# Adaptive Parallel Job Scheduling with Flexible CoScheduling*

Eitan Frachtenberg† Dror G. Feitelson‡ Fabrizio Petrini†
Juan Fernández§

**Abstract**

Many scientific and high-performance computing applications consist of multiple processes running on different processors that communicate frequently. Because of their synchronization needs, these applications can suffer severe performance penalties if their processes are not all coscheduled to run together. Two common approaches to coscheduling jobs are batch scheduling, wherein nodes are dedicated for the duration of the run, and gang scheduling, wherein time slicing is coordinated across processors. Both work well when jobs are load-balanced and make use of the entire parallel machine. However, these conditions are rarely met and most realistic workloads consequently suffer from both internal and external fragmentation, in which resources and processors are left idle because jobs cannot be packed with perfect efficiency. This situation leads to reduced utilization and suboptimal performance. Flexible CoScheduling (FCS) addresses this problem by monitoring each job's computation granularity and communication pattern and scheduling jobs based on their synchronization and load-balancing requirements. In particular, jobs that do not require stringent synchronization are identified, and are not coscheduled; instead, these processes are used to reduce fragmentation. FCS has been fully implemented on top of the STORM resource manager

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†CCS-3 Modeling, Algorithms, and Informatics Group, Computer and Computational Sciences Division, Los Alamos National Laboratory, USA

on a 256-processor Alpha cluster and compared to batch, gang, and implicit coscheduling algorithms. This paper describes in detail the implementation of FCS and its performance evaluation with a variety of workloads, including large-scale benchmarks, scientific applications, and dynamic workloads. The experimental results show that FCS saturates at higher loads than other algorithms (up to 54% higher in some cases), and displays lower response times and slowdown than the other algorithms in nearly all scenarios.

**Keywords**: Cluster computing, load balancing, job scheduling, gang scheduling, parallel architectures, Flexible coscheduling

# 1 Introduction

Clusters of workstations are steadily growing larger and more prevalent. Although cluster hardware is improving in terms of price and performance, cluster utilization remains poor. Load imbalance is arguably one of the main factors that limits resource utilization, in particular in large-scale clusters [5]. Load imbalance can have a marked detrimental effect on many parallel programs. A large subset of high performance computing (HPC) software can be modeled using the bulk-synchronous parallel (BSP) model. In this model a computation involves a number of *supersteps*, each having several parallel computational threads that synchronize at the end of the superstep [6, 13, 23]. A load imbalance can harm the performance of the whole parallel application because each thread of computation requires a different amount of time to complete, and the entire program must wait for the slowest thread before it can synchronize. Since these computation/synchronization cycles are potentially executed many times throughout the lifetime of the program, the cumulative effect on the application run time and the system resource utilization can be quite high [20].

Load imbalance has three main sources: application imbalance, workload imbalance, and heterogeneity of hardware resources. Application load imbalance occurs when different parallel threads of computation take varying times to complete the superstep. This can occur either as a result of poor programming, or more typically, because of a data set that creates uneven loads on the different threads.

for instance, when the compute nodes are not entirely dedicated to the parallel computation because they are also being used for local user- or system-level programs, or because the resource management system cannot allocate an even workload to all processors. This uneven taxing of resources creates a situation in which some parts of the parallel program run slower than others, and a load imbalance occurs [20].

Load imbalance can also be generated by heterogeneous architectures in which different nodes have different computational capabilities, different memory hierarchy properties, or even a different number of processors per node. Two examples of such situations are grid computing and HPC systems that accrue additional processing nodes over a period of time, thus taking advantage of technological improvements.

The traditional approach to tackling load imbalance is at the application level: the programmer tries to balance the resources by changing the structure of the parallel program. This approach is usually time-consuming and yields diminishing returns after an initial phase of code restructuring and optimizations. In fact, there are some problems that are inherently load-imbalanced. This approach is also not economically feasible with legacy codes. For example, the Accelerated Strategic Computing Initiative (ASC) program [25] invested more than a billion dollars in recent years in parallel software.

An alternative approach is to attack load imbalance at the run-time level. Rather than optimizing a single parallel job, we can coschedule (time-slice on the same set of processors) multiple parallel jobs and try to compensate for the load imbalance within these jobs. This approach is also better suited to handling complex workloads and/or heterogeneous architectures. Ideally, we would like to transform a set of ill-behaved user applications into a single load-balanced, system-level workload. This approach has the appealing advantage that it does not require any changes to existing parallel software, and it is therefore able to deal with existing legacy codes. For example, coscheduling algorithms such as Implicit CoScheduling (ICS) [3], Dynamic CoScheduling (DCS) [21] or Coordinated CoScheduling (CC) [4] can potentially alleviate load imbalance and increase resource utilization. [1] However, they are not always able to handle all job types because they do not rely on global

coordination. On the other hand, global resource coordination and job preemption can have a significant cost, if they are implemented using only software mechanisms [12, 17].

In this paper, we show that it is possible to increase the resource utilization in a cluster of workstations substantially and to perform system-level load balancing effectively. We introduce an innovative methodology called Flexible CoScheduling (FCS), that can dynamically detect and compensate for load imbalance. Dynamic detection of load imbalances is performed by (1) monitoring the communication behavior of applications, (2) defining metrics for their communication performance that attempt to identify possible load imbalances, and (3) classifying applications according to these metrics. On top of this, we propose a coscheduling mechanism that uses this application classification to execute scheduling decisions. The scheduler strives to coschedule those processes that require coscheduling, while scheduling other processes to increase overall system utilization and throughput. This approach does not alleviate the specific situation of an application that suffers from load imbalances. Obviously, any given application receives the best service when running by itself on a dedicated set of nodes. However, the proposed approach will prevent each job from wasting too many system resources, and the overall system efficiency and responsiveness will be improved, which, in turn, lowers the single application's waiting time.

We demonstrate this methodology with a streamlined implementation on top of STORM (Scalable TOol for Resource Management) [9]. The key innovation behind STORM is a software architecture that enables resource management to exploit low-level network features. As a consequence of this design, STORM can enact scheduling decisions, such as a global context switch or a heartbeat, in a few hundreds of microseconds across thousands of nodes. Thus, STORM avoids much of the nonscalable overhead associated with software-only versions of gang scheduling. An important innovation in FCS is the combination of a set of local policies with the global coordination mechanisms provided by STORM in order to coschedule processes that have a high degree of coupling.

In preliminary work, we presented initial benchmark results for FCS running on a cluster of Pentium-III machines [8]. This paper extends that work with new experiments on a

and workloads. Additionally, FCS was further tuned and simplified and provides better performance results. In the experimental section, we provide an empirical evaluation, which ranges from simple workloads that provide insights on several job scheduling algorithms to experiments with real applications representative of the ASC workload.

# 2 Flexible CoScheduling

To address the problems described above, we propose a novel scheduling mechanism called Flexible CoScheduling (FCS). The main motivation behind FCS is the improvement of overall system performance in the presence of load imbalance, gained by using dynamic measurement of applications' communication patterns and classification of applications into distinct types. Some applications strictly adhere to the BSP model with balanced, fine-grained communications. Others deviate from this model because of little communication or inherent load imbalances. We can therefore restate FCS' goal as identifying the proper synchronization needs of each application and process and trying to optimize the entire system's performance while addressing these needs. FCS is implemented on top of STORM [9], a tool that allows for both global synchronization through scalable global context-switch messages (heartbeats) and local scheduling by a dæmon run on every node (based on its locally-collected information). User-level as opposed to kernel-level scheduling incurs some additional overhead but eliminates the need to communicate frequent scheduling information to the kernel [2].

## 2.1 Process Classification

FCS employs dynamic process classification and schedules processes using this class information. Processes are categorized into one of three classes (Figure 1):

1. *CS* (coscheduling): These processes communicate often, and must be coscheduled (gang-scheduled) across the machine to run effectively, because of their demanding synchronization requirements.

2. *F* (frustrated): These processes have enough synchronization requirements to be

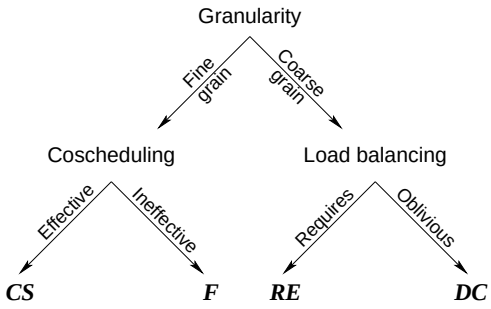



Figure 1: Decision tree for process classification

allotted CPU time. This load imbalance can result from any of the reasons detailed in the introduction.

3. *DC* (don't-care): These processes rarely synchronize and can be scheduled independently without penalizing the system's utilization or the job's performance. For example, a job using a coarse-grained workpile model would be categorized as *DC*. We include in *DC* also the processes of a fourth class, *RE* (rate-equivalent). *RE* is characterized by jobs that have little synchronization, but require a similar (balanced) amount of CPU time for all their processes. Since detection of *RE* processes cannot be made in run-time with local information only, they are classified as *DC* instead, due to their low synchronization needs.

Figure 1 shows the decision tree for process classification. Each process is evaluated at the end of its time slot.[2] If a process communicates at relatively coarse granularity, it is either a *DC* or *RE* process and classified as *DC*. Otherwise, the process is classified according to how effectively it communicates when coscheduled. If effective, it is a *CS* process. Otherwise, some load imbalance prevents the process from communicating effectively, and it is considered *F*. To estimate the granularity and effectiveness of a the communication of a process, we modified the MPI library so that blocking communication calls take time measurements and store them in a shared-memory area, where the scheduling layer can access them. Only synchronous (blocking) communication calls are monitored, since nonblocking

[2] In strict gang scheduling, each job is assigned a dedicated time slot and can only be run in that slot. FCS also assigns a time slot to each job, but local scheduling decisions can cause the job to run in other time slots as well, possibly sharing them with other jobs. We call the original time slot to which a process is mapped the

communications do not require tight synchronization and need not affect scheduling. (Thus a call to MPI_Isend() is nonblocking, but MPI_Wait() is considered blocking.)

Processes of the same job will not always belong to the same class. For example, load imbalance or system heterogeneity can lead to situations in which one process needs to wait more than another. To allow for these cases and to avoid global exchange of information, processes are categorized on an individual basis rather than per-job.

This classification differs in two important ways from a similar one suggested by Lee et al. [14]. First, we differentiate between the *CS* and *F* classes, so that even processes that require gang scheduling do not tax the system too much if heterogeneity prevents them from fully exploiting coscheduling. Second, there is no separate class for *RE* applications. *RE* applications are indistinguishable (from the scheduler's point of view) from *DC* processes, and they are scheduled in the same manner. The classification also differs from the one suggested by Wiseman [24], which is based on CPU utilization and is done at the job rather than the process level.

## 2.2 Scheduling

The scheduling principles in FCS are as follows:

- *CS* processes are always coscheduled and should not be preempted.
- *F* processes need coscheduling but are preempted if synchronization is ineffective.
- *DC* processes impose no restrictions on scheduling.

The infrastructure used to implement this scheduling algorithm (STORM) is based on an implementation of conventional gang scheduling [9]. A single systemwide manager, the machine manager dæmon (MM), packs the jobs into an Ousterhout matrix. It periodically sends multi-context-switch messages to the node manager dæmons (NM), instructing them to switch from one time slot to another. A crucial characteristic is that the node managers are not obligated to comply. They are free to make their own scheduling decisions based on their local measurements and classifications.

Algorithm 1 shows the behavior of the node manager upon receipt of a multi-context-

**Algorithm 1:** Context switch algorithm for FCS

```
// context_switch: switch from one process to another process
// Invoked for each processor by a global multi-context-switch
procedure context_switch (current_process, next_process)
begin
   if current_process == next_process then return
   if type of next_process is CS then
      suspend whatever is running on this PE
      run next_process for its entire time slot
      use polling for synchronous communications
   else
      resume DC and F processes belonging to this PE
      let local OS scheduler schedule all processes
      use spin-blocking in synchronous communications
      if next_process is of type F
          prioritize it over all other processes.
   end
end
```

ule *DC* processes according to its usual criteria (fairness, I/O considerations, etc.), as well as to use *DC* processes to fill in the gaps that *F* processes create because of their synchronization problems. An *F* process that waits for pending communication does not block immediately, but rather spins for some time to avoid unnecessary context-switch penalties, as in ICS [3].

This scheduling algorithm represents a new approach to dynamic coscheduling methods, since it can benefit both from scalable global scheduling decisions and local decisions based on detailed process statistics. Furthermore, it differs from previous dynamic coscheduling methods like DCS [21] and ICS in that:

1. A *CS* process in FCS cannot be preempted before the time slot expires even if a message arrives for another process. (Processes classified as *CS* have shown that it is not worthwhile to deschedule them in their time slot, because of their fine-grained synchronization.) Blocking events therefore do not cause yielding of the CPU.

2. The local scheduler's decision in choosing among processes in the *DC* time slots and *F* gaps is affected by the communication characterization of processes, which could lead to less-blocking processes and higher utilization of resources. Another improvement over the work presented in [8] is that *CS* processes are no longer allowed

| | Name | Description |
|---|---|---|
| MPI monitoring | $T_{cpu}$ | CPU time since last reset (sec) |
| | $T_{comm}$ | Total time waiting for blocking commun. to complete since last reset (sec) |
| | $C_{comm}$ | Count of blocking commun. operations since last reset |
| | $\overline{T_{cpu}}$ | Average CPU time per commun.: $\frac{T_{cpu}}{C_{comm}}$ |
| | $\overline{T_{comm}}$ | Average wait per commun.: $\frac{T_{comm}}{C_{comm}}$ |
| Scheduling | *class* | Either *CS*, *F*, or *DC* |
| | *cslots* | Assigned times slots in current class |
| | *tslots* | Total assigned time slots since start |
| | $g$ | Granularity (sec): $\overline{T_{cpu}} + \overline{T_{comm}}$ |

Table 1: FCS parameters

in worse overall performance. This is probably because both competing processes are essentially fine-grained and cannot run both well at the same time, while on the other hand, context-switch and cache-flushing issues degrade their performance.

## 2.3 FCS Parameters

There are three types of parameters used in FCS:

- Process characteristics measured by the MPI layer, summarized in Table 1. (The "reset" mentioned in the table is either a class change or a predetermined age expiration.)
- Parameters measured or determined by the scheduling layer, also detailed in Table 1.
- Algorithm and run-time constants, shown in Table 2.

Measurements are taken whenever a process is running. For highly synchronized processes, we have verified that processes typically make progress only in their assigned slots, so the measurements indeed reflect their behavior when coscheduled. For other processes, the assigned slot does not have a large effect on progress, except possibly for *F* processes that get a higher priority in their slot. For *DC* and *F* processes, the assigned time slot is used mainly to track the age of a process using the *cslots* and *tslots* counters.

| Name | Description | Value |
|---|---|---|
| $T_{slice}$ | Time slice quantum | 100 *ms* |
| $T_{spin}$ | Spin time for spin-block communications | 120 $\mu s$ |
| $cslots_{MIN}$ | Minimum value of *cslots* for process to be evaluated for a class change | 20 |
| $DC_{thresh}$ | *DC* granularity threshold: above this value process is *DC* | 1s |
| $CS_{thresh}$ | *CS* granularity threshold: below this value process is *CS* | 2 *ms* |
| $F_{thresh}$ | threshold of computation granularity to identify processes waiting for communication as *F* | $0.85 \times CS_{thres}$ |
| $tslots_{MAX}$ | Maximum value of *tslots*, after which a reset to class *CS* is forced | 32768 |

Table 2: FCS constants and values used in experiments.

- $T_{slice}$ was chosen to be low enough to enable interactive responsiveness and high enough to have no noticeable overhead on the applications as measured in [7].
- $T_{spin}$ was chosen to be high enough to accommodate twice the average communication operation (in our setup, $\approx 60$ *us* [19]) and low enough so that resources are not wasted unnecessarily.
- $cslots_{MIN}$ should allow enough time for some initializations to occur, but without overly delaying proper classification.
- For $CS_{thresh}$ it was found that proper classification has the most effect for processes with a granularity finer than $\approx 5$ *ms* on this architecture.

All constants, and the last two in particular, were found by careful tuning and testing on all our hardware and software combinations to offer good average performance across the board [7, 9].

## 2.4 Characterization Heuristic

Algorithm 2 shows how a process is reclassified. This algorithm is invoked for every process that has just finished running in its assigned time slot, so this happens at deterministic, predictable times throughout the machine. Thus, when the time to reset a process to class *CS* arrives, it is guaranteed that all the processes of the same job will be reset together. (Otherwise they might not actually be coscheduled.)

The algorithm can be illustrated with the phase diagram shown in Figure 2. Recall that

**Algorithm 2:** Classification function for FCS

```
// re-evaluate, and possibly re-classify the process
// using FCS parameters and measurements
procedure FCS_reclassify
begin
  old_class = class
  if cslots < cslots_MIN
    return          // Not running long enough in current class
  if tslots mod tslots_MAX == 0 OR g < CS_thresh
    class = CS      // Reset or change class back to CS
  else if g < DC_thresh AND T_cpu < F_thresh
    class = F       // Communication too slow
  else class = DC   // Coarse granularity

  if class != old_class
    cslots = 0
end
```

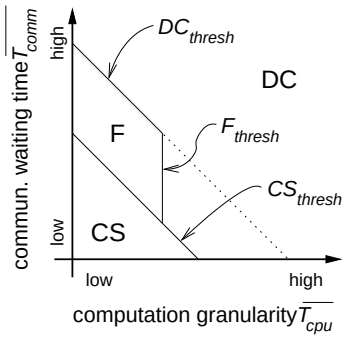



Figure 2: Phase diagram of classification algorithm

computation and communication times. Therefore, constant granularity is represented by diagonals from upper left to lower right. *CS* processes occupy the corner near the origin, whereas *DC* processes are those that are far from this corner. *F* processes are those that should be in the corner because of their low $\overline{T_{cpu}}$, but suffer from a relatively high $\overline{T_{comm}}$.

## 2.5 Implementation Framework

We have implemented FCS and several other scheduling algorithms in STORM [9], a scalable, flexible resource management system for clusters, implemented on top of various Intel- and Alpha-based architectures. STORM exploits low-level collective communication mechanisms to offer high-performance job launching and management. As mentioned above, the basic software architecture is a set of dæmons, one for the entire machine (ma-

architecture allows the implementation of many scheduling algorithms by "plugging-in" appropriate modules in the MM and NM. Thus, FCS was added to STORM with two relatively simple enhancements: an MPI hook to measure and export information on process synchronous communication to the NM, and a module in the NM that translates this information into classification, and schedule processes based on their class. Note that the MM was not modified relative to GS.

## 2.6 Implementation Issues

Measuring process statistics can be both intrusive and imprecise if not performed carefully. It is important to take measurements with as little overhead as possible, without significantly affecting or modifying the code. To realize this goal, we implemented a lightweight monitoring layer that is integrated with MPI. Synchronous communication primitives in MPI call one of four low-latency functions to note when the process starts/ends a synchronous operation and when it enters and exits blocking mode. Applications only need to be relinked with the modified MPI library, without any change. The accuracy of this monitoring layer has been verified using synthetic applications for which the measured parameters are known in advance and found to be precise within 0.1%.

The monitoring layer updates the MPI-level variables shown in Table 1. These variables reside in shared memory to allow the NM to read them without issuing a system call. While this transfer is asynchronous and a lag could exist between the actual communication event and the time the NM gathers the information, these parameters converge quickly to an accurate picture of the process characteristics.

To count communication events ($C_{comm}$), we employed the following guideline: multiple communication events with no intervening computation are considered to be a single communication event. This heuristic works very accurately as long as the granularity of the process is greater than that of the local operating system. Otherwise, the computation intervals are too short to be registered by the operating system. We found this value to typically be around twice the Linux 1/HZ value (the timer interrupt frequency), which defaults to $\approx 1$ *ms* on our cluster. To detect finer granularities, we increased the HZ value to 4096.

# 3 Synthetic Scenarios

In this section we analyze the characteristics of FCS under four basic synthetic benchmarks and compare it to three scheduling algorithms: batch scheduling (first-come-first-serve, or FCFS), gang scheduling (GS), and spin-block (SB). SB is an instance of implicit coscheduling (ICS) [3] and has been shown to perform on a par with other implicit algorithms without global coordination as in gang scheduling [1, 4]. With SB, processes that wait for a synchronous communication poll for a given interval—and only if the communication has not completed by this time they do block (in contrast, gang-scheduled processes always busy-wait). Thus, processes tend to self-synchronize across the job, so relatively good coordination is achieved without the need for a explicit coscheduling. In ICS, the spin time can be adaptive [3], thus decreasing inefficiencies resulting from spinning too long. In our implementation of SB we chose a small constant time for spinning (120 $\mu$s), so that very little time is wasted. Note that typical communication operations with this hardware and software setup complete in far less than this time (a few tens of $\mu$s), so if two communicating processes are coscheduled, they are almost guaranteed to complete the communication within this time interval.

We use two metrics to compare the performance of different scheduling algorithms [6]:

- turnaround time—the total running time (in seconds) of the entire workload; and
- average response time—the mean time it takes a job to complete running from the time of submittal (enqueuing), which is not necessarily the actual execution time.

Turnaround time is considered a system-centric metric, since it describes the reciprocal of the system's throughput. Response time on the other hand is more of interest to users who would like to minimize the time they wait for their individual jobs to complete. In practice, it is difficult to discuss these metrics in isolation, since with real dynamic workloads, various factors and feedback effects create interactions between the metrics [6, 7]. However, the four scenarios we describe in this section are simple enough to allow a comprehensive understanding of the factors involved. We believe that this set of synthetic tests covers a

For all four scenarios, we use a simple synthetic application as the "building-block" of the workload. This job is modeled after the BSP model [23], containing a simple loop with some computation followed by a communication phase in a nearest-neighbor, ring pattern. The computation granularity (per iteration) in the basic case was chosen to be 1 *ms*, which is considered to be a relatively fine granularity when compared to real scientific applications' performance in the given hardware environment [10]. When running in isolation, the basic "building block" job takes approximately 60 *s* to complete.

The hardware used for the experimental evaluation was the "Wolverine" cluster at LANL. This cluster consists of 64 HP Alpha compute nodes and a dual-rail QsNet network [19]. Each compute node contains four 833 MHz EV6 processors, 8 GB of ECC RAM, two independent 32 MHz/64-bit PCI buses, two Quadrics QM-400 Elan3 NIC [19] for the data network, and a 100 Mbit Ethernet network adapter for the management network. All the nodes run Red Hat Linux 7.3 with Quadrics kernel modifications and user-level libraries. Our tests used a simple workload of up to three jobs arriving concurrently using half the cluster, 128 processors on 32 nodes. This cluster architecture and size combined with the very fine granularity, is a good stress test for scheduling algorithms. This configuration is not conducive for good performance with fine-grain applications and/or global context switching because of the machine's high sensitivity to noise created by system dæmons and our own scheduling system [20]. To mitigate this problem, we used a context-switch interval of 100 *ms*, which is high enough to reduce most of the overhead and noise effects while still being responsive enough to be considered interactive. Every experiment was repeated five times, and the best result was taken for each algorithm.

## 3.1 Balanced Jobs

Many HPC applications are latency-bound in the sense that they synchronize often with short messages. These synchronous applications require that all their processes be coscheduled to communicate effectively. If another application or system dæmon interrupts their synchronization, large skews can develop that significantly hamper their performance [20].

In the first scenario, we emulate such situations by running two identical, fine-grained

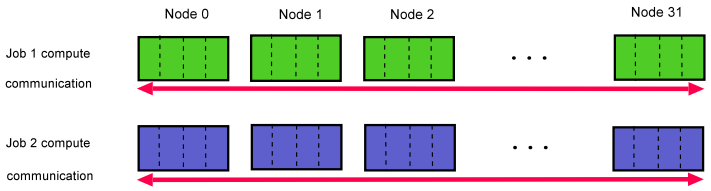



Figure 3: One iteration of two "building-block" jobs

jobs concurrently. Figure 3 depicts the run time *per iteration*, which is balanced and equal for both jobs.[3] The following table presents the results for running this workload, giving the termination time in seconds for each job and for the complete set. It also shows the total turnaround and mean response times, all in seconds.

| **Algorithm** | **Job 1** | **Job 2** | **Turnaround** | **Mean Response** |
|---|---|---|---|---|
| FCFS | 60 | 120 | 120 | 90 |
| GS | 124 | 124 | 124 | 124 |
| SB | 126 | 134 | 134 | 130 |
| FCS | 125 | 126 | 126 | 126 |

Since synchronous, balanced jobs require a dedicated environment to run effectively, FCFS scheduling and GS offer the best performance. SB scheduling shows noticeable slowdown when compared to the others, because of the lack of global coordination. FCS exhibits performance comparable to that of GS, since all processes are classified as *CS* and are therefore gang-scheduled. Still, total turnaround time is slightly higher than that of GS because of the added overhead of process classification. When one is considering response time, batch scheduling is the only algorithm that has a significant advantage over the other algorithms, since job 1 that runs in isolation terminates quickly and lowers the average.

## 3.2 Load-Imbalanced Jobs

This scenario represents a simple load-imbalanced case with two complementing jobs, as depicted in Figure 4. Every alternating node (four processes) in the first job computes twice

[3] In this and the following figures, the compute and communicate phases are shown per iteration. Scheduling determines which processes run together and for how many iterations.

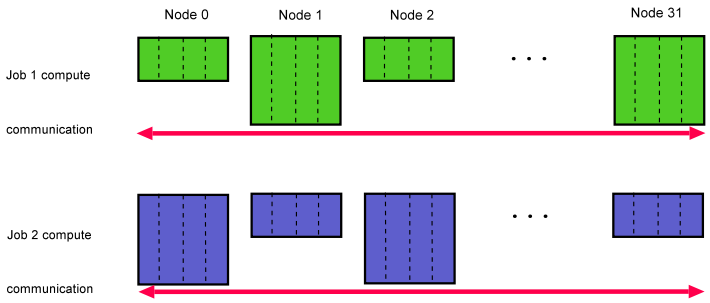



Figure 4: Two load-imbalanced jobs

as much *per iteration* as the other node, while the situation is reversed for job 2[4]. The faster processes compute for the same amount of time as in the previous scenario. In a sense, this workload represents the exact opposite of the previous one, in which jobs need a dedicated partition to communicate effectively. In contrast, these unbalanced jobs are guaranteed to waste compute resources when running in isolation. The following table shows the performance of each scheduling algorithm.

| **Algorithm** | **Job 1** | **Job 2** | **Turnaround** | **Mean Response** |
|---|---|---|---|---|
| FCFS | 120 | 240 | 240 | 180 |
| GS | 244 | 245 | 245 | 245 |
| SB | 193 | 194 | 194 | 194 |
| FCS | 197 | 197 | 197 | 197 |

It can be seen from the data that both FCFS and GS take almost twice as much time to run each job (compared to the previous scenario), whereas the total amount of computation per job is only increased by 50%. SB does a much better job at load-balancing, since the short polling interval allows the algorithm to yield the CPU when processes are not coscheduled, giving the other job a chance to complete its communication and wasting little CPU time. FCS is also successful in exploiting these computational holes. After a brief interval, it classifies the first job's processes in alternating nodes as *F,F,F,F,DC,DC,DC,DC,...*, and the second job's as *DC,DC,DC,DC,F,F,F,F,...*. The resulting scheduling is effectively the same as SB's, with the exception that *F* processes are prioritized when their assigned slot

[4]In reality, the speed ratio is slightly over 2:1, bringing the total run time of each job to 120 *s*. The gap is

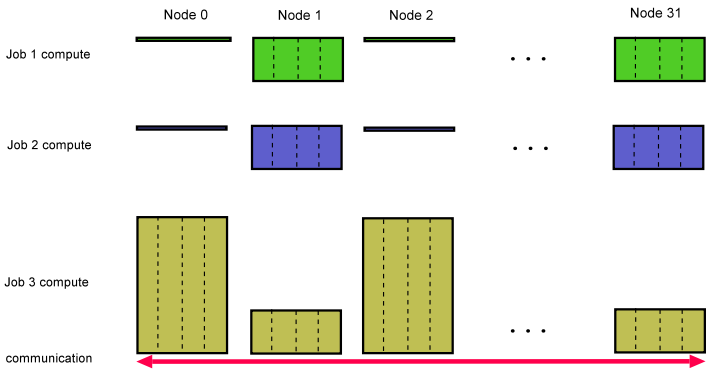



Figure 5: Complementing jobs

is the active one. The total turnaround time is similar to SB's, and represents close to optimum resource utilization: both jobs complete after running for $\approx 159\%$ of the time it took the previous scenario, which corresponds to $\approx 6\%$ more than the total amount of compute work.

The response-time metric again shows some preference for batch scheduling, although FCS and SB are not far behind, because of their lower turnaround time. GS exhibits approximately the same turnaround time as FCFS, but since all the processes terminate concurrently, the mean response time is actually higher.

## 3.3 Complementing Jobs

The third scenario exposes the ability of various algorithms to pack jobs efficiently in a more imbalanced workload. It consists of two noncommunicating 60 *s* jobs and one communicating 180 *s* job that are arranged so that alternating nodes run for different amounts of time, taking a total of 180 *s* per processor when aggregated over all processors. (See Figure 5.) An optimal scheduler should pack all these jobs so that the total turnaround time does not exceed that of the third job when run in isolation (assuming zero context-switch overhead). The following table again shows the performance for each algorithm.

| Algorithm | Job 1 | Job 2 | Job 3 | Turnaround | Mean Response |
|---|---|---|---|---|---|
| FCFS | 60 | 121 | 301 | 301 | 161 |
| GS | 185 | 186 | 308 | 308 | 226 |
| SB | 144 | 142 | 244 | 244 | 177 |
| FCS | 192 | 193 | 197 | 197 | 194 |

Once more, FCFS and GS exhibit similar turnaround time—the combined run time of all the jobs run in isolation. SB shows some ability to load-balance the jobs, reducing the overall turnaround and response times, but since it lacks a detailed knowledge of the processes' requirements, it can only go so far. Job 3 still shows a significant slowdown ($\approx 36\%$) when compared to FCFS. With FCS, the situation is even better. The scheduler classifies all the processes as *DC*, except for the faster processes of job 3, which are classified as *F*. As such, they receive priority in their time slot, and thus, the total run time of job 3 suffers a slowdown of $\approx 9\%$ from the interference of the other jobs, which pack neatly into the other time slices. This approach not only reduces the turnaround of this workload to $\approx 9\%$ of the optimal packing value (paying some price to overhead), but also minimizes the mean response time, which is competitive with that of FCFS. A reordering of the jobs would not affect FCS' metrics, while it would worsen FCFS' response times. Time-sharing algorithms are not as sensitive to job order, which becomes an advantage when the order is not known in advance.

## 3.4 Balanced and Imbalanced Job Combination

The last synthetic scenario is designed to expose the interaction between synchronous balanced and imbalanced jobs in a mixed workload. This situation might occur when a machine is running more than one type of application or with different data sets that have different load-balancing properties. Even if the workload of a parallel machine is composed of only balanced applications, this situation can occur whenever job arrivals and sizes are dynamic. For example, in a time-sharing system, different nodes might run different numbers of jobs, thus creating a dynamic imbalance.

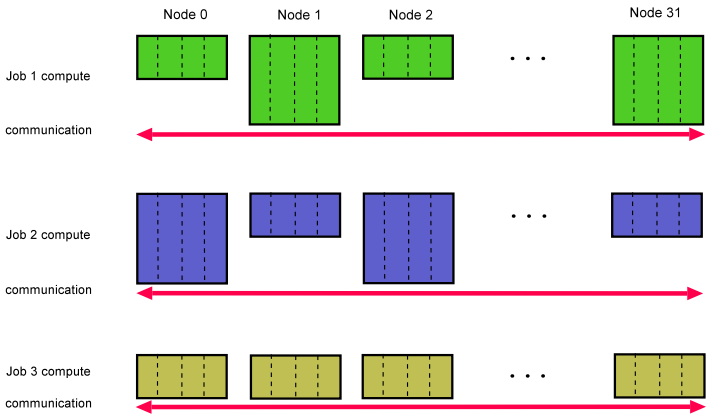



Figure 6: Balanced and imbalanced job combination

plementary imbalanced and identical to jobs 1 and 2 of the second scenario (Section 3.2). The third job is the basic, load-balanced job used in the first scenario (Section 3.1). The following table shows the run time results for the four algorithms.

| **Algorithm** | **Job 1** | **Job 2** | **Job 3** | **Turnaround** | **Mean Response** |
|---|---|---|---|---|---|
| FCFS | 120 | 241 | 302 | 302 | 221 |
| GS | 185 | 185 | 305 | 305 | 225 |
| SB | 213 | 214 | 276 | 276 | 234 |
| FCS | 252 | 253 | 155 | 253 | 220 |

Once more, batch and gang scheduling demonstrate similar performance. Shuffling the job order so that job 3 is actually first would have improved the response time for FCFS even further, to around 181 *s*.

Another weakness of SB scheduling is exposed in this scenario. Since it gives an equal treatment to all processes, fine-grained jobs suffer from the noise generated by other jobs. This effect is clearly shown in the performance of job 3 under SB, which is much worse than that under FCS. Since FCS identifies the special requirements of job 3, it classifies it as *CS*. As such, it receives dedicated time slots that allow it to communicate effectively, hindered only by context-switch overhead. The overall result is a decrease in turnaround time and mean response time when compared to the other algorithms.

### Summary

These basic benchmarks demonstrate the inherent strengths and weaknesses of multiprogramming vs. batch schedulers and dynamic vs. rigid schedulers. In all cases, FCS' performance was close to or better than that of the scheduling algorithm most suited to each scenario, attesting to its flexibility. The next section explores how these properties are translated to two actual scientific applications.

## 4 Application Tests

For a more realistic experimental evaluation, we compared FCS to the other three scheduling algorithms when running two real MPI applications. The results presented in this section describe three scenarios based on different job mixes: two fine-grain applications, two medium-grain applications, and a combination of both. The applications used in this section are SWEEP3D and SAGE, both running on 128 processors.[5] We used a multiprogramming level of 2 for these experiments to reflect the fact that these real applications have significant memory footprints, preventing the accommodation of many instances of these applications entirely in physical memory. In addition, because of the applications' large working set and the cluster's susceptibility to noise when using four processors per node [20], these experiments were run with a time slice of 200 *ms* to amortize some of the context-switching cost. Still, some overhead was noticeable for all the scheduling algorithms—and especially with the explicit algorithms (GS and FCS).

**SWEEP3D:** SWEEP3D [10] is a time-independent, Cartesian-grid, single-group, discrete ordinates, deterministic, particle transport code taken from the ASC workload. SWEEP3D represents the core of a widely used method of solving the Boltzmann transport equation. Estimates are that deterministic particle transport accounts for 50% to 80% of the execution time of many realistic simulations on current DOE systems. SWEEP3D is characterized by very fine granularity (averaging $\approx 1$ *ms* in the configuration tested) and a nearest-neighbor communication stencil. We used a realistic input file comprising 10,000 cells per proces-

[5] These two applications are representative of the ASC workload.

sor and taking $\approx 270\ MB$ of memory per process. We increased the number of iterations from 12 to 600 so that a single run took $\approx 111\ s$[6]. The combination of this data set and architecture represents a rather extreme case of a load-balanced, fine-grained application, as different configurations and architectures typically result in coarser granularities [8, 9].

We ran a simple workload consisting of two identical SWEEP3D jobs (similar to the first synthetic scenario of the previous section). We present the results in the same format.

| **Algorithm** | **SWEEP3D 1** | **SWEEP3D 2** | **Turnaround** | **Mean Response** |
|---|---|---|---|---|
| FCFS | 111 | 222 | 222 | 167 |
| GS | 232 | 232 | 232 | 232 |
| SB | 275 | 275 | 275 | 275 |
| FCS | 244 | 244 | 244 | 244 |

All the multiprogramming algorithms are hindered by the overhead associated with multitasking between highly synchronous jobs with an active working set. Context-switch overhead, interruptions to synchronous communication, cache flushing, and skew caused by noise (and exacerbated by the fine granularity of SWEEP3D) causes a per-job slowdown of $\approx 2.25\%$ and $\approx 4.95\%$ for GS and FCS respectively, compared to batch scheduling. FCS suffers from relatively high reclassification overhead, because of the high number of communication events. In the case of GS and FCS, there is also the occasional interruption by the NM, which is awakened to perform the context switch. While SB has the potential for less overhead, since the NM does not intervene with the scheduling, the lack of explicit coscheduling is shown to have a significant effect on SWEEP3D's performance, with a per-job slowdown of 11.93% compared to FCFS.

**SAGE:** SAGE (SAIC's Adaptive Grid Eulerian hydrocode) is a multidimensional (1D, 2D, and 3D), multimaterial, Eulerian hydrodynamics code with adaptive mesh refinement (AMR) [11]. SAGE comes from the LANL Crestone project, whose goal is the investigation of continuous adaptive Eulerian techniques to Stockpile Stewardship problems. SAGE has also been applied to a variety of problems in many areas of science and engineering includ-

ing water shock, stemming and containment, early time front design, and hydrodynamics instability problems.

SAGE is more load imbalanced than SWEEP3D, which implies that SAGE does not always follow the classic BSP model as the granularity varies across processes and over time. The effective granularity is thus much coarser than the computation granularity. While most processes reach a synchronization point every 5 *ms* or less, because of unequal partitioning of the input data, they are often waiting for their peers for a few more *ms*, so the average granularity over all processes is closer to 8 *ms*. Most such "computational" fragments are not large enough to fill effectively with another process, but are still large enough to classify $\approx 75\%$ of the processes as class $F$. Once more, we ran two concurrent copies of SAGE with the "timing_h" input file, (using 335 *MB*/process) and we present the results in the following table:

| **Algorithm** | **SAGE 1** | **SAGE 2** | **Turnaround** | **Mean Response** |
|---|---|---|---|---|
| FCFS | 126 | 252 | 252 | 189 |
| GS | 260 | 261 | 261 | 261 |
| SB | 274 | 276 | 276 | 275 |
| FCS | 264 | 264 | 264 | 264 |

The different algorithms' performance in this workload shows less disparity than with SWEEP3D, indicating that SAGE lends itself rather well to multiprogramming. When one compares this workload to the previous one, the most obvious difference is the relatively coarser granularity of SAGE, which lowers the performance penalty for context switching. Another mitigating factor is the occasional success of the dynamic algorithms (SB and FCS) in overlapping some computation and communication of competing, load-imbalanced processes.

**Combined Workload:** In the last part of this section, we analyze a workload composed of both SAGE and SWEEP3D—somewhat similar to the workload of the fourth synthetic scenario. This workload offers the opportunity to see how the two different types of jobs

jobs ran for a similar amount of time in isolation (after adjusting SWEEP3D), and were launched together. The results are presented in the following table:

| Algorithm | SAGE | SWEEP3D | Turnaround | Mean Response |
|---|---|---|---|---|
| FCFS | 126 | 238 | 238 | 182 |
| GS | 245 | 240 | 245 | 243 |
| SB | 240 | 272 | 272 | 256 |
| FCS | 235 | 224 | 235 | 230 |

Once more, this scenario demonstrates the adverse effect of context-switch overhead on gang scheduling (compared to batch scheduling), and the significant slowdown a fine-grained application (SWEEP3D) can suffer from the lack of coordination in SB. FCS fares somewhat better than both and slightly better than batch scheduling, since on the one hand, it can coschedule SWEEP3D explicitly, and on the other, make use of the small amount of load-imbalance in SAGE to fill the computational holes. As noted in the synthetic experiments and on other hardware configurations, when the load imbalance is higher or the context-switch overhead is lower, FCS can significantly outperform the other scheduling algorithms. A situation in which load imbalances are constantly created and changed because of a more realistic, dynamic workload is even more conducive to improved utilization with FCS. This scenario is discussed in the next section.

# 5 Dynamic Workloads

The workloads evaluated so far were relatively simple and static. Many if not most real HPC centers run more complicated workloads, with different jobs of different sizes and run times arriving dynamically. With these machines, issues such as queue management, scheduling algorithms and multiprogramming levels, interactions between jobs and specific hardware configuration have significant implications. A detailed evaluation of these aspects was reported in previous work [7]. In this section, we reproduce the main results, namely, the effect of offered load on an actual cluster running a relatively long, dynamic workload under the four scheduling algorithms.

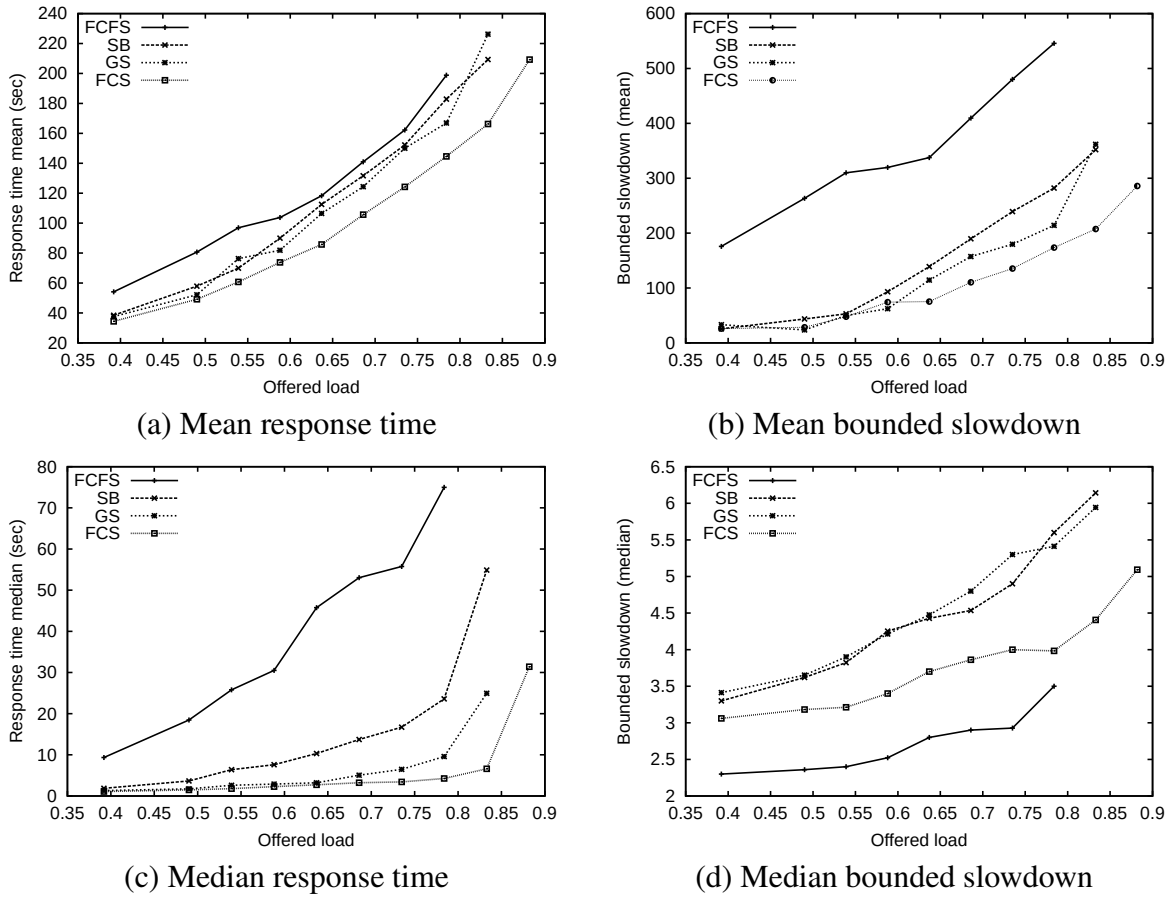
## 5.1 Workload and Methodology

We used a workload of 1000 jobs, whose size, run time, and arrival times are modeled using an accurate workload model [7, 15]. We use this workload as a mold for two sets of experiments, with synthetic and real applications respectively. For each set, we created a series of workloads with varying offered load by multiplying job-arrival times by a constant.

The first set ran the same synthetic application as the previous section, but with different job sizes and run times as determined by the model, and with different granularity and communication pattern, chosen randomly. The second set consisted of multiple instances of SAGE and SWEEP3D with input files chosen randomly from a set of scenarios representing different physics problems. This choice meant that we could not control the run time of each job, only its arrival time. Moreover, there was less variety in run times in the second set. On the other hand, the applications were real and produced representative calculations, making the internal communication and computation patterns more realistic than those of the first set. We ran both sets with four algorithms, FCFS with backfilling, GS, SB, and FCS. The first set, having no real memory constraints, was run with a multiprogramming level (MPL) of 6, while the second set was limited to an MPL of 2 to avoid physical memory overflow, which would have required a memory-aware scheduling algorithm [18].

To estimate the offered load for each workload, we first measured the run time of each job in isolation. The offered load was then calculated as the ratio between the requested resources (the sum of all jobs' run time multiplied by their sizes) and the available resources (the number of processors multiplied by the last arrival time). Accepted load could not be measured precisely, but could be indirectly inferred from the accumulation of jobs in the queue [8]. Additionally, we stopped the experiments at each algorithm's saturation point, as witnessed by a relatively constant accepted load.

We used EASY backfilling [22] for queue management, which was shown to be very effective in lowering the average response time, especially for short jobs and batch scheduling [16]. Since it is also beneficial for multiprogramming schedulers, we used EASY for them as well, multiplying the requested run time by the MPL to estimate run and reser-




(a) Mean response time

(b) Mean bounded slowdown

(c) Median response time

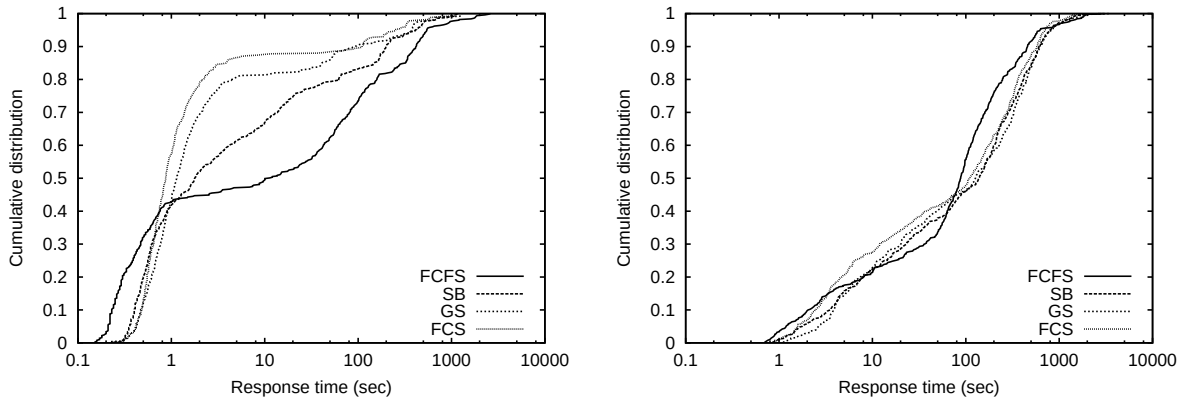
(d) Median bounded slowdown

Figure 7: Performance as a function of offered load—synthetic applications

vation times [7]. The first experiment set was executed out on a different LANL cluster (*Crescendo*), using 32 Pentium-III processors (16 nodes), and the second set was executed on 64 processors of Wolverine (16 nodes).

## 5.2 Results and Discussion

Figures 7(a) and 7(b) show the average response time and slowdown respectively, for different offered loads and scheduling algorithms for the first set. The near-linear growth in response times with load is the result of our method of varying load, by multiplying run times of jobs by a load factor. Both metrics suggest that FCS performs consistently better than the other algorithms, and FCFS seems to perform consistently worse than the others. Also, FCFS saturates at a load of $\approx 78\%$, while FCS supports a load of up to 88% in this set.



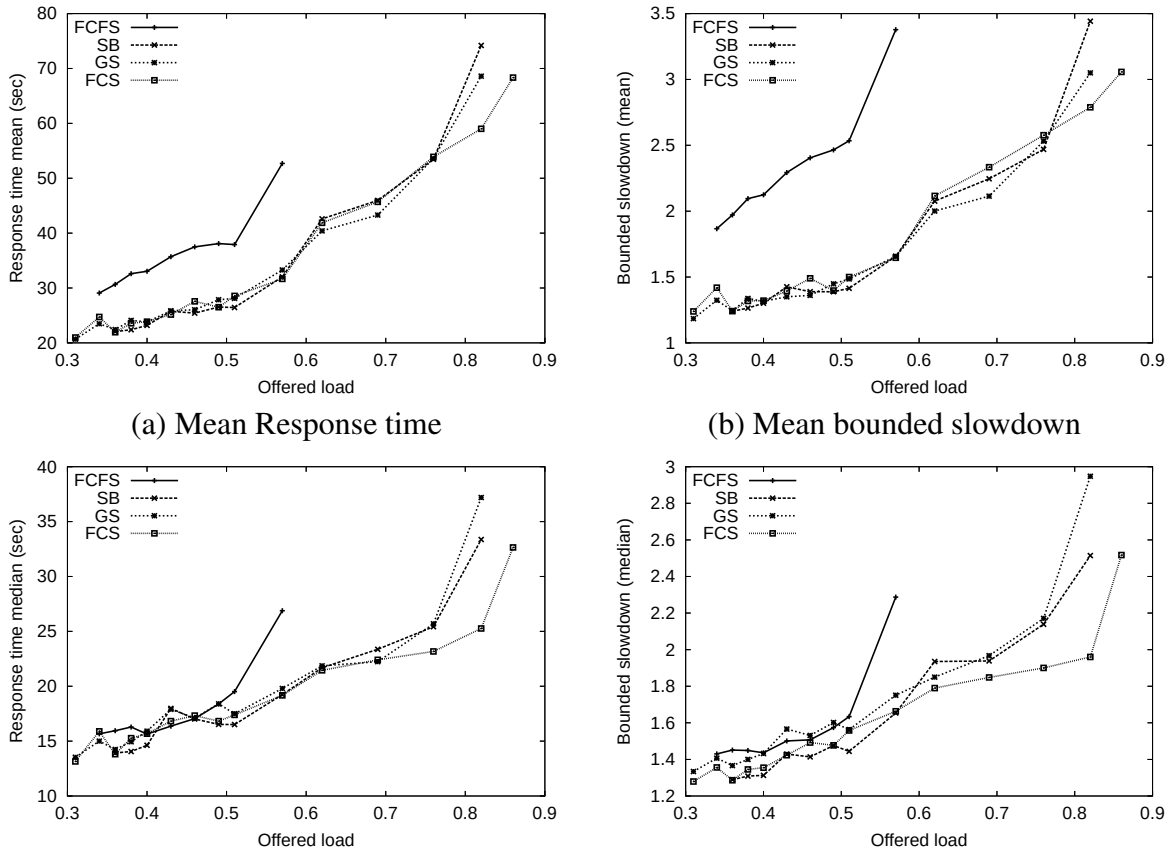

(a) 500 shortest jobs (b) 500 longest jobs

Figure 8: Cumulative distribution of response times at 74% load and FCS scheduling.

and slowdown in Figures 7(c) and 7(d) respectively. A low median response time suggests good handling of short jobs, since most jobs are comparatively short. On the other hand, a small median slowdown indicates preferential handling of long jobs, since the lowest-slowdown jobs are mostly long jobs that are less affected by wait time than short jobs. FCFS shows a high average slowdown and a small median slowdown. This result indicates that while long jobs benefit from shorter waiting times (driving the median slowdown lower), short jobs suffer enough to raise the average response time and slowdown significantly.

To verify these biases, we looked at the cumulative distribution function (CDF) of response times for the shorter 500 jobs and longer 500 jobs separately, as defined by their run time in isolation (Fig. 8). The higher distribution of short jobs with FCS attests to the scheduler's ability to "push" more jobs toward the shorter response times. Similarly, FCFS' preferential treatment of long jobs is reflected in Fig. 8(b).

Figure 9 shows the response time and bounded slowdown results for the second set, running SAGE and SWEEP3D. The differences between the three time-sharing algorithms is not as dramatic as in the first set, mostly because the lower MPL allows less room to express the differences between the algorithms. Still, FCS performs a little better than the other algorithms, particularly in the higher loads. FCS also saturates at an offered load higher than that of the other algorithms, while FCFS saturates at a very early point compared to the other algorithms and previous set.




(a) Mean Response time

(b) Mean bounded slowdown

(c) Median response time

(d) Median bounded slowdown

Figure 9: Performance as a function of offered load—scientific applications

We believe the reason for FCS' good performance is its ability to adapt to various scenarios that occur during the execution of the dynamic workload. In particular, FCS always coschedules a job in its first few seconds of running (unlike SB), and then classifies it according to its communication requirements (unlike GS). If a job is long and does not synchronize frequently or effectively, FCS will allow other jobs to compete with it for machine resources. Thus, FCS shows a bias toward short jobs, allowing them to clear the system early. Since short jobs dominate the first workload, this bias actually reduces the overall system load and allows long jobs to complete earlier than with GS or SB. The opposite can be said of the FCFS scheme, which shows a bias toward long jobs, since they do not have to compete with other jobs.

# 6 Conclusions

An important problem with traditional parallel job-scheduling algorithms is their specialization for specific types of workloads, which results in poor performance when the workload characteristics do not fit the model for which they were designed. For example, batch and gang scheduling perform poorly under dynamic or load-imbalanced workloads, whereas implicit coscheduling suffers from performance penalties for fine-grained synchronous jobs. Most job schedulers offer little adaptation to externally and internally fragmented workloads. The result is reduced machine utilization and response times.

We designed Flexible CoScheduling (FCS) to alleviate these problems specifically by dynamically adjusting scheduling to varying workload and application requirements. FCS was fully implemented on top of STORM and tested on three cluster architectures using both synthetic and real applications, static and dynamic workloads. The results clearly show that FCS deals well with both internal and external resource fragmentation, and is competitive with batch scheduling, gang scheduling, and implicit coscheduling. The performance advantages of FCS over other algorithms in the more realistic, dynamic workloads is rather significant: FCS saturates at an offered load approximately 16% higher than that of backfilling for synthetic applications, and 54% higher for scientific applications. The difference in saturation compared to gang scheduling and implicit coscheduling is less dramatic but still favors FCS. In all the dynamic scenarios but one, FCS performs equally well or better than the other algorithms in terms of response time and bounded slowdown.

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