.

5.5 Discussion

Many applications show a high degree of locality in communication. However, an important question is how that property scales with the size of the system. If global communication operations are not intense in the application, then team-based message-logging has a high probability of maintaining a high reduction in memory overhead while keeping low the recov-



(a) Effect of dynamic load balancing in LBTest.

(b) Impact of team size in reducing memory overhead.

Figure 5.7: Performance evaluation of TeamLB. The dynamic team creation and load balancer allows TeamLB to achieve its two-fold mission when changes occur in the application: increase the performance and decrease the memory overhead of message-logging.

ery cost. More explicitly, if the team size and the memory reduction can be kept constant as the application scales to high number of cores, then teams will find the best scenario. This property may not always be feasible in applications, due to programming practices that force more global communication. Scaling techniques similar to scale-free networks will provide an environment where the communication graph scales without requiring the size of the team to grow accordingly.

For most of the benchmarks analyzed in this chapter, the communication volume carried by collective communication operations was relatively low. It is usually the case that these operations are used to run small reductions or broadcast and do not represent large messages. For those cases where significative amounts of information is transmitted via collective, Chapter 6 will offer an alternative method.

The idea of grouping objects into teams can be applied to most message-logging protocol. In fact, the initial implementation of the team-based approach [83] used a pessimistic message-logging protocol. The trade-off imposed by teams is, for the most part, orthogonal to how consistency in recovery is achieved.

5.6 Related Work

The idea of using subgroups of tasks to decrease the overhead of information logging has been used in the context of large-scale debugging [87]. Record/replay is a well known debugging

technique that offers a framework where a particular faulty execution can be deterministically reproduced. Such reproducibility of results and conditions helps in determining more easily the causes of problems and limitations in the programs. There are two kinds of record/replay mechanisms. *Data replay* consists in storing all incoming messages to each of the tasks in an execution and replaying them during debugging. Although there is a high memory consumption with this technique, during replay the user can choose which tasks in particular will be replayed. Alternatively, *order replay* strategies only store the outcome of non-deterministic events in the execution. To generate the messages during replay, all the tasks are forced to execute. Memory consumption is minimum, but the cost of replay may be too high. This is particularly problematic in a large-scale environment. MPIWIZ is a record/replay tool that offers a middle ground between the two types of mechanisms previously described. It introduces a *subgroup reproducible replay* (SRR) that balances the benefits of both data replay and order replay. Each SRR is a disjoint group of tasks. MPIWIZ only records the messages crossing group boundaries. For intra-group messages, it records the ordering but not the messages themselves. In the replay phase, each group will be replayed as a unit, but it will not require the replay of additional groups, since inter-group messages are always recorded. A key value in MPIWIZ is the size of each group. To find an appropriate value for the group size, MPIWIZ uses the strong communication locality present in many HPC applications [88].

In distributed computing settings, like grid or cloud infrastructures, the cost of coordinated checkpoint may be prohibitive. In those environments interconnection technologies are still dominated by Ethernet. That means bandwidth may not be an issue, but latency will hurt performance of tightly coupled applications. In particular, coordinating a global checkpoint of a large number of machines may result in a significant delay in the progress rate of an execution. Message-logging does not require coordinated checkpoint and as such represent a clear opportunity to provide fault tolerance in this type of scenarios. However, the memory overhead of the message log could offset the benefit of message-logging. One of the first approaches to explore a trade-off between coordinated checkpoint and message-logging is called *coarse-grained pessimistic message-logging* [41, 89]. The system of N processes is divided into g groups. Each group checkpoints in a coordinated fashion following a time-based coordinated checkpoint scheme. A causal message-logging protocol is used inside each cluster, but a pessimistic message-logging is used across clusters. Hence, the granularity of the pessimistic protocol is increased from a process level to a cluster level. Messages that are exchanged between members of the same cluster are not logged. The experimental evaluation of this approach did not go beyond 16 processes.

The notion of distributed recovery units (DRUs) offers the same tradeoff between size of

message log and overhead of recovery [90]. A DRU is a collection of processes that may reside on different processors. The whole distributed system is seen as a collection of DRUs. Similar to teams, a DRU can be formed by only one process in the extreme case. However, processes are dynamically assigned to DRUs according to the needs of the application. The particular partition of processes into DRUs may have different goals. For instance, processes may be assigned to the same DRU if there is a high frequency of messages between them. Alternatively, processes may belong to the same DRU if they reside on a predetermined set of processors. Recovery in DRUs follows a simple scheme [91]. Each DRU recovers using a local recovery scheme, whereas the system as a whole relies on a global recovery system. The difference between the implementation of DRUs and teams resides in the fact that DRUs use receiver-based optimistic message-logging. The DRU approach dumps the messages to the storage system as opposed to main memory.

A similar argument was followed to create a *group-based checkpoint/restart* technique [42]. The authors of the paper justify the approach by showing that coordinated checkpoint may take several seconds in a system with less than 100 processes. To reduce the coordination cost, the authors resort to groups of processes that checkpoint in a coordinated way. Each group will checkpoint at its own pace, but to guarantee a successful recovery, message-logging is used to store messages across groups. There is no notion of determinants in the message-logging mechanism, making this scheme only effective for fully deterministic applications. The paper introduces a greedy algorithm to create the groups dynamically, based on the communication graph of the program. The only parameter of the clustering algorithm is the maximum size of a cluster. The algorithm proceeds in a similar manner to other greedy clustering methods, like hierarchical agglomerative clustering (HAC). The evaluation of this approach used up to 144 processes.

The programming pattern of the application can be used in determining the proper fault tolerance mechanism for a particular application [92]. In particular, that paper presents a master-worker pattern and how the set of workers can be divided into *communication subgroups*. Each subgroup shows a highly concentration of the communication in the application. If those subgroups are sparsely connected, then a failure in one group should affect only the members of its same group. This assumes message-logging occurs between the groups. A color mechanism is employed to form checkpoints inside each group. Each checkpoint will have a particular color and members of a group will be colored according to which is the latest successful checkpoint. The colors also help to keep track of the causal dependencies between checkpoints in the groups. The paper presents no evaluation and its applicability is limited to master-worker programs.

A different approach to generate groups of highly connected processes uses a string match-

ing algorithm [43]. The paper is motivated by the need to co-migrate processes in case of load imbalance in a grid setting. If a node becomes overloaded, a group of processes running on that node can be checkpointed and migrated away and overall utilization can be increased. In order to do that, groups of processes that exchange a high communication volume must be detected. The analogy used in the paper is that an MPI process sequence of messages can be seen as a string. A function maps every pair of MPI processes to a unique symbol. Using these strings, an algorithm can dynamically identify similar strings that will correspond to MPI processes that exchange a significant amount of messages among them. These groups of similar sequences will determine the group of MPI processes that will migrate together. The evaluation used only 8 processes.

In a specialization of a message-logging based on send-deterministic programs [71], groups of ranks are formed to provide failure containment. Thus, the failure of one rank will not propagate beyond its enclosing group.

CHAPTER 6

Collective-Aware Message-Logging

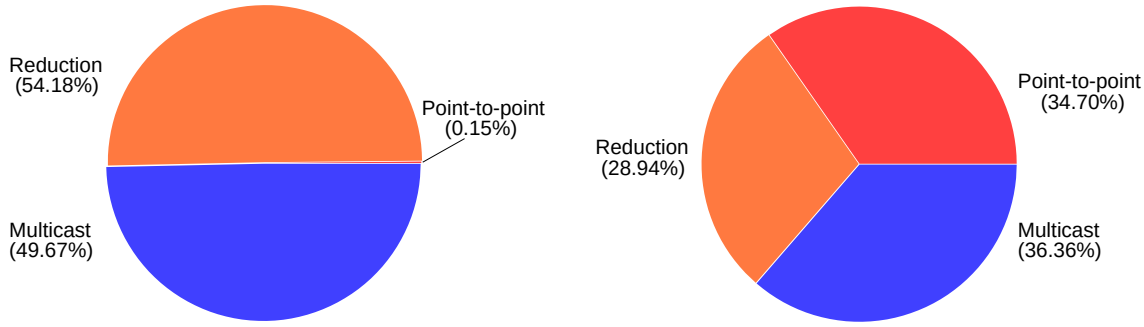
Collective communication operations offer a convenient way to coordinate the work of the objects involved in a parallel computation. This type of operations are commonly found in most HPC programs. They play an important role in efficiently scaling parallel codes. In fact, improving the implementation of collectives may bring a substantial performance benefit [93]. The research question we will answer in this chapter is how message-logging can be tailored for this type of operations. The design of a collective-aware message-logging protocol has two major goals: a reduction in memory overhead and a reduction in the number of determinants generated as part of a collective operation.

The use of collective communication operations can be substantial in some codes. For instance, a typical implementation of Fast Fourier Transform (FFT) involves exchange of data between groups of tasks in an all-to-all fashion. There is little computation in FFT relative to the use of collectives. In other applications, computation may be substantial but collective operations represent the main mechanism to transport data. Figure 6.1 presents a couple of applications with that profile.

The molecular dynamics benchmark LeanMD (see Appendix C) carries most of the data through two collective operations: multicast and reduction, as shown in Figure 6.1(a). This is justified by the program structure in LeanMD, where a three-dimensional space is divided into *cells* and each cell contains a subset of the total collection of particles. In each iteration, the cells exchange the positions of their particles with the neighboring cells. The number of neighbors changes according to the parameters in the program. To make the code scalable, LeanMD employs the same strategy as NAMD [94]. A set of objects, called *computes* perform the interaction computation between particles of cells. Each compute is associated with two cells, but a cell is associated with potentially many computes. In some cases, depending on the range of the interaction, a cell many interact with dozens of computes. When a cell

distributes its particles to all the computes, it employs a multicast operation. Conversely, a reduction mechanism is used to aggregate the result of the interaction computation of particles from all the computes a cell is associated with.

The other application in Figure 6.1(b) is OpenAtom, a quantum chemistry code that implements a fine-grained Car-Parrinello *ab initio* molecular dynamics (CPAIMD) mechanism [95]. The CPAIMD method consists in numerically solving Newton's equations of motion using forces derived from the electronic structures of *ab initio* calculations. The computational structure of CPAIMD includes several phases: multiple concurrent sparse three-dimensional FFTs, non-square matrix multiplications and several concurrent dense three-dimensional FFTs. These phases in OpenAtom include many reduction and multicast operations that carry a significant amount of data. Although the amount of communication that occurs in collective communication operations is not as high as in LeanMD, it still reaches two thirds of the total communication volume.



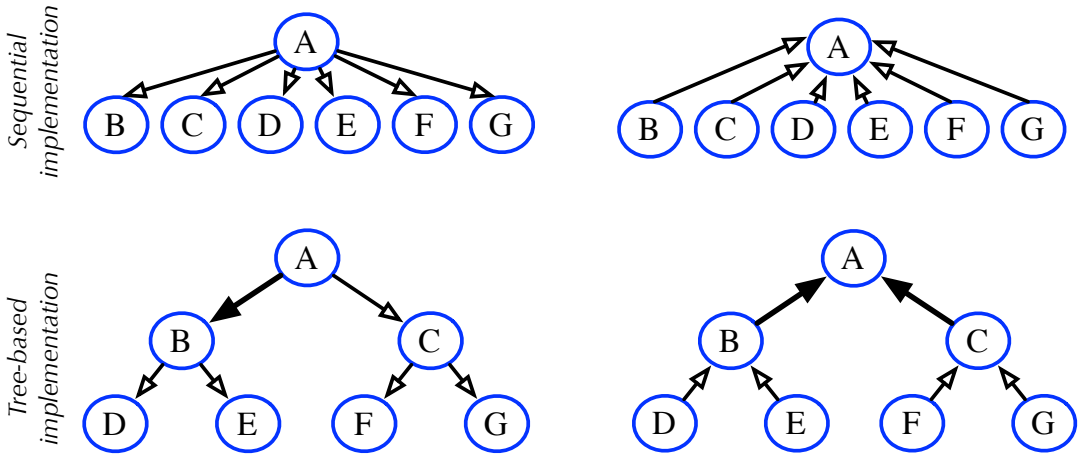
(a) LeanMD. (b) OpenAtom.

Figure 6.1: Communication volume captured by collective communication operations. LeanMD practically sends all the information through either multicast or reduction operations. OpenAtom uses collectives heavily and two-thirds of the communication load travels through collectives.

The two collective operations that we analyze in this chapter are *multicast* and *reduction*. Imagine a scenario with the set of tasks A, B, C, D, E, F, G and these two operations: a multicast from A to the rest of the set and a reduction from the rest of the system to A. There are two fundamental ways to implement these operations. Figure 6.2 shows for each operation the sequential and the tree-based implementation. Figure 6.2(a) presents the two possibilities for multicast. The top diagram shows a sequential implementation that logically corresponds with the definition of a multicast. That is, a multicast from A to the rest of

the set of tasks can be seen as many individual messages to each of all the other tasks. For message-logging purposes, this is a natural implementation that does not need any chance of standard protocols. Message-logging libraries include this type of implementation [53]. A key advantage of this implementation is that the sender can only save a copy of the message, regardless of the number of recipients. The equivalent version for reduction is presented in the top part of Figure 6.2(b). Even though this mechanism to implement multicast and reduction is straightforward and simple, it represents a clear obstacle for scalability. The sender of the multicast message becomes a serial bottleneck, hampering parallelism in communication. Additionally, a traditional message-logging protocol will make the sender store an excessive amount of information for each multicast and reduction operation.

A scalable solution to implement both multicast and reduction is to use a structure to diffuse and collect information. For instance, a hypercube or a tree of the tasks involved in the collective operation may offer an efficient way to implement the operations. The bottom part of Figure 6.2(a) shows a tree-based implementation of multicast. Thus, the multicast operation can scale at the expense of losing central control to send the multicast message. A straightforward implementation of this structure in a message-logging protocol would store several copies of the multicast message at different levels of the spanning tree. The bottom part of Figure 6.2(b) offers the corresponding reduction tree. Therefore, a tree-based implementation presents a tradeoff: more scalability at a higher memory overhead for message-logging. The goal of this chapter is to provide an extension of traditional message-logging techniques to achieve high scalability without increasing memory overhead.



(a) Multicast. (b) Reduction.

Figure 6.2: Minimizing memory overhead in collective communication operations.

If the two operations, multicast and reduction, use a spanning tree and a way to track a

collective message to the sender, it is possible to only save the minimum amount of messages to reproduce the result of the collective after a failure. The bottom part of Figure 6.2 shows two types of arrows. The head-hollow arrows denote messages that are not necessary to store, while bold arrows represent message that have to be stored. Part 6.2(a) shows the multicast operation, where task A sends a message to all the other tasks. The whole operation consists of 6 messages been transmitted through the spanning tree. However, it is necessary to store only one of them in order to recover from a failure. A typical implementation of message-logging, unaware of collectives, would save all 6 messages through the spanning tree. A similar situation happens with reduction, shown in Figure 6.2(b), where only the last contributing messages are the ones that have to be logged.

The message-logging protocols reviewed in Chapter 2 can be extended to be collective-aware and achieve two major objectives. First, a reduction in the memory overhead for collective messages is possible. Second, the amount of control information stored can be reduced. Using a spanning tree for collective requires only certain messages coming or reaching the root of the tree to be stored. However, there are particular situations to consider if a failure happens while the collective operation is in progress.

The focal points in this chapter are listed below:

- An algorithm to reduce the memory overhead of message-logging in multicast operations is introduced (§6.1). This algorithm extends the simple causal message-logging protocol of Chapter 2. An algorithmic description and a formal proof of correctness complement the section.

- The design and implementation of a scalable multicast and reduction message-logging protocol is presented. This protocol drastically reduces the memory overhead and tolerates failures at the PE level (§6.2).

- An empirical evaluation of the protocol demonstrates the reduction in memory pressure for two applications (§6.3). The experimental results scale up to thousands of cores.

- A discussion on how other collectives can be incorporated in the algorithm is presented (§6.4).

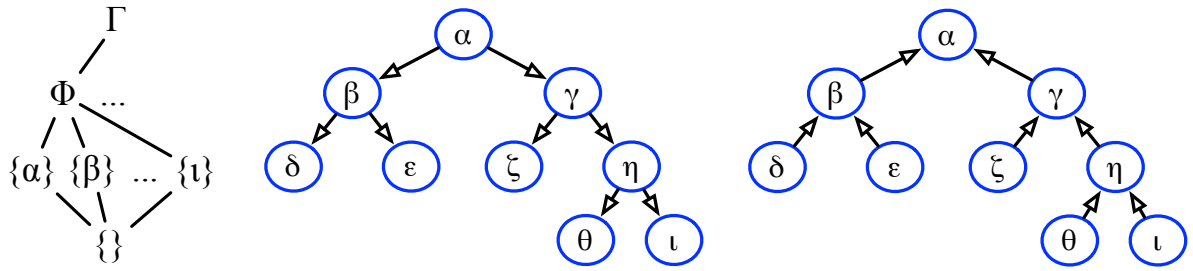
6.1 Message-Logging Protocol

This section contains a description of a specialized protocol to handle two important types of collective communication operations: multicast and reduction. The Collective-Aware

Message-Logging (CAML) protocol is an extension to traditional message-logging protocols [34]. Regardless of how determinants are handled (optimistic, pessimistic, causal), the new formulation should always generate the same determinants in all cases. For illustration purposes, we will extend the simple causal message-logging protocol presented in Section 2.4.

The extended protocol will use the computational model of Section 2.5. Therefore, we assume a collection Γ of migratable objects that exchange information via asynchronous method invocation. The network may reorder messages from the same source to the same destination. The machine is composed of a collection Σ of PEs. The objects are distributed among the different PEs and may be migrated by the runtime system during execution. We assume migration only occurs right before the checkpoint phase. Also, checkpoint is supposed to be globally coordinated. Collective communication operations will be implemented among a subset Φ of the objects. The usual meaning of these collectives applies. In other words, a multicast operation from object α to subset Φ implies that the same message m is delivered to every object in Φ and its sender is α. Similarly, a reduction from subset Φ to object α means every object in Φ sends a message to α and messages are agglomerated at the root in a deterministic fashion.

Figure 6.3 shows the two operations in the example we will use throughout this section. We will assume each multicast and reduction operation over a subset $\Phi = \{\alpha, \beta, \gamma, \delta, \epsilon, \zeta, \eta, \theta, \iota\}$ has a unique identification number. This is necessary in order to distinguish multiple concurrent multicast or reduction operations.



(a) Hasse diagram for subsets of objects.

(b) Multicast tree.

(c) Reduction tree.

Figure 6.3: Spanning tree for multicast and reduction operations.

6.1.1 Multicast Considerations

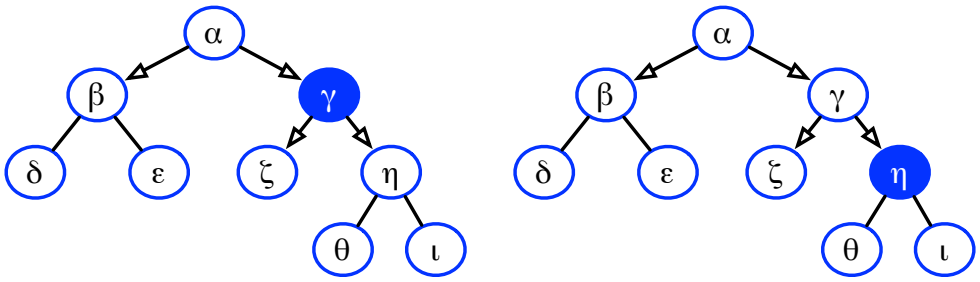
There are a handful of details that we should consider regarding multicast messages:

Message type. Each multicast message must carry a special flag in the envelope. Collective communication operation messages will be handled differently than regular messages in most cases. Therefore, it is necessary to identify such messages.

Determinant. The determinant for a regular message is formed by the following components $\langle sender, receiver, ssn, rsn \rangle$. A multicast message has the following determinant $\langle sender, receiver, group, mssn, rsn \rangle$, where *group* refers to the particular subset of objects the multicast is applied, *mssn* stands for *multicast sender sequence number* and it is the identification number of a multicast sent from the sender to the multicast group. For example, in Figure 6.3(b), the sender would be α and the message would target Φ.

Failure scenarios. The only place where the multicast message will be stored is at the original sender. In our example, only α will retain a copy of the message. In case of a failure, α will re-send all regular messages and multicast messages bound to failed objects. If object θ fails, α will send a multicast message with destination Φ, because $\theta \in \Phi$. The most critical scenarios are those when the multicast operation is not completed. Figure 6.4 offers a couple of scenarios of failures during a multicast operation. Arrows in the figure represent how far the multicast has reached. Colored nodes are failed objects. In the scenario of Figure 6.5(a) the multicast has passed the failed object γ. Thus, the multicast will eventually finish as η will propagate the multicast message to its children. As for the recovery of γ, it will receive the message from α. Once α receives the multicast message during recovery, it will forward that message to ζ and η. However, all objects are equipped with a mechanism to discard duplicate multicast messages. The scenario in Figure 6.4(b) presents the case where object η crashes and the multicast has not been propagated to the children of η. Since γ does not store the message, as it is not the original sender, it can not re-send the multicast message to η. However, α will re-send it and after the reception of that message, η will forward it to its children in the tree θ and ι.

Network-based multicast. In machines where multicast messages are implemented directly in the network, it is possible to use that optimization instead of a spanning tree. The logic of the algorithm will remain intact.



(a) Failure after forwarding multicast. (b) Failure before forwarding multicast.

Figure 6.4: Different failure scenarios for a multicast operation.

6.1.2 Reduction Considerations

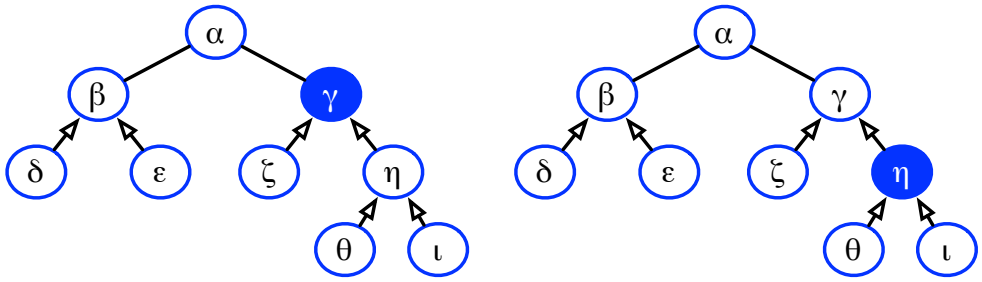
Reductions are operations that require a more careful analysis. These are the main details to consider:

Message type. Similar to multicast messages, reduction messages require a special flag in the envelope to identify themselves as special collective communication messages.

Determinant. Since the only messages that will be stored in a reduction are the ones contributing to the root of the spanning tree, only those messages will create a determinant. The rest of the messages are free to be handled in non-deterministic ways during recovery. The reason for this is explained below.

Garbage Collection. Contributing messages to a reduction must not be stored unless they are sent directly to the root of the spanning tree. However, they cannot be removed from the message log as soon as they are sent, regardless of the level in the spanning tree. If a failure strikes the system while a reduction is in progress, some of the intermediate contributing messages may be required. Therefore, contributing messages to reductions must be kept in the message log until an update message is received with the latest committed reduction number. At that point, all reduction messages not going to the root and with a reduction number lower or equal to the latest committed reduction number can be removed. There are two possible ways to send the update message. One, the root may lazily send through the spanning tree an update message with the latest reduction number when it considers that appropriate. Second, as soon as the grandparent of a node acknowledges the reception of the contribution, the node can remove its reduction messages. This more proactive strategy reduce the memory overhead as soon as it is possible, but it may require more messages to update the message log.

Failure scenarios. All objects must store the current reduction number for a particular subset Φ. This single bit of information will be fundamental in discarding old contributions and buffering future ones. As opposed to multicast, reduction messages must be stored until the root of the spanning tree has received all the contributions and completed the reduction. Figure 6.5 presents a couple of scenarios for a failure during a reduction. The first case, depicted in Figure 6.5(a) presents a failure in γ before it is able to submit the contribution to its parent. During recovery, γ will obtain the latest committed reduction number. Therefore, it will ignore contributions to reduction with a lower reduction number. As for the current reduction, its children will both have the reduction message available, as it has not been committed by the root of the tree. Hence, ζ and η will re-send the reduction messages to γ. The reduction will eventually be completed. The second scenario, shown in Figure 6.5(b) presents the case when η fails after submitting the contribution to its parent. Since the reduction has not been completed, the children of η will re-send the contribution messages to η, which will send the contribution message to its parent. At that point, γ will discard the message, because it has locally advanced to the next reduction number.



(a) Failure before forwarding reduction. (b) Failure after forwarding reduction.

Figure 6.5: Different failure scenarios for a reduction operation.

6.1.3 Algorithmic Description

We present an extension to the simple causal message-logging protocol (Chapter 2) that includes considerations for two collective communication operations: multicast and reduction. The `ssnTable` and `rsnTable` have the same usual meaning. The same happens with the structures `detLog`, `msgLog` and `detList`. The additional data structure for multicast messages is named `mssnTable` which stores the unique identification number of a multicast message to a subset Φ. Similarly, table `rssnTable` holds the current reduction

number for each group Φ. Each object has two methods, $getMssn$ and $getRssn$, to access `mssnTable` and `rssnTable`, respectively. Additionally, the envelope of a message will have an additional entry `group` to store the multicast or reduction group. Algorithms 1, 2, 3 and 4 in Chapter 2 remain unchanged.

Algorithms 16 and 17 present the steps to send and receive multicast messages, respectively. When a multicast message gets sent, it is bound for subset Φ. In other words, it does not have a specific target object, but the whole collection in the multicast spanning tree. We assume the spanning tree is rooted at α. This assumption is trivial to remove as we will see in Section 6.2. As for the reception of the multicast message, once it is received by object β, it proceeds as if it were a regular message. The symbol Φ serves as a placeholder for all the objects in the multicast spanning tree. Note that upon reception of the multicast message, the object verifies if the reception progress has passed that message. If that is the case, the message gets discarded. Otherwise, the message gets processed and it is forwarded to the rest of the spanning tree. A fundamental difference with the regular message reception lies in the fact that the new determinant now contains information about the group for multicast or reduction. This additional data will help in separating regular messages and multicast messages with the same sender and ssn, which otherwise would be identical.

Algorithm 16 SendMulticast(α, msg, Φ): object α send a multicast message to set Φ

1: $msg.sender \leftarrow \alpha$
2: $msg.receiver \leftarrow \Phi$
3: $msg.group \leftarrow \Phi$
4: $msg.ssn \leftarrow \alpha.getMssn(\Phi)$
5: $msg.dets \leftarrow$ `detList`
6: `msgLog.add`(msg) ▷ Storing message
7: **for all** children objects π in multicast spanning tree **do**
8: `NetworkSend`(msg)
9: **end for**

The send and receive counterpart for reduction messages are presented in Algorithms 18 and 19, respectively. A reduction message is usually aggregated along its way to the root of a spanning tree. Therefore, before it can be submitted up in the tree, the object has to verify whether all the expected messages have been received. The function `Ready` checks if it is time to proceed with the sending of the contribution for the reduction. We require the `Agglomerate` function to be deterministic at the root of the spanning tree. That is, the way the different contributions are glued together has to get always the same result. This includes considerations for floating point arithmetic. A way to get rid of this restriction is to add additional determinants. The agglomeration function at other levels of the tree

Algorithm 17 ReceiveMulticast(α, msg, β, Φ): object β receives multicast message msg for group Φ from original sender α

```
 1: rsn ← β.getRsn(α, msg.ssn)
 2: if β.beyond(rsn) then
 3:     DiscardDuplicate(msg)                          ▷ Ignoring repeated message
 4:     return
 5: end if
 6: detLog.add(msg.dets)
 7: NetworkSendAck(msg.dets)
 8: detList.add(⟨α, β, msg.group, msg.ssn, rsn⟩)
 9: Process(msg)
10: for all children objects π in multicast spanning tree do
11:     NetworkSend(msg)
12: end for
```

(other than the root) does not need to be deterministic. After all, repeated contributions to reductions will always be discarded.

Algorithm 18 SendReduction(β, msg, α, Φ): object β sends contribution message msg to group Φ with a final destination α

```
 1: msg.sender ← β
 2: msg.receiver ← α
 3: msg.group ← Φ
 4: msg.ssn ← β.getRssn(Φ)
 5: if Ready(msg) then
 6:     msg ← Agglomerate(msg)
 7:     msg.dets ← detList
 8:     if α is parent of β then
 9:         msgLog.add(msg)                              ▷ Storing message
10:     else
11:         tmpMsgLog.add(msg)                ▷ Storing message temporarily
12:     end if
13:     NetworkSend(msg)
14: end if
```

Algorithm 20 shows the procedure to send determinants and messages required during recovery. This algorithm extends Algorithm 5 by considering messages in `tmpMsgLog`. The garbage collection method is described in Algorithm 21. This method works at the PE level and accepts different implementations, as discussed above. In general, it removes the contribution messages belonging to the already committed reductions.

Algorithm 19 RECEIVEREDUCTION(β, msg, α, Φ): object β receives a reduction message for group Φ to final destination α

```
1: if Ready(msg) then
2:     msg ← Agglomerate(msg)
3:     msg.dets ← detList
4:     if α is parent of β then
5:         msgLog.add(msg)                          ▷ Storing message
6:     else
7:         tmpMsgLog.add(msg)                ▷ Storing message temporarily
8:     end if
9:     NetworkSend(msg)
10: end if
```

Algorithm 20 RESTART(A): sends determinants and messages bound to objects in A

```
1: for all objects α in A do
2:     Send all determinants of α in detLog
3:     Send all messages bound to α in msgLog
4:     Send all messages bound to α in tmpMsgLog
5:     Send all messages bound to Φ in msgLog where α ∈ Φ
6: end for
```

Algorithm 21 GARBAGECOLLECT($\Phi, index$): removes reduction messages with an identification number lower than $index$

```
1: for all messages msg in tmpMsgLog do
2:     if msg.group = Φ ∧ msg.ssn ≤ index then
3:         Remove msg from tmpMsgLog
4:     end if
5: end for
```

6.1.4 Formal Proof of Correctness

Lemma 6.1. *All required determinants are successfully retrieved during recovery.*

Proof Sketch. Determinants for regular messages are handled in the same way as in simple causal message-logging. Therefore, Lemma 2.1 applies here. Thus, for regular messages, all the required determinants can be recovered. For multicast messages, a determinant is generated in every recipient of the multicast. In the case of reduction messages, only one determinant is generated at the root of the reduction. We assume the agglomeration of messages in the root of the spanning tree is deterministic. □

Lemma 6.2. *All required messages are successfully replayed during recovery.*

Proof Sketch. All regular messages are available in the message logs of the sender or are recreated during recovery if they correspond to local messages. As for the multicast messages,

they are stored only in the message log of the original sender at the root of the spanning tree. They are sent along with regular messages during recovery. Reduction messages may not all be available, but the current reduction number ensures that all the required reduction messages should be in the message logs of the children in the spanning tree. If the root fails, the children nevertheless store all contributing reduction messages. □

Lemma 6.3. *There are no orphan objects.*

Proof Sketch. By contradiction. Imaging an object β receives a message that is not re-sent when its original sender α recovers. By the PWD assumption, all determinants can be recovered and the same sequence of decisions is made during recovery. Therefore, α re-sends the message. □

Theorem 6.4. *The recovery process in collective-based message-logging is correct.*

Proof Sketch. By Lemmas 6.1 and 6.2 all determinants and messages are available during recovery. The PWD assumption ensures Lemma 6.3 and there are no orphan objects after recovery. Finally, recovery is correct in the collective-based message-logging protocol. □

6.2 Design and Implementation

In implementing the algorithm described above, there are important design choices to make. One of them relates to the fact that a PE may hold more than one object. The second deals with the structure of the spanning tree for different roots. Figure 6.6 shows a spanning tree for a subset Φ containing the objects $\{\alpha, \beta, \gamma, \delta, \epsilon, \zeta, \eta, \theta, \iota\}$ distributed in some fashion among PEs $\{A, B, C, D, E\}$. The figure depicts a special kind of object, called a *manager*, that deals with the different collective communication operations, particularly multicast and reduction. This objects are represented by a rhombus in the figure.

This design offers an advantage when more than one object in the reduction set live on the same PE. For instance, β and γ both live on PE B. A multicast message coming from α goes directly through the manager M on PE B. From there, the manager contacts all the local objects that belong to the subset Φ. This design simplifies the logic in each object and basically performs the functions of forwarding messages down the spanning tree and discarding old messages. Additionally, it helps in buffering early messages. The agglomeration logic is also contained in the managers.

Another useful case for the managers appears when the source of different multicast messages (or destination for reduction) over the same subset is different. In the previous sections

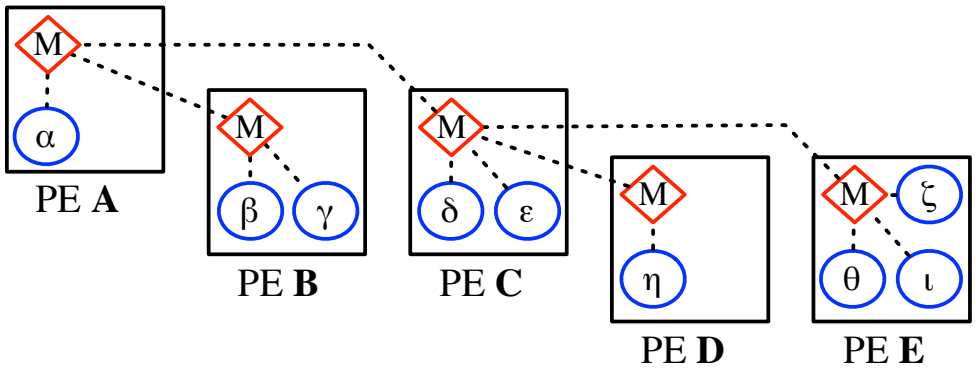


Figure 6.6: Implementation of collective-aware message-logging. Each PE has a special object called a manager that handles the collective communication operations.

we assume that the spanning tree is always rooted at α. However, if ι wants to send a message to the whole subset, it would need its own spanning tree. Having managers helps in handling these cases. For instance, ι would first contact the manager of the root of the spanning tree and then that manager will transmit the message.

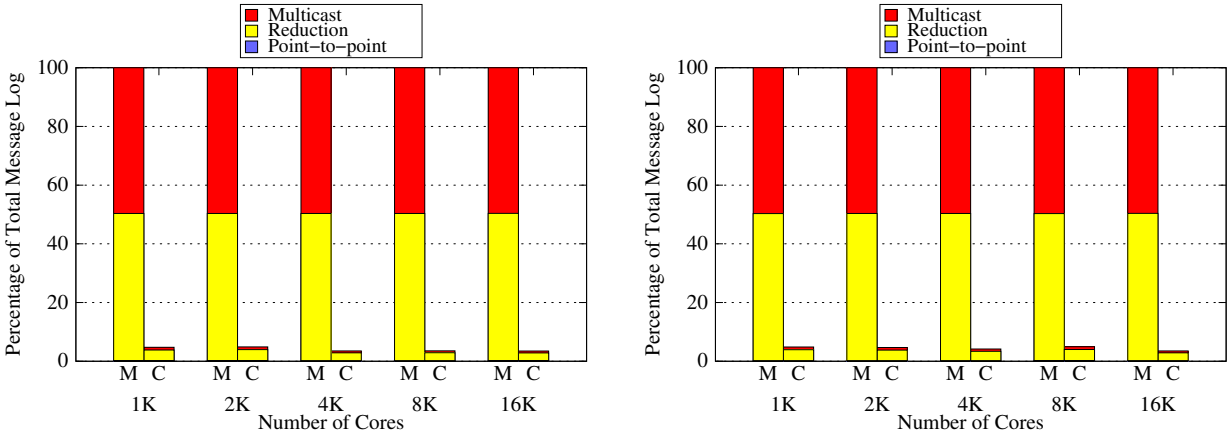
Finally, this design is more akin to the computational model of migratable objects. If an object migrates from one PE to another, the new manager will adopt the object and deliver all multicast messages, as well as receive all the contribution from the object. This flexible feature avoid reconstruction of spanning trees in many cases of migrations. Since the managers are the ones participating in the spanning tree, the migration of a regular object does not necessarily modify the spanning tree. In many situations, the spanning tree can be built with topology information in consideration.

6.3 Experimental Results

To measure the potential of collective-aware message-logging in reducing the memory overhead, we proceed to investigate the two applications in Figure 6.1. The results were collected on Stampede and Intrepid and represent one single run. There is no reason to believe multiple runs would significantly change the numbers reported here.

LeanMD has a high communication volume carried by both multicast and reduction. Figure 6.7 shows the result of strong-scale experiments on different datasets and compares the simple causal message-logging protocol from Chapter 2 versus the collective-aware protocol in this chapter. These strategies are represented by "M" and "C", respectively. The runs were made on Stampede and range from 1K to 16K cores. Since, the regular simple causal

protocol stores all remote messages, it always represents the 100% of the message log. The "M" column in the figures represents the potential for CAML to reduce the memory overhead. Figure 6.7(a) shows the strong scale results for a system with 1 million particles. The reduction in memory footprint for the message log is massive. In general, the reduction exceeds 96% of the memory required to store messages. The reduction improves as the program scales and reaches almost 97% at the high end. Figure 6.7(b) contains the results for a larger dataset with 4 million particles. The strong scale results are similar to Figure 6.7(a) and provides support for the overall scalability of CAML.



(a) 1-million particle dataset.

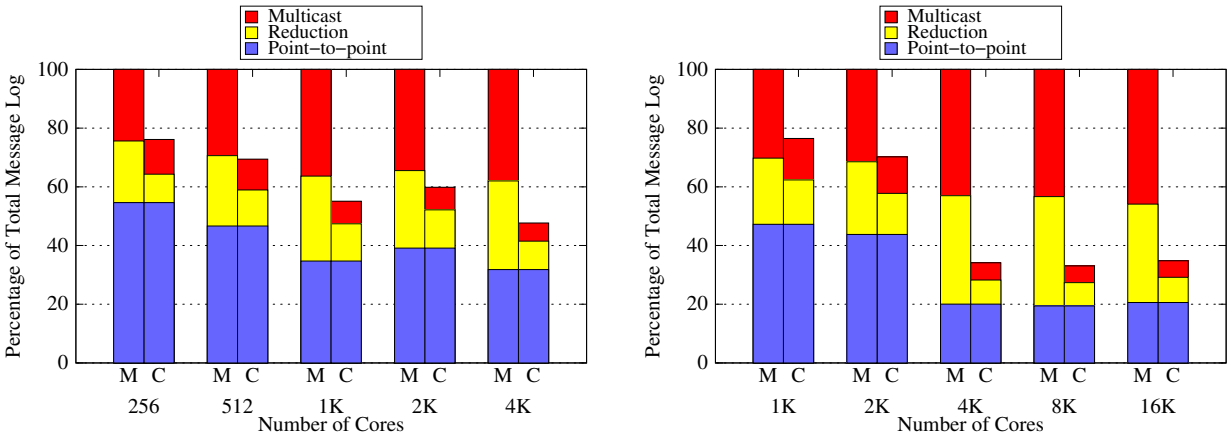
(b) 4-million particle dataset.

Figure 6.7: Memory overhead reduction in LeanMD with CAML. The figure contrasts simple causal message-logging (represented by "M") and the CAML algorithm (represented by "C").

The gigantic reduction in memory overhead presented in Figures 6.7(a) and 6.7(b) come from the very nature of the code in LeanMD. Since most of the data is transmitted through either multicast or reduction, CAML has the highest potential to reduce the message log. Additionally, the configuration used for the experiments uses a modest reach for each cell in terms of the number of neighbors. This configuration directly defines the size of the spanning tree. Each cell sends its particles to other 75 computes. The spanning tree for each of these compute sets contains 75 nodes. These 75 computes are mainly distributed to different PEs and therefore conform a large spanning tree. The reduction factor in multicast is higher than 64x, close enough to 75.

Figure 6.8 shows the results on Intrepid for OpenAtom. The total communication volume that gets transported through collective is not as dominant as in LeanMD. However the improvement for multicast and reduction is significant. Figure 6.8(a) shows a 32-molecule water system that scales from 256 to 4K cores. The higher the scale, the more prominent multicast and reduction operations become and then the higher the reduction in the message

log. At the higher end of the scale, CAML is able to reduce the total memory overhead by 50%. Figure 6.8(b) presents the strong scale results for a 256-molecule water system. A similar effect occurs with this problem size, and the larger the core count, the higher the use of multicast and reduction. However, for this case the relative amount of point-to-point volume is lower than the 32-molecule system and the reduction in the message log is more important. At the higher end, the reduction in the message log represents almost two-thirds of the total communication volume.



(a) 32-molecule water system.

(b) 256-molecule water system.

Figure 6.8: Memory overhead reduction in OpenAtom with CAML. The figure contrasts simple causal message-logging (represented by "M") and the CAML algorithm (represented by "C")

6.4 Discussion

The ideas presented in this chapter are meant to work in conjunction with parallel recovery. The implementation details presented in Section 6.2 are useful in explaining how this is possible. Once an object α migrates to a different PE for accelerated recovery, the manager of α in the original PE keeps track of α by adding it to a list of *emigrants*. Similarly, in the new PE, α is treated as an *immigrant* by the new manager. Thus, if α moves from PE A to PE B, all multicast messages received at the manager on A will be forwarded to α. Analogously, α will contribute to the manager on A, not to the one on B.

The agglomeration operation in reduction operations was assumed to be deterministic. It means, for each reduction number it always reduces the contributing messages in exactly the same order. This guarantees the results will always be the same in spite of overflow/underflow

floating-point arithmetic operations. It is well-known that floating point arithmetic is not associative. Round-off errors can cause the same parameters in the same operation to give different results. A way to remove this assumption is to add determinants in the reception of the contributing messages at the root of the reduction spanning tree. Thus, each message coming from a child will get a determinant that will keep agglomeration deterministic during recovery. Note that intermediate levels in the spanning tree do not require determinants. Since the contribution of all those intermediate levels (except for the children of the root) will be discarded, there is no need in ensuring determinism.

More collective communication operations can be added to the algorithms described in this chapter. Some of them can be directly implemented using the multicast and reduction. For instance, the *all-reduce* operation may be interpreted as a reduction immediately followed by a broadcast. Also, an *all-to-all* operation is a broadcast executed in every element of the collection. A *scan* operation is similar to a set of reduction operations. Hence, it can be handled by CAML. The *gather* and *scatter* operations present a different scenario. The former may be treated as a reduction that agglomerates the individual results through a spanning tree. The latter can not be optimized by CAML, because it inherently involves a different message for every task. Other operations may require a deeper analysis, but the principles should remain the same. Fundamentally, intermediate nodes should not play other role than mere forwarding of collective messages. Roots of the spanning tree carry most of the burden at sending and receiving messages.

Figure 6.3(a) shows the partial order of subsets in the collection of objects. There is a parallel between the lattice of partial order sets and a hierarchical distribution of objects. As the multicast message travels down the tree, the set of targets become more and more concrete. If the system is hierarchically divided, then it is possible to associate a level in the spanning tree with a subgroup of nodes that behave as a recovery unit. Similar to the team-based message-logging protocol in Chapter 5, if a multicast message enters a new *domain* on its way throughout the spanning tree, then it may be necessary to store that message to satisfy the restrictions of a hierarchical method.

6.5 Related Work

A proposal on building fault-tolerant collective communication operations on MPI showed an efficient mechanism to achieve low overhead [96]. The main goal behind this idea is to promote algorithm-based fault tolerance (ABFT) based on a resilient implementation of MPI collectives. That way, the programmer of the algorithm can incorporate the optimized

implementation of resilient collectives. A recent proposal in the MPI Forum addressed the need for resilient MPI calls and, among other operations, defined `MPI_Comm_validate_all` that helps a rank to recognize all failures in a communicator. That way, the application is aware of the failure in different ranks. The authors of the paper review three different designs for tree-based collectives. First, a rerouting approach would check for a failed process before interacting with it and route around crashed processes in a recursive fashion. Second, the lookup-avoiding design would remove the check for failures and calculate the relationships parent/child at the end of `MPI_Comm_validate_all`. Third, a rebalancing method will remove the check for failures and balance the tree for the collective call at the end of `MPI_Comm_validate_all`. This last design provides the best performance and a negligible overhead compared to the fault-unaware implementation. The results in their paper scale up to 256 processes.

A protocol for application-level coordinated checkpoint that targetted applications without global synchronization points had an extension for collective communication operations [97]. Their checkpoint infrastructure was based on an algorithm that would create a coordinated checkpoint similar to Chandy-Lamport algorithm [20]. Therefore, an *initiator* would start the checkpoint process and coordinate the rest of the procedure. Since this protocol assumes the checkpoint calls are not made in global synchronization points, there are special measures to log messages and non-deterministic events during checkpoint. That way, recovery can work properly by replaying the necessary messages and reproducing all non-deterministic events. The algorithm creates two important distributed cuts. The first is composed by the collection of local checkpoints of the processes. This cut will form a recovery line to which all processes will roll back. The second cut is composed by the points at which processes stop recording messages and non-deterministic events. The algorithm makes strong claims about the consistency of both cuts. In particular, there must not be any data flow from collectives crossing the stop-recording cut.

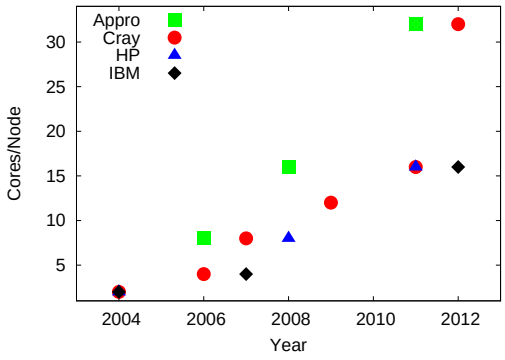
CHAPTER 7

Multicore-Node Message-Logging

For a long time, the HPC world used the continuous increase in processor speed as a mechanism to make supercomputers more powerful. While Moore's Law held, smaller and faster processors provided the needed additional FLOPS to move from megascale to terascale. However, as the new millennium dawned, the fundamental tenet of an ever increasingly faster processor came to an end. It was unfeasible to increase the clock rate of processors without melting the chip. But, a few tricks fetched additional time to keep miniaturizing the transistors and have more transistors per chip. Those additional transistors would provide the real state in the chip to have multiple cores. Thus, processor speeds converged to a few gigahertz and the multicore era was born. It is likely this same technology will take us to exascale, but not beyond [73].

In the last decade, the rising availability of parallelism at the chip level has changed the nature of supercomputers. A quick view at the most recent machines shows how this trend has impacted the architecture of parallel computers. Figure 7.1 presents a selected set of machines installed in the last decade. Using the four major vendors of supercomputers (Appro, Cray, HP, and IBM), Figure 7.1(a) presents a historical picture of the ratio cores versus nodes in different machines. The trend is to exponentially increase this ratio. Also presented in the figure is the relative speed at which each vendor adopts the newest level of chip parallelism. From the particular dataset presented here, it seems Appro is the earliest adopter, while IBM is the latest. The name of the systems, along with their introduction date is presented in Table 7.1(b). Although this dataset only includes few systems, the entire Top 500 list follows a similar pattern [98].

Thus, the nature of processors in current supercomputers is multicore. Each machine is composed of a set of multicore nodes assembled in a hierarchical fashion. Nodes are grouped into blades, several blades form a rack, and so on. This particular organization must have



(a) Historical view of number of cores per node in systems from the four major vendors of supercomputers.

Year	Vendors			
	Appro	Cray	HP	IBM
2004		XT3	MPP2	BG/L
2005				
2006	Atlas	XT4		
2007		XT5		BG/P
2008	T2K		Chinook	
2009		XT6		
2010				
2011	Trestles	XK6	Carter	
2012		BW		BG/Q

(b) List of systems and their introduction year to the Top500 list.

Figure 7.1: Adoption of multicore nodes by major supercomputer vendors. There is a difference in the speed at which vendors incorporate larger multicore-nodes into their products, Appro seems to be the fastest adopter, whereas IBM the slowest.

an effect on the type of failures supercomputers have. A fundamental challenge in designing message-logging protocols is to consider the architectural peculiarities of current machines to optimize for the common case. An important goal is to find an appropriate failure unit in multicore-node supercomputers. Most of the traditional schemes for fault tolerance have considered a core as the unit of failure. This unit may seem too fine grained, since many failures affect the entire node [31]. On the other hand, tolerating failures of multiple nodes with message-logging has a higher impact on performance [58]. A compromise has to be found between a single core and multiple cores as the appropriate unit of failure.

This chapter features the following contributions:

- An analysis of system-log data to determine the appropriate unit of failure in current supercomputers. Along with data analysis, a couple of functions are used to model the distribution of failures in supercomputers (§7.1).
- The design of a message-logging protocol specialized for multicore-node supercomputers. This protocol assumes the unit of failure as found in the system logs (§7.2).
- A theoretical framework to analyze the probability of a catastrophic failure in the protocol given different types of failures (§7.3).
- Experimental results of an implementation of the protocol and scalability results up to 1,024 cores (§7.4).

7.1 Unit of Failure

The design of a fault tolerance protocol heavily depends on what is considered the failure unit. Whether it is a core, a socket, a node, a rack, or something else, the selection of this unit will dictate the performance characteristics of the protocol. Finding the appropriate failure unit is not a trivial task because of the complex nature of failure in HPC systems. Failures come in different shapes and occur due to several different reasons [72]. Nevertheless, it is possible to abstract one feature and classify failures according to that characteristic. For instance, failures could be classified according to the number of components that go down as a result of a crash. Literature on failures in supercomputers shows that most of the failures affect the system at the node level [31,72]. This means, a failure will bring down one or more nodes at the same time. Thus, a node is a good candidate to become the *unit* of failure. A collection of crashes could be presented as a histogram according to the number of nodes a failure affects.

Understanding the distribution of the number of nodes that crash in a failure has important implications in the design of message-logging protocols. It is well known that tolerating the simultaneous failure of any k nodes in a system has a high impact on the performance of message-logging protocols [47, 58]. On the other side, it has been shown that protocols designed to tolerate one single failure at a time present low overhead and good scalability [6].

To obtain the distribution of nodes brought down by a failure, we inspected failure information in HPC systems from several available sources. The Computer Failure Data Repository (CFDR) [99] contains failure information collected at different institutions and made public for scientific use. We used the failure information of several different machines from CFDR. These machines were anonymized and will be called System i (for $i = \{12, 18, 19, 20, 21\}$) from Los Alamos National Laboratory. Failure logs of MPP2 supercomputer from Pacific Northwest National Laboratory were also used. We also gathered failure information from Mercury machine at National Center for Supercomputing Applications [100], Tsubame supercomputer at Tokyo Institute of Technology [101], and Jaguar supercomputer at Oak Ridge National Laboratory [102]. All those machines have architectures with multicore nodes and exhibit different features about number of nodes and number of cores per node. Table 7.1 summarizes the list of machines, their total node and core count, and the number of cores per node.

Although CFDR makes available some failure information about supercomputers, finding recent information about failures on any machine is not always possible. Several reasons justify that situation. First, this information is very sensitive. It is considered that making public the failure record will make a supercomputing facility less attractive for scientists.

Feature	Machines								
	System 12	System 18	System 19	System 20	System 21	MPP2	Mercury	Tsubame	Jaguar
Nodes	512	1024	1024	512	128	968	923	1936	18,618
Cores	1024	4096	4096	2048	512	1936	1846	30,976	224,256
Cores/Node	2	4	4	4	4	2	2	16	12

Table 7.1: List of supercomputers for which failure information is available. Each machine has different sizes and types of multicore nodes.

Releasing failure data will expose the weaknesses of the system, potentially imposing a threat to the contractors that supply parts or the whole machine. Second, even if all system logs were released for public consumption, parsing, filtering, and interpreting failure data is a complex task. One single failure may manifest itself as a series of disconnected messages in the failure log. In other cases, a failure is not reported until certain thresholds in number of warnings or timeouts are reached. Fortunately, all the failure datasets we had access to were already cleaned and filtered by system administrators, who could understand the nature of each failure.

Thus, each dataset we analyzed is basically a list of failures. Each failure typically includes nodes affected, possible reason for the failure, date, and time and an arbitrary classification of the nature of the failure (hardware, software, environment, human). In order to generate a histogram of failures according to the number of nodes each failure affects, we proceeded to examine each dataset in two stages. The first stage goes through the whole data set *coalescing* failures of the same node that occur within a time window smaller than Δ_C. This stage eliminates repeated failures (multiple instances of the same node failure). Our value for Δ_C was 6 hours, in accordance with a reasonable estimate of a repair time of a node [72]. The second stage traverses the reduced list obtained after the first stage and counts how many nodes failed in a time window defined by Δ_M. Our value for Δ_M was based on the time it takes for a system to detect a failure and restart. We chose a value of 1 minute (a conservative estimate according to recent results [103]). Thus, if k nodes fail within a time frame of Δ_M, we consider that as a multiple failure affecting k nodes, as if all of them had failed simultaneously.

The mechanism described above permitted us to obtain the distribution of failures with respect to the number of nodes affected. Figure 7.2 presents the histogram of failures for each of the machines we studied. We only present the percentage of failures that involve 1, 2, 3, 4, and more than 4 nodes. The most important observation is that all distributions are very skewed. This means that a very high percentage of the time a failure involves only one node. This is consistent with the findings of other researchers [31]. This result supports the claim that tolerating the failure of one single node at a time is a good probabilistic rule to

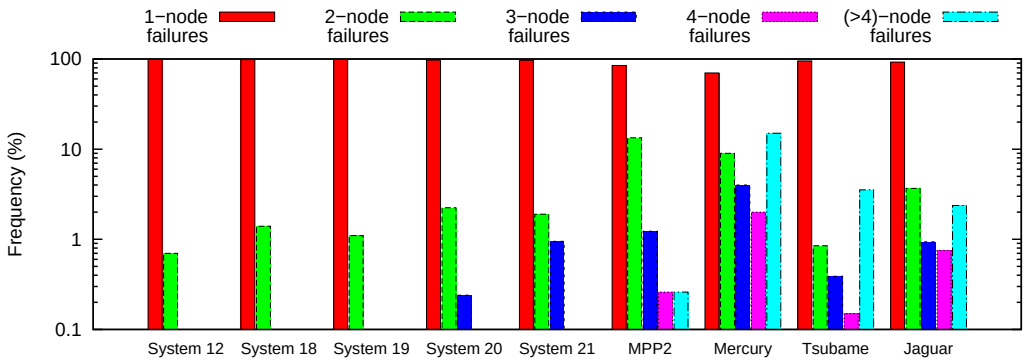


Figure 7.2: Distribution of failures according to the number of nodes affected. For all systems in Table 7.1 the distribution is very skewed: a high percentage of the failures involve only one node.

build a resilient system.

The next step in understanding the unit of failure in HPC systems is to model the distribution of failures in Figure 7.2. For that, we chose two well-known distributions: geometric and Zipf's. The geometric distribution is based on Bernoulli trials. A Bernoulli trial is an experiment with only two possible outcomes. The outcome has probability p of being a *success* and probability $(1-p)$ of being a *failure*. What the geometric distribution models is the probability of having x failures before getting the first success. Mathematically,

$$f(x) = (1-p)^{(x-1)}p$$

where p is the only parameter of the distribution. The geometric distribution can be considered as the discrete counterpart of the exponential distribution. That means, it decays quickly as x grows and for a large x the probability of x tends to zero.

The Zipf's distribution is well known for being applied to information retrieval to model the frequency of words in a text. It is described by the following formula,

$$f(x) = \frac{\frac{1}{x^s}}{\sum_{i=1}^{n} \frac{1}{i^s}}$$

which has two parameters. The first parameter, s, is a parameter controlling how skewed the distribution is. If s equals 1, then the denominator of the fraction is x multiplied by the generalized harmonic number. The second parameter, n, is the maximum value of x, being 1 the minimum. A property of Zipf's distribution is that it does not decay exponentially and provides a long tail. This means, the accumulated probability of values larger than x is never negligible, no matter how big x is.

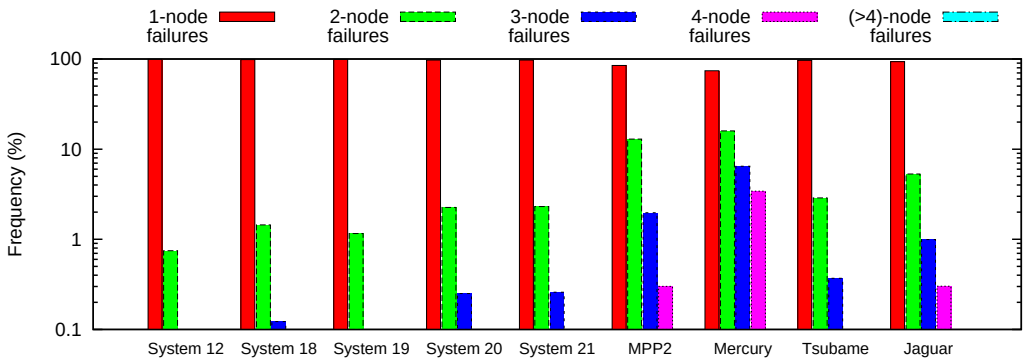


Figure 7.3: Best-fit curves for distributions in Figure 7.1(b) obtained using the Newton-Raphson method to minimize the least-squares distance. System 12 and MPP2 are modeled through a geometric distribution. The rest of the systems are modeled via a Zipf's distribution.

Using these two functions, we chose proper parameters to model the distributions in figure 7.2. The results are shown in figure 7.3 and the results of a Newton-Raphson best-fit analysis are presented in Table 7.2. The *error* was represented by the least-square distance. A value of n equals to 1024 was used for the Zipf's distributions. Table 7.2 shows that System 12 and MPP2 were better matched by a geometric distribution. The rest of the systems are better modeled by a Zipf's distribution. There are systems that are markedly well represented by the model function (low least-squares error). However, the failure distribution of Mercury is hard to match for any model distribution. Part of the reason is the long tail the original distribution has.

Best Fit	**Machines**								
	System 12	System 18	System 19	System 20	System 21	MPP2	Mercury	Tsubame	Jaguar
Geometric									
p	**0.9924**	0.9848	0.9878	0.9755	0.9755	**0.8473**	0.7498	0.9699	0.9395
Error	3.66E-7	2.20E-6	2.54E-6	7.37E-6	1.20E-4	7.72E-5	1.21E-2	8.08E-4	7.76E-4
Zipf's									
s	7.0410	**6.0875**	**6.4146**	**5.4300**	**5.3970**	2.9451	**2.2190**	**5.0671**	**4.1365**
Error	4.89E-7	2.81E-7	5.62E-7	9.63E-8	7.04E-5	1.19E-3	7.35E-3	6.67E-4	4.16E-4

Table 7.2: Best-fit functions and errors for distributions of Figure 7.2. A low error points to a distribution easily represented by one of the model functions. Other cases, such as Mercury failure distribution, are hard to match and the error is relatively high.

To decide what function matches the data better and perform statistical hypothesis testing, a chi-square goodness-of-fit test can be used. This test applies to data coming from discrete distributions. It also works for binned data. Giving a series of *observations* o_i and *expected*

values e_i coming from a model function, we can compute the statistic,

$$\chi^2 = \sum_{i=1}^{k} \frac{(o_i - e_i)^2}{e_i}$$

where k is the number of bins (5 in the case of Figure 7.2) and χ^2 is a statistic following a chi-square distribution with $(k - c)$ degrees of freedom. In this case, $(c - 1)$ is the number of estimated parameters for the distribution.

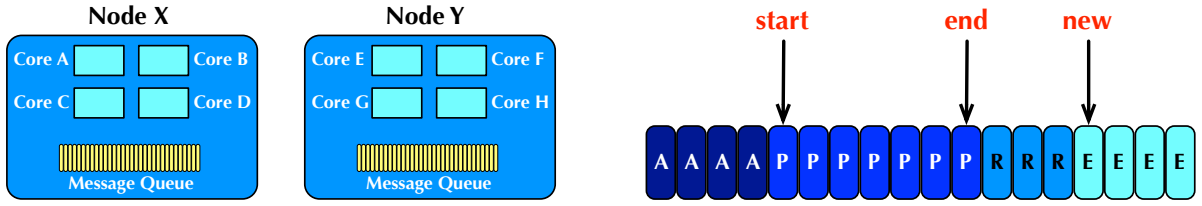
7.2 Message-Logging Protocol

The previous section showed that a high percentage of the failures in HPC multicore-node systems bring down only one node. Thus, a node should be used as the failure unit and it should suffice for a protocol to tolerate single-node failures. There is little statistical incentive to develop a resilience protocol that tolerates multiple-node failures.

Having a multicore node as the unit of failure is a design decision that can be applied to the protocols reviewed in Chapter 2, particularly checkpoint/restart and message-logging. In a multicore-node system, the whole machine is composed by a set of *nodes*, each containing a set of *cores*. Each core will host a PE and, as such, a set of objects. Figure 7.4(a) presents a graphical view of a multicore-node system. In this case, the system has only two nodes, X (grouping cores A, B, C and D) and Y (with cores E, F, G and H). Since a node is also a computational unit, there is only one network connection in each node. That means all communication is centralized in one single agent, that we will call *communication thread*. This thread will be in charge of polling the network and assigning each message to the corresponding core. Both outgoing and incoming messages will be enqueued in a *message queue*, common to all cores in the node.

A checkpoint/restart version for multicore-node systems is straightforward. Instead of checkpointing each PE, the system will checkpoint each node. Buddy assignment will be done on a node basis. If a node crashes, all other nodes will rollback along with it, following the same procedure as in the PE-based case.

The design of a message-logging protocol for a multicore-node system presents several challenges and opportunities. A message-logging protocol for this environment must deal differently with messages and determinants. For messages, it is not necessary to store intra-node messages, since they will be lost in case of a failure anyways. This is exactly the same rationale applied in the team-based message-logging of Chapter 5. Only inter-node



(a) A multicore-node system. Each node contains several cores that shared data structures for communication.

(b) A determinant queue in one node. This shared data structure must be accessed by all cores every time a communication operation is performed.

Figure 7.4: A multicore-node system and its implications on the design of a message-logging protocol.

messages will be logged. Using a smart allocation of objects to nodes, a big reduction in memory overhead can be obtained.

Handling determinants in this new scenario is more challenging. We will present the case of a causal message-logging protocol. A determinant is the result of a non-deterministic decision made at the object level. On a PE-based environment, determinants were handled at the PE level, because a PE was the failure unit. On a multicore-node system, a node is the failure unit and determinants must be handled at that level. This means, a common queue must hold determinants in a node. Figure 7.4(b) shows the determinant queue in a node. Each entry represents one determinant and entries may have different states: *acknowledged* (A), the determinant has been safely stored in other node; *piggybacked* (P), the determinant must be piggybacked in the next outgoing messages until it has been acknowledged; *reserved* (R), one core is currently filling up that entry; and *empty* (E). Thus, an outgoing message will piggyback all determinants with state P. As soon as an acknowledgment is received, entries are transitioned to A and as messages are received, entries are taken and set to R before moving to P. The determinant queue is shared among all cores in a node and should handle concurrent access. Here we show an efficient implementation of the three major operations over the determinant queue.

We assume the determinant queue Q has three global indexes depicted in Figure 7.4(b), called *start*, *end* and *new*. The first two determine where piggybacked determinants start and end and *new* stores the position of the first empty position. The first operation is to add determinant d to Q and it is described in Algorithm 22. The second operation consists ini retrieving all the determinants that must be piggybacked at a particular point in time when a message is leaving the node. Algorithm 23 represents this operation. Finally, the third operation stands for the acknowledgment of a particular determinant and it is specified in

Algorithm 24.

Algorithm 22 ADD(d, Q): determinant d is added to queue Q

```
1: t ← AtomicFetchAndIncrement(new)
2: Fill entry t with d
3: while t ≠ (end + 1) do
4:     NO OP
5: end while
6: AtomicIncrement(end)
```

Algorithm 23 PIGGYBACK(Q): determines all pending determinants in Q

```
1: last ← end
2: first ← start
3: if last ≥ first then
4:     Piggyback(first, last)
5: end if
```

Algorithm 24 ACK$(index, Q)$: acknowledges all determinants in Q up to $index$

```
1: if index ≥ start then
2:     AtomicSet(start, index + 1)
3: end if
```

Figure 7.5 presents a view of the message-logging protocol for multicore-node systems. It simulates a tiny part of an execution in the system of Figure 7.4(a). In this case, only cores C, D, E and F are shown. Note that m_1 is an inter-node message and as such, it must be logged. When m_1 is received at core E, determinant d_1 is generated. Conversely, m_2 is an intra-node message and is not stored, but it generates determinant d_2 nevertheless. At that point, node Y has accumulated two determinants in its queue. The next outgoing message, m_3 piggybacks the two determinants which get stored in node X. Node X will be the one providing those determinants in case node Y crashes. Since a node is a failure unit, all cores in node Y crash simultaneously. The recovery process restarts and messages are sent again, along with determinants. For instance, message m_1 is sent again. Other messages will be reproduced, such as m_2 and m_3. There is an important difference between these last two messages. Message m_2 is necessary for the computation and is reconstructed as part of recovery. Message m_3 is not necessary for the correctness of recovery. It is a *duplicate* message and will be discarded at core C when it is received the second time.

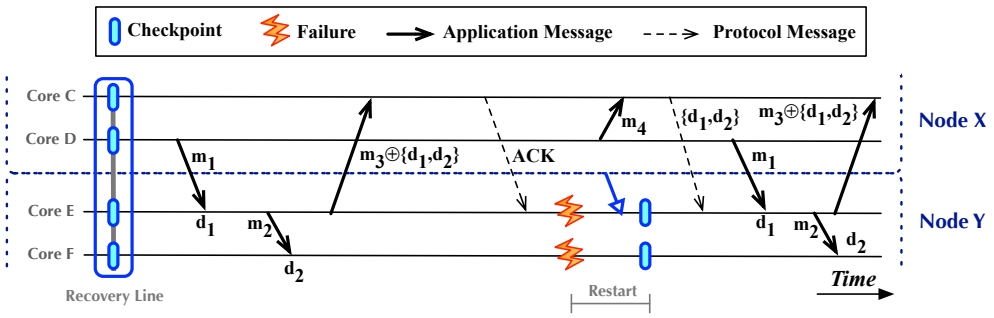


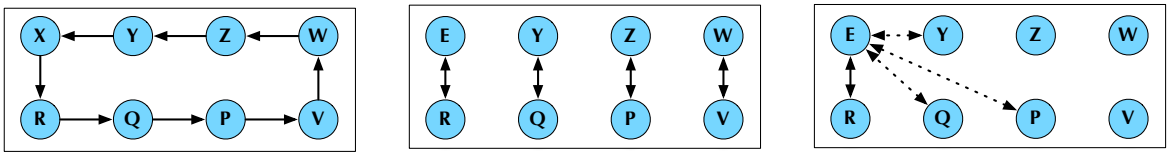
Figure 7.5: Sample execution of an application using the message-logging protocol for multicore-node systems. All message receptions create determinants, but only inter-node messages piggyback determinants.

7.3 Analysis of Survivability

The design of the fault tolerance protocols in the previous section assumes a node is the unit of failure and ensures that the system can recover from single-node failures. Nevertheless, there are situations in which multiple-node failures can be tolerated by the protocols. This depends on whether the necessary information for recovery is available or not after the crash. The survivability of a protocol tells us the probability of surviving a multiple-node crash, even when that protocol was designed to tolerate only single-node failures. In the end, what we would like to know is the probability of a protocol to survive a failure, considering the likelihood of every type of failure and the probability of surviving each type.

The first thing we must analyze is the buddy assignment for checkpoint. Each node will store its checkpoint in the memory of a buddy node and it is fundamental that a multiple-node failure does not bring down both nodes. Otherwise, recovery would be impossible. A natural question to ask is which mapping would give the higher chance of survival. Figures 7.6(a) and 7.6(b) present two different mappings for choosing a checkpoint buddy. In the *ring map*, a total order of the nodes is used to make node i checkpoint in node $(i+1)$. The *pair map* divides the system into pairs an make node pairs buddies of each other. It turns out that pair map is more resilient than ring map. As an example, consider a system with n nodes (n is an even number for simplicity) and all possible failures involving 2 nodes. Clearly, the latter number is $\binom{n}{2}$. The number of catastrophic failures in ring map is n (all possible pairs of consecutive nodes in the ring), whereas in pair map is $\frac{n}{2}$ (any of the pairs). Thus, the chances of ring map to survive a random failure affecting 2 nodes is $\frac{n-3}{n-1}$, while pair map will have a probability of $\frac{n-2}{n-1}$. For further discussions, we assume all protocols use pair map.

Message-logging, contrarily, is also sensitive to communication and how connected nodes



(a) Ring Map. (b) Pair Map. (c) Communication Map.

Figure 7.6: Different mappings for storing checkpoints and determinants. If a node fails along with other node having a checkpoint or a determinant, recovery is compromised.

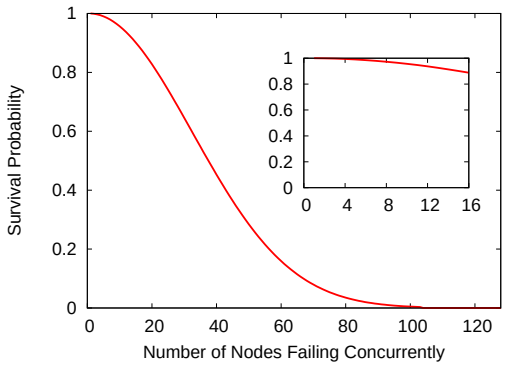
are. Figure 7.6(c) shows a *communication map* that connects each node with all other nodes it exchanges messages with. In this example, only the map for node E is presented. Let node R be the checkpoint buddy of node E and Y, P and Q the *acquaintances*, i.e., nodes that exchange messages with node E. This set of nodes is fundamental in analyzing the survivability of a fault tolerance protocol, because those nodes will potentially store determinants of E. If one of them crashes along with E, then recovery may not be possible. We will denote by g the cardinality of the set of acquaintances. To some extent, g determines the degree of communication. The higher the value of g, the more tangled the communication graph is. The analysis of communication graphs from Chapter 5 applies equally well here.

Let us consider a failure involving f nodes out of the n nodes in the system. The question we need to answer is how likely it is that the failure is not catastrophic. In other words, what is the probability that among the f nodes we do not have checkpoint buddies (in the case of checkpoint/restart) and we do not have acquaintances (in the case of message-logging). Given a total of n nodes and a subset of size f nodes failing, the total number of such subsets is $\binom{n}{f}$. Thus, we need to compute how many of those subsets are not catastrophic. We start with checkpoint/restart. We must compute how many subsets of f nodes do not take down a node and its buddy. Let us choose f nodes where there is not a single node buddy of a node already in the set of f nodes. If we need to choose f nodes with such property, then the first node of the f has n options, the second has $n-2$ (since we do not want to include the buddy of the first), the third has $n-4$, and so on. In the end we have this total number of subsets size f that will not make the whole system collapse $\frac{n(n-2)(n-4)...(n-2(f-1))}{f!}$, which gives us the following expression for the probability of surviving f concurrent failures:

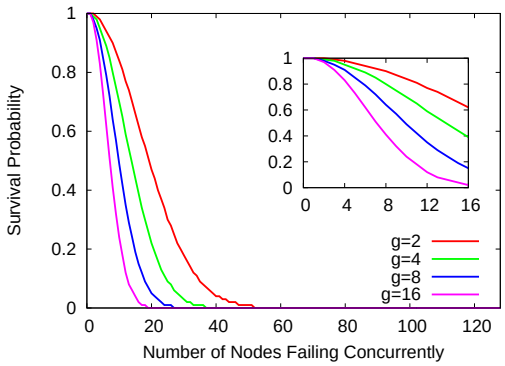
$$\frac{n(n-2)(n-4)...(n-2(f-1))}{n(n-1)(n-2)...(n-f+1)} = \frac{\prod_{i=0}^{f-1}(n-2i)}{\prod_{i=0}^{f-1}(n-i)}$$

Figure 7.7(a) presents the probability of survival for checkpoint/restart as the value of f increases. In this particular case, the value of n is equal to 1024. The curves drops smoothly,

showing a value higher than 80% for up to 16 nodes failing concurrently. We will denote this quantity as $\mathcal{CKPT}(n, f)$.



(a) Multiple-node failure survival probability in checkpoint/restart.



(b) Multiple-node failure survival probability in message-logging for different g values.

Figure 7.7: Survival probability to multiple-node crashes for different fault tolerance protocols. Checkpoint/restart is oblivious to communication. But, communication has an important impact in the survival probability of message-logging protocols.

For the causal message-logging protocol, we need to guarantee that the set of f nodes does not include a node and any of its g acquaintances. Let us denote by F the set of f nodes in the multiple-node failure. To compute the probability to survive the failure of set F, we need to compute how likely it is for F to *not* intersect the f different communication subgroups of elements in f. In other words, there cannot be 2 or more nodes in F that communicate with each other. Let us pick one element x in F and compute how likely it is that the rest of F does not intersect the subset of g elements x communicates with (denoted by G). Since the system has n elements, the number of subsets of g elements that x may contact is $\binom{n-1}{g}$. Now, the number of subsets of size g that do *not* intersect F are given by $\binom{n-f}{g}$. With these two quantities we are ready to compute the probability of the set G not intersecting F. Moreover, the probability of set F not intersecting any of the communication subsets of its members and, by definition, the probability of tolerating a multiple concurrent failure of f nodes, denoted by $\mathcal{COMM}(n, f, g)$, is:

$$\left[\frac{\binom{n-f}{g}}{\binom{n-1}{g}}\right]^f$$

Figure 7.7(b) shows the probability of survival for the message-logging protocol and dif-

ferent values of g. Clearly, the higher the value of g the more quickly the curve drops.

7.3.1 Survivability

The final question we should answer is about the probability of surviving a random failure. To compute this, we should sum over all the cases and multiply each case by its corresponding probability (expected value). Let us define *survivability* as the probability of survive a *random* failure, regardless of how many nodes are involved in the failure. The formula is given by:

$$\mathcal{S} = \sum_{i=1}^{n} s(i)p(i)$$

where $s(i)$ represents the probability of surviving a failure that involves i nodes and $p(i)$ is the probability of a random failure involving i nodes. For checkpoint/restart, $s(i)$ is equal to $\mathcal{CKPT}(n, i)$. This is the probability of not losing a node and its buddy if i nodes out of n fail simultaneously. In message-logging, $s(i)$ is equal to $\mathcal{CKPT}(n, i) \times \mathcal{COMM}(n, i, g)$. This probability requires that all checkpoint buddies remain available and that no determinant is lost.

Using the definition of $\mathcal{S}$, we can compute the survivability of the different approaches in this section. In order to model the probability of each type of failure we use the two functions discussed in the beginning of this section. Other authors found evidence that single node failure probability is higher than 85% [31]. We use parameters of the different distributions accordingly. For the geometric distribution we set p value to be 0.85 and for the Zipf's distribution we used s value equals to 3.2. Table 7.3 shows the survivability values for the different fault tolerance protocols. From the results above, it is clear that the survival probability of checkpoint/restart is better than message-logging, which has a curve that drops exponentially as the number of concurrent failures increases. However, that difference does not translate into a big difference for survivability. The reason comes from the fact that functions to model the probability of multiple concurrent failures are very skewed, making negligible the contribution of larger values of f.

7.4 Experimental Results

An implementation of the checkpoint/restart and causal message-logging protocols for multi-core-node systems was integrated into Charm++ runtime system [59]. This code is able to

Protocol	Geometric	Zipf's
Checkpoint/Restart	0.9997	0.9992
Message Logging (g=2)	0.9988	0.9966
Message Logging (g=4)	0.9980	0.9945
Message Logging (g=8)	0.9964	0.9911
Message Logging (g=16)	0.9933	0.9854

Table 7.3: Survivability of different fault tolerance protocols.

tolerate the failure of one complete node, including all objects running on cores on that node.

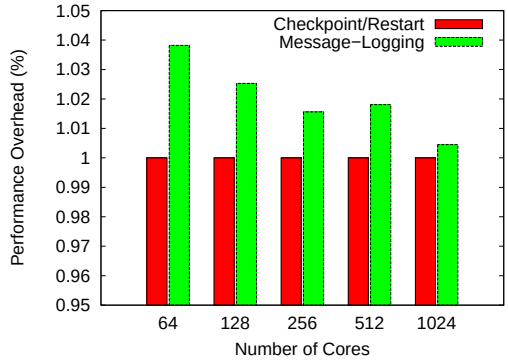
Figure 7.8(a) presents the performance overhead of Jacobi3D on Trestles. Ranging from 64 to 1,024 cores (or from 2 to 32 nodes), the overhead is always lower than 4%. This is a weak-scaling experiment and there are no barriers between iterations. Each core has four objects. Each object has a block size $128 \times 128 \times 128$ elements. Thus, there is no fundamental reason for having an increasing overhead. Figure 7.8(b) presents the average number of determinants piggybacked in a remote (inter-node) message. That number comes close to 16. This is not a small number, since results in Chapter 2 presented an average of less than 5 determinants piggybacked per message in a non multicore-node system. The fact that Trestles has 32 cores per node directly dictates a high number of determinants on a remote messages, because of the high amount of internal messages that are delivered before an external communication takes place.

Table 7.4 shows in detail the total number of messages and determinants created in this example. The number of remote messages is small compared to the total number of messages (around 32%). This is due to the fact that most of the communication is local to the node. An interesting observation is that the number of times a particular determinant is piggybacked goes up to 5.17, on average. That means the systems keeps more than 5 copies of a determinant when it is only necessary to have 1.

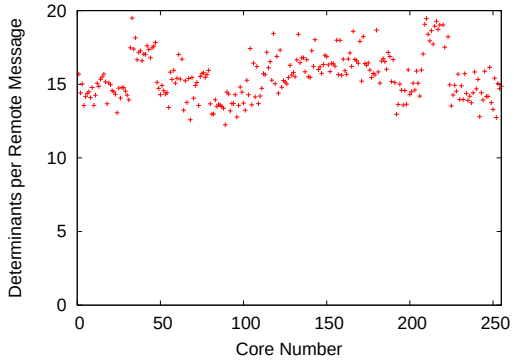
Determinants Generated	648,656
Determinants Piggybacked	3,357,762
Remote Messages	206,375
Determinants per Message	16.27

Table 7.4: Determinants and messages.

The same experiment was run on two additional machines, Ranger and Steele. Table 7.5 shows the memory overhead relative to the total communication volume. In other words, a memory overhead of 1.00 would mean every single message is stored. The trend is clear,



(a) Performance overhead of message-logging with respect to checkpoint/restart.



(b) Average number of determinants per remote message.

Figure 7.8: Performance indicators of message-logging on multicore-node systems. The performance overhead can be kept low even when the number of determinants piggybacked on an inter-node message is modest.

the higher the core count per node, the less communication data is stored. Remember that only inter-node messages are logged, thus larger nodes decrease the memory pressure of message-logging.

	Steele	**Ranger**	**Trestles**
Cores per Node	8	16	32
Relative Memory Overhead	0.42	0.33	0.17

Table 7.5: Relative memory overhead in message-logging.

7.5 Discussion

When designing the determinant queue for a node, the obvious implementation is via a single lock. However, this mechanism performed poorly. It was clear that a finer granularity in the critical region was needed. Therefore, atomic operations were used in the final implementation of the determinant queue. Table 7.6 shows the cost in microseconds of the 3 different operations on the determinant queue using a single lock.

All the optimizations described in this dissertation can be applied to the multicore case. The fast message-logging protocol of Chapter 3, where no determinants are generated, can be easily adapted to multicore-node systems. The concurrent failure of several PEs does not

Add	Piggyback	Acknowledge
41μs	60 μs	79μs

Table 7.6: Lock contention costs.

affect the correctness of the protocol. Parallel recovery, reviewed in Chapter 2, is equally applicable to the multicore-node case. It this case, once a node crashes, the objects on that node can be distributed to other nodes for parallel recovery. The team-based message-logging protocol of Chapter 5 is also useful in multicore-node machines, with the property that now teams contain nodes instead of PEs. This would bring a further decrease in the memory overhead, because even some inter-node messages may not be logged (those traveling within team boundaries).

It is impossible not to connect this chapter with the MPI+X programming model, where MPI is used to transmit messages from one node to another and a different programming model is used within the node. The MPI+X model would precisely render unnecessary the work in this chapter. The reason is that having only one communication agent per node would be equivalent to have a PE-based system. There is no need for the additional shared-memory data structures.

It has been noted that node failures may co-occur in supercomputers [72]. This phenomenon is specially relevant during the first stage of the lifetime of a machine. Since there is a period of instability where the system administrators are still tuning up the components, several nodes may crash due to a common reason.

It is possible to collect evidence for this type of failures from the open repositories of failures in supercomputers. Using that information it will be useful to understand what reach the failure correlation has. In other words, how many nodes a failure may bring down simultaneously. If nodes X and Y appear to crash altogether in a high percent of the cases, we may adjust the runtime system to deal with this type of failure. There are at least a couple of alternatives: i) using the load balancer to distribute objects in a way that a simultaneous failure does not make the system lose any determinants, and ii) strengthen the causal message-logging protocol to piggyback determinants along with messages until they are safely stored.

Before describing both alternatives in more detail, we need to define a couple of terms. Failure data analysis can provide a *node-failure correlation graph* of the system. This graph has nodes as vertices and there is an edge between two nodes if they happen to fail concurrently. Each edge may be labeled with the probability of the two nodes failing altogether. Using this graph, we can form *failure domains* by applying a partitioning algorithm. Nodes

belonging to the same failure domain will be more likely to fail concurrently than nodes belonging to different domains.

The load balancer strategy may avoid locating objects that communicate with each other on nodes that exhibit failure correlation. Using the node-failure correlation graph, a load balancer can make more informed decisions about where to locate the objects. Node buddies for checkpoint will be assigned with this graph in mind too. Figure 7.9 presents a scenario with four nodes and two failure domains. For two objects α and β that exchange messages, the load balancer may put them on the same node (without a risk of losing determinants, since we consider a node as a minimum unit of failure) or assign them to different failure domains.

The strategy of enhancing the causal message-logging protocol will address a type of dynamic applications, where communication pattern changes during execution. Using this protocol, determinants will travel from the source node until they exit the failure domain. If objects α and β exchange messages they may reside on nodes of the same failure domain. If α lives on node A and β on node B, a message from α to β carrying a determinant will make that determinant to be piggybacked to messages going out of node B to another failure domain, where they can be safely stored.

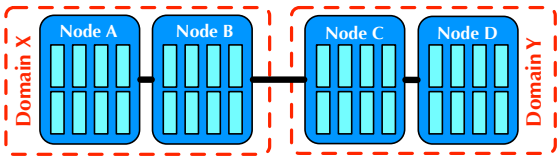


Figure 7.9: Node-failure correlation in multicore-node systems.

7.6 Related Work

Schroeder and Gibson [72] performed the first comprehensive study of failures in HPC systems. They analyzed failure data from several supercomputers at Los Alamos National Laboratory. Most of their work consisted in modeling different distributions and finding best-fit curves in each case. For instance, they found Poisson and exponential distributions to be poor fits for number of failures per node and time between failures, respectively. On the contrary, Weibull and lognormal distributions were shown to be a good model for time between failures and repair time, correspondingly. Their analyses helped to understand better the behavior of failures in large-scale computing systems. One of their findings was that

failure rates do not grow significantly faster than linearly with system size. Based on that fact, we can assume failure frequency will scale as supercomputers grow within the same architecture type.

Traditionally, fault tolerance message-logging protocols have had a core, not a node, as the unit of failure. Whereas some of the protocols only tolerate the failure of one single core [5,6], others tolerate the failure of multiple cores but only at the cost of a high overhead [34]. Recently, protocols based on properties of HPC applications have been shown to tolerate multiple simultaneous crashes [51], but they may have a high cost on recovery. Moody *et al* [31] mention that 85% of the failures disable at most one compute node on the clusters at Lawrence Livermore National Laboratory where the Scalable Checkpoint/Restart (SCR) library is run.

Previous work on checkpoint/restart for multicore machines has focused on reducing the jitter at the time of checkpoint by merging multiple requests to the file system into coarser writes. Ouyang *et al* have identified the benefits of write aggregation and interleaving in this scenario [22].

Ropars and Morin [104] developed a distributed event logger to store the non-deterministic events in an active optimistic message-logging protocol for MPI applications. Each node holds a certain portion of the total number of determinants and there is some redundancy among the event loggers in the different nodes. In this dissertation, determinants are always stored at the receivers of the messages according to a causal message-logging protocol. Therefore, we do not handle the notion of event logger. Alternatively, we always use a distributed logging of determinants.

Bouteiller *et al* [105] explored the failure correlation of cores in the same node. They propose a technique to enhance message-logging and deal with correlated failures. In their approach, a group of cores that have correlation according to their failure pattern checkpoint coordinately and rollback as a unit in case of failure.

CHAPTER 8

Concluding Remarks

This thesis provides theoretical and empirical support for a scalable message-logging approach to improve fault tolerance in HPC applications. It contains a set of strategies to ameliorate the overheads introduced by traditional message-logging protocols. Such overheads come in the form of performance penalization and increased memory footprint. The simple causal and the fast message-logging protocols decrease the former, while team-based and collective-aware message-logging strategies alleviate the latter.

Our philosophy for providing an effective fault-tolerance solution in HPC applications is to maintain the progress rate of the application as high as possible even in the case of a faulty hardware. Additionally, energy consumption is an important concern. Thus, strategies that provide a high progress rate and reduce energy consumption should be preferred. Message-logging is one of those promising strategies, particularly when combined with the migratable-objects model.

8.1 Conclusions

This thesis concludes the following:

- Message-logging is faster than traditional checkpoint/restart in a faulty environment. Chapters 2 and 3 contain experimental results that confirm such a claim. With fast message-logging it is possible to maintain the scheme efficient and alleviate the three major sources of overhead of fault-tolerance mechanisms. The forward-path overhead can be kept below a small margin. Checkpoint can be performed on local storage to keep it fast. Recovery can be accelerated with migratable objects that recover in parallel.

- Message-logging is a green alternative for resilient HPC applications. Since it relies on local recovery, the vast majority of the system does not draw peak power during recovery, as shown in Chapter 2. Instead, the power drawn by most nodes goes down to almost the idle power level until the crashed node catches up.

- The popular belief that *minimize time is sufficient to minimize energy* is false. A clear demonstration of this appears in Chapter 4 where message-logging may sometimes increase total execution time over checkpoint/restart, but it always consumes less energy.

- The future of message-logging on supercomputers looks bright as the failure rate increases. The analytical model of Chapter 4 predicts message-logging with parallel recovery can halve the execution time and energy consumption of parallel programs at large scale.

- Determinants play a major role in the performance penalization of message-logging protocols. However, high-level description of the program may help in removing the need for determinants. The fast message-logging protocol of Chapter 3 shows the benefits in both weak and strong-scale settings.

- The most important limitation of message-logging lies on its increased memory footprint. To address this critical issue, it is possible to trade off memory consumption for recovery cost.

- The team-based message-logging protocol reduces the memory overhead of the message log by grouping nodes into groups and avoiding the internal communication to be logged. The groups, however, recover as a unit: if one of the team members fails, the entire team has to roll back. Applications that naturally exhibit communication locality are good candidates for this protocol.

- Programs with a heavy use of collective communication operations can substantially decrease the memory pressure of message-logging by using the protocol explained in Chapter 6.

- Multicore nodes are commonplace in current machines. The trend of adding more cores per node seems to hold in the foreseeable future. Resilient solutions that address this type of architectures will definitively be easier to deploy in modern supercomputers. Furthermore, a multicore node can be taken as the unit of failure.

- Application-level message-logging can help in reducing the performance penalization of building the same message multiple times during a single step of iterative applications. Chapter A introduces an example where logging messages at the application level may dramatically reduce the size of a message log and speed up the execution.

- Asymmetry in communication represents a formidable opportunity to reduce memory consumption in the message log in exchange for a small cost during recovery. Chapter A presents a protocol that takes advantage of such scenarios.

- An overall observation from the results in this dissertation is that standard message-logging should not be blindly used as an infallible resilient mechanism for all types of applications. Chapter 5 shows how a communication-bound application can quickly saturate the available memory. Therefore, specific message-logging techniques should target particular kinds of applications.

8.2 Contributions

This thesis makes the following contributions:

- The design, implementation and evaluation of *simple* causal message-logging. This protocol is presented in Chapter 2. It has several advantages in performance over the more popular pessimistic approach. Those advantages play a major role in the migratable-objects model.

- An evaluation of the energy profile of different fault-tolerance methods. Chapter 2 contains a comparative study between three strategies and some insights on how the different methods can reduce energy consumption.

- The fast message-logging protocol, which removes an important part of the performance overhead by eliminating determinants, is introduced in Chapter 3. This protocol uses information from a high-level description of the program that contains clues on reception determinism. Therefore, determinants can be safely removed. We demonstrated the scalability of this approach using up to $131,072$ cores.

- A performance and energy model for message-logging protocols that may use parallel recovery. This analytical formulation, explained in Chapter 4, allows us to make predictions at extreme scale and evaluate the potential of different optimizations.

- The team-based message-logging protocol that trades off a reduction in memory overhead for an increase in recovery cost. It manages to reduce the size of the message log by grouping highly-connected tasks and only logging messages across groups. Chapter 5 presents a load balancing framework that permits the dynamic formation of teams and also achieves a competitive load balance.

- A message-logging protocol that stores the minimum number of messages necessary for recovery when collective communication operations are used intensely. It assumes the implementation of this type of operations is scalable and uses a tree structure. Chapter 6 offers experimental results where the memory overhead reduction can be dramatic.

- The adaptation of a well-known message-logging protocol to fit the architectural constraints of multicore-node systems. Chapter 7 shows the details of the protocol along with an experimental evaluation.

8.3 Future Work

This is an incomplete list of promising ideas derived from the contributions in this thesis:

One-sided message-logging. It is well known that message copying has a significant impact on the performance of applications. One-sided communication operations were introduced to alleviate the synchronization cost of data exchange and to eliminate the need of copying the same message several times before delivering it. At the same time, this type of operations leverage the architecture of many network designs that allow remote memory access. The semantics of one-sided communication operations is very particular to each programming language. In fact, the MPI-2 standard [106] defines three possible mechanisms to use this type of operations. In most cases, languages may define a region in the code where data transmission with one-sided operations will occur. In these regions the order of completion is unimportant, as long as all the operations are completed by the end of the region. This assumption opens up an opportunity for an optimized message-logging protocol that manages determinants in a way similar to the *overlap* regions of Chapter 3.

Partial determinism. The fast message-logging protocol in Chapter 3 showed that an explicit control flow description of the program can eliminate the need of determinants for a particular kind of programs. The next logical step consists in examining scenarios

where *some* determinants can be eliminated and some not. This situation will lead to partial ordering of events in a program. As opposed to a traditional message-logging protocol that imposes a strict linear order in the non-deterministic events, a partially deterministic program would allow commutative events to happen in any order but it would require a strict order for other events.

Application-level message-logging. Keeping a copy of sent messages may bring an additional benefit in performance if the same message is generated multiple times in a short period of time. An example of such type of applications appears in Appendix A. Section A.1 describes ChaNGa, a cosmology simulation program that splits a group of particles into a set of objects. On average, each object receives dozens of requests per iteration. Each request will return the same message consisting in the set of particles of that object. Therefore, the application may cache that response and save time. Additionally, the stored messages could be kept across iterations to be used by a message-logging protocol. A similar pattern may be found in other applications, making application-level message-logging an alternative to increase performance and resilience.

Message-logging protocol for asymmetric communication applications. The traditional message-logging techniques are sender-based. In other words, the sender stores the messages it sends in main memory. To alleviate the potentially high memory footprint, asymmetries in the communication volume of different tasks can be exploited. For instance, if the distribution of bytes sent is highly skewed, with few tasks sending most of the data, then these tasks may become non-loggers. They do not store messages, albeit they still generate and handle determinants. If a tasks fails, and it needs a message from a non-logger, it will request the non-logger to roll back along with it. This mechanism is transitive until all needed messages come from sender-loggers. A different kind of asymmetry may force some tasks to be receiver-based instead of sender-based. Appendix A describes the different types of loggers that may be possible in this new ecosystem and some of the additional considerations for a message-logging protocol.

Node-correlated failures. Chapter 7 presents a protocol for multicore-node systems, where multiple PEs need to share some data structures in order to effectively achieve recovery. A single node was assumed to be the unit of failure. However, different scenarios may bring a higher frequency of node-correlated failures. As some nodes may share power source, network link or cooling equipment, they may present a high chance of corre-

lated failures. Developing message-logging techniques for such scenarios is required to further improve the reliability of the protocol.

Immediate recovery. This thesis reviews, in Chapter 2, the most relevant techniques to provide fault tolerance in HPC. It presents rollback-recovery as the most popular mechanism. Parallel recovery relies on rollback to a previous checkpoint, but accelerates recovery via object migration. That same chapter presents replication as a way to offer fault tolerance without having to rollback. Every computational unit gets replicated. If a node fails, its replica will take over its role and execution can continue. The main disadvantage of replication is that it requires an investment of at least half the machine to run the redundant nodes. A strategy that avoids rollback without sacrificing additional resources could have an enormous impact in faulty scenarios. We envision this strategy for particle interaction applications. In this type of programs, a node is constantly sending the positions of its particles to other nodes. This data is basically the state of the node. The insight consists in using the messages from a node as its checkpoint. Therefore, the recipients of the messages from a node will store those messages and provide the latest one in case of a failure. We foresee message-logging techniques playing a vital role in keeping the whole recovery consistent. At the same time we believe the recovery will be immediate because the "checkpoint" of a node will have the state of the node in the previous iteration.

APPENDIX A

Further Opportunities for Message-Logging

This chapter presents a couple of promising directions to decrease the memory overhead in message-logging. Section A.1 discusses how application-level awareness of what messages are being sent can help to dramatically decrease the message log size. Section A.2 presents a type of applications for which communication in some tasks is asymmetric. On those programs, a specific message-logging protocol can decrease memory pressure.

A.1 Application-level Message-Logging

Chapters 5 and 6 presented two different approaches to decrease the memory overhead of message-logging. These two strategies, however, are based on a lower-level protocol. In other words, the application is unaware of message-logging. The protocols take advantage only of the communication features in the applications. Either by finding communication locality and forming teams or by exploiting the implementation of collective communication operations, those protocols do not receive any direct information from the application.

We will present a guiding example throughout this section. This application is called ChaNGa [82] and represents one of the major applications in Charm++. ChaNGa (Charm++ N-body GrAvity solver) is a program that computes gravitational forces among a set of particles. It performs collisionless N-body simulations. The major application of ChaNGa is to cosmological simulations with periodic boundary conditions in comoving coordinates. It has also been used for simulations of isolated stellar systems. Additionally, it can include hydrodynamics using the Smooth Particle Hydrodynamics (SPH) technique. ChaNGa relies on a Barnes-Hut tree to calculate gravity, with hexadecapole expansion of nodes and Ewald summation for periodic forces. Timestepping is achieved with a leapfrog integrator with

individual timesteps for each particle.

There are four major stages in each step of ChaNGa: *i*) domain decomposition, which creates a division of the space according to the set of particles and their positions, *ii*) load balancing, which migrates particles to balance the load across the set of processors *iii*) tree building, where a Barnes-Hut tree is rebuilt for the new set of particles and their distribution, and *iv*) gravity computation, which performs the actual computation on each particles.

It is the gravity computation step we will focus on. After the tree building, a set of objects called Tree Pieces will hold each a subset of the particles. During the gravity computation, each Tree Piece is responsible for computing the total gravity on its particles. In doing so, it may require the particle information from potentially many other Tree Pieces. Several Tree Pieces will reside on the same PE. To avoid multiple identical requests, ChaNGa has a receiver-side Cache. These set of objects behave as a *group* in Charm++, meaning there is exactly one per PE. Thus, each Tree Piece will try contacting its local Cache first to get the particles it needs. If the Cache has the particular set of particles stored, it will return them to the requesting Tree Piece. Otherwise, the Cache will contact the remote Tree Piece, cache the content of the message and forward it to the requesting Tree Piece. Figure A.1 shows a diagram of the overall scheme of objects in ChaNGa where Tree Piece A requires the information from Tree Piece B and that request always goes through the local Cache on PE X.

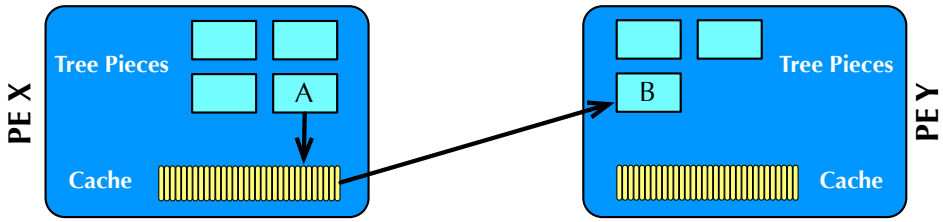
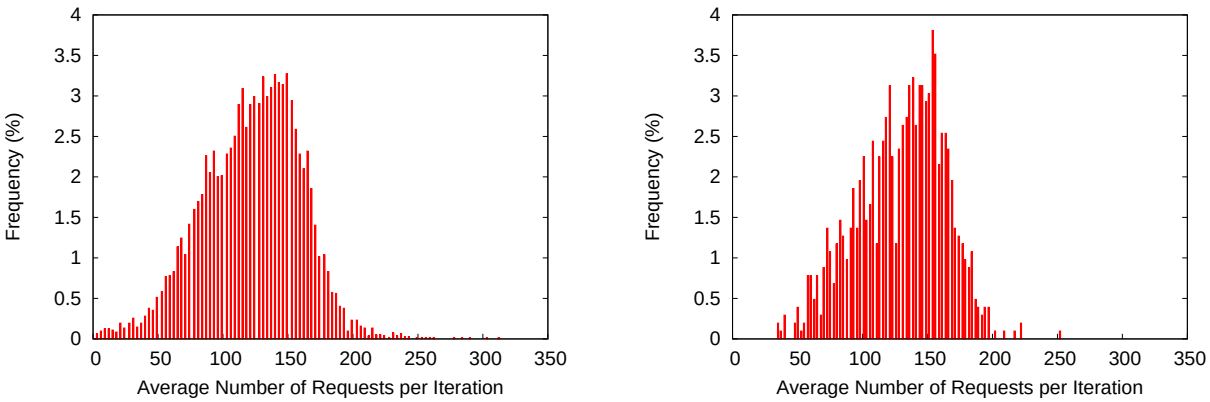


Figure A.1: Simplified diagram of objects in ChaNGa. A Tree Piece that requires the particle information of another Tree Piece will first contact its local Cache to avoid a remote transmission. If the local Cache has the particle message, it will provide them, otherwise it will contact the remote object.

The current implementation of ChaNGa provides (accidentally) a receiver-based message-logging mechanism. However, the failure of a PE will immediately disappear the Cache and all its content. Additionally, messages are cached per iteration. Therefore, not all the messages would be available for a recovering Tree Piece even in the case that the Cache would survive a crash. What is encouraging about this scenario is the relative advantage of logging the messages, at least in terms of performance. The message-logging techniques we

have described in this dissertation all belong to the sender-based family, where messages are stored in the main memory of the sender. If ChaNGa were to be seen from that perspective, there would be a fertile land to implement a message-logging protocol.

To understand the potential of application-based message-logging in ChaNGa, we measured the average number of requests per iteration. We ran for 10 iterations the `dwf1.2048` dataset with 8,192 Tree Pieces. The dataset contains 5 million particles. The results were gathered on Intrepid with 1,024 cores. Figure A.2 shows the distribution of requests for ChaNGa. We only counted remote request, i.e., coming from a remote PE. In Figure A.2(a) appears the distribution of average number of requests per TreePiece. Although most of the distribution follows a normal shape, the tail is significant with a few Tree Pieces showing a high number of requests per iteration. The story changes a little once PEs are considered. Figure A.2(b) offers the distribution of average number of requests per iteration per PE. Both distributions show the immense potential for having a sender-based message-logging at the Cache objects. On average, the number of requests is higher than 100, meaning per iteration the very same message has to be built 100 times.



(a) Distribution of requests per Tree Piece.

(b) Distribution of requests per PE.

Figure A.2: Distributions of average number of requests per iteration on ChaNGa.

Using a strong-scale approach, we ran the same experiment from 512 to 4,096 cores. Table A.1 summarizes the results of this experiment. As the number of cores increases, the average number of requests raises. This can be explained by the fact that more cores, means a higher chance that the Tree Piece is not local, requiring a remote request. However, the dispersion of the data also changes drastically. The absolute maximum of requests reports the Tree Piece with the maximum number of requests and it roughly doubles as we go from 512 to 4,096 cores. The averages in the number of requests per iteration are always higher for the Tree Piece version. This is a natural result of load balancing that will balance Tree

Pieces with different request profiles on the different PEs.

Number of Requests	Number of Cores			
	512	1024	2048	4096
Absolute Average	97.05	124.50	160.51	202.28
Absolute Maximum	508.00	670.00	936.00	1154.00
Average per PE	100.99	131.45	171.66	218.95
Maximum Average per PE	165.89	252.90	407.33	521.00
Average per Tree Piece	92.04	118.46	152.87	192.68
Maximum Average per Tree Piece	260.00	312.40	473.40	607.30

Table A.1: Average number of requests per iteration in ChaNGa.

The lesson extracted from ChaNGa is that applications may have a high potential to eliminate unnecessary creation of messages and at the same time provide a useful infrastructure for message-logging. In the particular case of ChaNGa, the Cache objects could be made sender-based too. This would avoid the cost of generating the same message multiple times and serve as the fundamental basis for message-logging protocols.

A.2 Asymmetric-Communication Applications

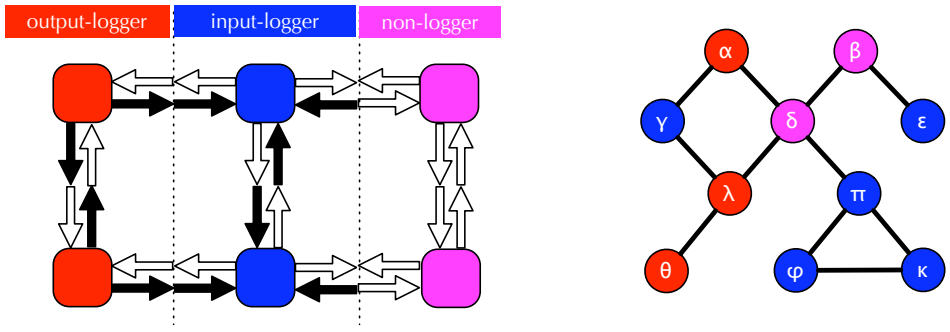
The sender-based model may not completely capture the complexities of an application. For instance, in some applications where different groups of objects achieve different goals (e.g. *masters* and *workers*), the communication load associated with those objects may be different. We call *asymmetric communication applications* those than exhibit an uneven communication load distribution. In some situations, due to transient load imbalance, certain objects may concentrate a high percentage of the communication too.

An opportunity to reduce the amount of memory due to message log is to have certain objects logging incoming messages (or no messages at all) rather than outgoing messages. There could be three types of objects, according to what messages they log:

- *Output-logger*. The traditional method we have employed so far. Every time the object sends a message, the message gets logged. Figure A.3(a) presents this type of objects on the leftmost part. Hollow arrows represent unlogged communication, whereas bold arrows stand for logged messages.

- *Input-logger*. Incoming messages are logged instead of outgoing messages. If an object sends more data than it receives, making it an input-logger will decrease its memory footprint. Figure A.3(a) shows an example of objects of this type in the middle portion of the picture.

- *Non-logger*. If a substantial amount of communication goes through an object, it may be worthwhile not to log any message. Figure A.3(a) shows on the rightmost section a pair of objects that handle lots of computation and thus lots of communication, so they do not store any message.



(a) Types of objects. (b) Communication graph.

Figure A.3: Different message-logging objects.

Having different types of message-logging objects brings its own tradeoffs. As opposed to traditional message-logging, where only the crashed objects are rolled back, more objects may have to be rolled back even if the failure did not impact them. If a crash hits an object α, it has to roll back. But, all its input-logger neighbors have to be rolled back with it. The cascade rollback stops there, since input-logger objets may resend the received messages and reconstruct the sent messages. The non-logger objects present a different story, where the cascading rollback must traverse all paths through non-logger objects until a different kind of object is reached.

Figure A.3(b) shows a communication graph example, where vertices are objects and an edge between two objects indicate they exchange messages. The number of objects to roll back depends on the topology of the graph and what object fails. We will consider three examples. If object γ fails, it is the only one rolling back, because all its neighbors are ouput-logger and they can just resend the messages to γ. The failure of ϕ is more costly, since both neighbors are input-logger and they have to be rolled back along with ϕ. However, both π and κ have enough information to restore their state and produce the messages required for ϕ to recover. Finally, the failing of λ is much more dramatic. It makes objects γ, δ, π, β, ϵ to roll back. Notice that both δ and β make other objects to roll back, since they do not store any messages at all.

The decision on whether to make an object to be output-logger, input-logger or non-logger has to be based on a balance between computational and communication load. For instance,

an object sending a disproportionate amount of data but receiving little data and performing low computation is a good candidate to be a input-logger, since rolling it back as a result of the crash of another object would not imply a high cost on recovery.

APPENDIX B

Supercomputer Descriptions

The experimental results in this thesis were collected on different machines. A summary of the supercomputers used in this thesis is presented in Table B.1. The diversity in the list of computers emphasize the wide applicability of the mechanisms described in this thesis. At the same time, different machines offer different tradeoffs worth exploring.

Name	**Vendor**	**Center**
Abe	Dell	NCSA
Energy Cluster	Dell	UIUC
Intrepid	IBM	ALCF
Ranger	Sun	TACC
Stampede	Dell	TACC
Steele	Intel	RCAC
Trestles	Intel	SDSC

Table B.1: Summary of features of supercomputers used in this thesis.

Abe

Abe was a supercomputer at NCSA (National Center for Supercomputer Applications). It was operational from July 2007 until April 2011. Abe consisted of 1200 blades Dell PowerEdge 1955, each blade having 8 cores for a total of 9600 cores. Every blade (or node) is comprised of two Intel 64 (Clovertown) 2.33 GHz dual socket quad core chips. The peak performance of Abe was 89.47 TFLOPS. A total of 8 GB is available per node (1 GB per core). The nodes were connected through a fat-tree Infiniband network.

Energy Cluster

It is a cluster of 32 nodes (128 cores) installed in the Department of Computer Science of the University of Illinois at Urbana-Champaign. Each node has a single socket with a four-core Intel Xeon X3430 processor chip running CentOS 5.7. The cluster nodes are connected by a 48-port gigabit Ethernet switch. It contains a Liebert power distribution unit (PDU) installed on the rack containing the cluster to measure the machine power after at 1-second intervals on a per-node basis.

Intrepid

Intrepid is an IBM Blue Gene/P machines with 40,960 nodes at the Argonne Leadership Computing Facility (ALCF) in Argonne National Laboratory (ANL). Each node in Intrepid consists of one quad-core 850MHz PowerPC 450 processor and 2GB DDR2 memory. With a total of 163,840 cores, 80 terabytes of RAM, Intrepid has a peak performance of 557 TFLOPS.

Ranger

Ranger was a machine installed at Texas Advanced Computing Center (TACC). Retired in April 2013, it was comprised of 3,936 16-way SMP compute nodes with a peak performance of 579-TFLOPS. Each node contained 32 GB of memory. Ranger had in total 15,744 AMD Opteron processors, which translates into 62,976 compute cores. The interconnect topology was a 7-stage, full-CLOS fat tree, which provides a 1GB/sec point-to-point bandwidth.

Stampede

Stampede is machine at Texas Advanced Computing Center (TACC). It is a 10-PFLOPS machine with more than 96,000 cores divided into 6,400 nodes. Each node contains 2 Intel Xeon processors (16 cores total) and 32GB of memory. The interconnect uses Mellanox FDR Infiniband technology in a 2-level fat-tree topology.

Steele

Steele is a supercomputer at the Rosen Center for Advanced Computing (RCAC) in Perdue University. Steele has 893 nodes, each with 16GB of memory and two Intel E5410 Harpertown 2.33 Ghz quad core processors. The nodes are connected through Infiniband for a total peak performance of 60 TFLOPS.

Trestles

Trestles supercomputer is installed at San Diego Supercomputer Center (SDSC). Trestles is a 100-TFLOPS machine with 324 nodes, each having 32 cores. There are 4 sockets in a node, each having an 8-core 2.4 GHz AMD Magny-Cours core. A fat tree Infiniband interconnect links all the nodes.

APPENDIX C

Benchmark Descriptions

To properly evaluate the different protocols in this thesis we resorted to a variety of parallel programs. Table C.1 summarizes the main features of these benchmarks and mini-applications. They range from linear algebra codes to hydrodynamics and come from two different programming languages.

Name	**Language**	**Domain**
Jacobi3D	Charm++	Physics
LBTest	Charm++	Stencil
LeanMD/Mol3D	Charm++	Molecular Dynamics
LULESH	Charm++	Hydrodynamics
NPB	MPI	Linear Algebra
OpenAtom	Charm++	Quantum Chemistry
Sweep3D	MPI	Physics
Wave2D	Charm++	Physics

Table C.1: Summary of features of benchmarks used in this thesis.

Jacobi3D

A 7-point stencil that computes the transmission of heat on a three-dimensional space. The global space is divided into *blocks* and the program proceeds iteratively, exchanging ghost cells with neighboring blocks and applying the computation to all internal elements. In each iteration, every element averages the values of all its 7 neighbors (including itself) to update its value. The set of blocks is implemented through a three-dimensional chare array in Charm++.

LeanMD/Mol3D

A mini-application that emulates the communication pattern in NAMD [94]. It computes the interaction forces between particles in a three-dimensional space. This computation is based on the Lennard-Jones potential. It does not include long-range force computation. The object decomposition follows the same pattern as in NAMD. A three-dimensional space is divided into orthotopes or hyperrectangles. Each of these boxes, called *cells* or *patches* in NAMD's nomenclature, contain a subset of the particles. To compute the interaction of the particles between each pair of cells, a specific object called a *compute* is connected to the two cells and receives the particles from both to perform the computation. In each iteration of LeanMD, each cell sends its particles to all the computes attached to it and receives the udpates from those computes. The groups of cells and the groups of computes are implemented each as a chare array in Charm++.

LBTest

It is a synthetic benchmark in Charm++ for load balancing experimentation. It creates a collection of objects with different customizable properties. Its parameters include the communication topology among the objects, a range for the load of objects, frequency of load balancing and whether the load in each object is static or dynamic (progressively changes across the execution). This program enables the analysis of the effect of one single parameter at a time and measure how susceptible the load balancer is to different scenarios.

LULESH

The Livermore Unstructured Lagrangian Explicit Shock Hydrodynamics (LULESH) is code for modeling hydrodynamics. This types of codes describe the motion of materials relative to each other when subject to forces. LULESH is a typical hydrocode and represents a proxy mini-application for more complex codes. LULESH approximates the hydrodynamics equations discretely by partitioning the spatial problem domain into a set of volumetric elements defined by a mesh. Each node on the mesh is a point where mesh lines intersect. The program proceeds iteratively, exchanging ghost elements with neighboring elements. The set of elements is implemented through a three-dimensional chare array in Charm++.

NAS Parallel Benchmarks (NPB)

The NAS Parallel Benchmarks suite (NPB) was adapted to AMPI to have migratable MPI threads. The NPB is a collection of linear algebra numerical methods [107]. We focused our experiments in some of the benchmarks from NPB: block-tridiagonal (BT), conjugate gradient (CG), data traffic (DT), multi-grid (MG) and scalar pentadiagonal (SP). The multi-zone version of the NAS Parallel Benchmarks (NPB-MZ) compute discrete solutions in three spatial dimensions for the unsteady and compressible Navier-Stokes equations. There are three different benchmarks in this version of NPB, lower-upper symmetric Gauss-Seidel (LU), scalar pentadiagonal (SP) and block tridiagonal (BT). In our experiments we only use BT since it presents the highest load imbalance among the three programs. BT solver operates on a logical cube that is seen as a structured discretization mesh. To describe a complex domain, BT uses multiple meshes (called *zones*) to cover it.

OpenAtom

It is a highly scalable and portable parallel application for molecular dynamics simulations based on fundamental quantum mechanics principles. Car-Parrinello ab initio molecular dynamics (CPAIMD) is a well-known approach that has proven to be relatively efficient and useful in this type of simulations. The parallelization of this approach beyond a few thousand processors is challenging, due to the complex dependencies among various sub-computations. This may lead to complex communication optimization and load balancing problems. OpenAtom is a mechanism to parallelize CPAIMD using the migratable-objects model in Charm++.

Sweep3D

A benchmark representing the core of a real Accelerated Strategic Computing Initiative (ASCI) application. It solves a 1-group time-independent neutron transport problem on discrete ordinates 3D cartesian geometry. The three-dimensional geometry is represented by a logically rectangular grid of blocks. The angular dependence in Sweep3D is handled by discrete angles with a spherical harmonics treatment for the scattering source. The solution process involves two steps: *i*) the streaming operator is solved by sweeps for each angle, and *ii*) the scattering operator is solved iteratively.

Wave2D

A benchmark that runs a finite difference method to compute pressure information on a two-dimensional grid. The global space is divided into rectangles or *blocks* that will contain a portion of the grids. In each iteration, each block exchanges its ghost cells with its four neighboring blocks. The computation updates all the elements in the grid using the two previous values of the neighboring cells. The set of blocks is implemented as a two-dimensional chare array in Charm++.

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