Towards Accommodating Real-time Jobs on HPC Platforms

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Abstract

Increasing data volumes in scientific experiments necessitate the use of high performance computing (HPC) resources for data analysis. In many scientific fields, the data generated from scientific instruments and supercomputer simulations must be analyzed rapidly. In fact, the requirement for quasi-instant feedback is growing. Scientists want to use results from one experiment to guide the selection of the next or even to improve the course of a single experiment. Current HPC systems are typically batch-scheduled under policies in which an arriving job is run immediately only if enough resources are available; otherwise it is queued. It is hard for these systems to support real-time jobs. Real-time jobs, in order to meet their requirements, should sometimes have to preempt batch jobs and/or be scheduled ahead of batch jobs that were submitted earlier. Accommodating real-time jobs may negatively impact system utilization also, especially when preemption/restart of batch jobs is involved. We first explore several existing scheduling strategies to make real-time jobs more likely to be scheduled in due time. We then rigorously formulate the problem as a mixed-integer linear programming for offline scheduling and develop novel scheduling heuristics for online scheduling. We perform simulation studies using trace logs of Mira, the IBM BG/Q system at Argonne National Laboratory, to quantify the impact of real-time jobs on batch job performance for various percentages of real-time jobs in the workload. We present new insights gained from grouping jobs into different categories based on runtime and the number of nodes used and studying the performance of each category. Our results show that with 10% real-time job percentages, just-in-time checkpointing combined with our heuristic can improve the slowdowns of real-time jobs by 35% while limiting the increase of the slowdowns of batch jobs to 10%.

1 Introduction

Scientific instruments such as accelerators, telescopes, light sources, and colliders generate large amounts of data. Because of advances in technology, the rate and size of these data are rapidly increasing. Advanced instruments such as state-of-the-art detectors at light source facilities generate tens of terabytes of data per day, and future camera-storage bus technologies are expected to increase data rates by an order of magnitude or more. The ability to quickly perform computations on these data sets will improve the quality of science. A central theme in experimental and observational science workflows is the need for quasi-instant feedback so that the result of one experiment can guide the selection of the next. Online analysis so far has typically been done by dedicated compute resources available locally at the experimental facilities. With the massive increase in data volumes, however, the computational power required to do the fast analysis of these complex data sets often exceeds the resources available locally. Hence, many instruments are operated in a blind fashion without
a quick analysis of the data to give insight into how the experiment is progressing.

Large-scale high-performance computing (HPC) platforms and supercomputers are required in order to do on-demand processing of experimental data. Such processing will help detect problems in the experimental setup and operational methods early on and will allow for adjusting experimental parameters on the fly [51]. Even slight improvements can have far-reaching benefits for many experiments. However, building a large HPC system or having a supercomputer dedicated for this purpose is not economical, because the computation in these facilities typically is relatively small compared with the lengthy process of setting up and operating the experiments.

We define real-time computing as the ability to perform on-demand execution. The real-time computation may represent either analysis or simulation. Recently NERSC set up a “real-time” queue on its new Cori supercomputer to address real-time analysis needs. It uses a small number of dedicated compute nodes to serve the jobs in the real-time queue, and it allows jobs in the real-time queue to take priority on other resources. It is also possible to preempt “killable” jobs on these other resources. NERSC is, however, an exception. The operating policy of most supercomputers and scientific HPC systems is not suitable for real-time computations. The systems instead adopt a batch-scheduling model where a job may stay in the queue for an indeterminate period of time. Thus, existing schedulers have to be extended to support real-time jobs in addition to the batch jobs. The main challenge of using supercomputers to do real-time computation is that these systems do not support preemptive scheduling. A better understanding of preemptive scheduling mechanisms is required in order to develop appropriate policies that support real-time jobs while maintaining the efficient use of resources.

In this paper, we present our work on evaluating various scheduling schemes to support mixes of real-time jobs and traditional batch jobs. We perform simulation studies using trace logs of Mira, the IBM BG/Q system at Argonne National Laboratory, to quantify the impact of real-time jobs on batch job performance and system utilization for various percentages of real-time jobs in the workload.

Parallel job scheduling has been widely studied [8,23,30,35,48], and surveys [15,17] and evaluations [10,24,27,29] have been published. We first explore several existing scheduling strategies to make real-time jobs more likely to be scheduled in due time. We then rigorously formulate the problem as a mixed-integer linear programming for offline scheduling and develop novel scheduling heuristics for online scheduling. Using Mira trace logs, we quantify the impact of real-time jobs on batch jobs performance for various percentages of real-time jobs in the workload. We present new insights gained from studying the performance of different categories of jobs grouped based on runtime and the number of nodes used. Our results show that our proposed heuristic could achieve reasonable slowdowns for the accommodated real-time jobs while limiting the increase of the slowdowns for batch jobs.

In summary, the main contributions of this work are: (1) Definition of real-time jobs on high-performance computing platforms, (2) Optimal formulation as a mixed-integer linear programming for offline scheduling of real-time jobs, (3) Adaptation and analysis of existing scheduling techniques for real-time jobs, (4) Novel sophisticated heuristics for scheduling of real-time jobs, and (5) Performance evaluation through extensive simulations using actual job logs of the Mira supercomputer.

The rest of the paper is organized as follows. Section 2 describes the background of supercomputers and parallel batch job scheduling, and the related work for real-time job scheduling on modern high-performance computing (HPC) systems. Section 3 formally states the real-time job scheduling problem. Section 4 presents basic scheduling techniques adapted for the real-time job scheduling problem. Section 5 presents the optimization formulation and its time complexity analysis, and Section 6 presents the novel heuristic algorithms. Section 7 describes the experimental setup and the simulation results of our novel heuristics and comparison with the optimization formulation. We conclude this paper with a summary in Section 8.
2 Background and Related Work

In this section, we describe the background of this study and do literature review related to the problem of real-time scheduling of parallel scientific jobs on production supercomputers.

2.1 Parallel job scheduling

Parallel jobs are usually batch jobs, which are served on parallel machines such as supercomputers in a first-come-first-served (FCFS) fashion traditionally. Most of the current systems support backfilling to address the low utilization issue with the strict FCFS policy. Batch jobs are queued in one or more queues, which are maintained by a parallel job scheduler. Parallel job scheduling has been widely studied [15–17]. It includes strategies such as backfilling [30, 35, 43, 45], preemption [26, 36], moldability [11, 40, 46], malleability [7], techniques to use distributed resources [38, 47], mechanisms to handle fairness [41, 50], and methods to handle inaccuracies in user runtime estimates [49]. Sophisticated scheduling algorithms have been developed that can optimize resource allocation while also addressing other goals such as minimizing average slowdown [18] and turnaround time.

In contrast to the conventional HPC applications, recently emerging HPC applications such as light source experiments [25] require on-demand processing capability to expedite the overall problem-solving time. However, few studies have been done regarding supporting real-time jobs as well as batch jobs on parallel machines. Existing HPC platforms make use of tweaks such as separate queues and dedicated resources for real-time jobs.

A survey on scalable system scheduling [39] compared traditional supercomputing jobs to high-performance data analytics jobs which are featured by very short-run and time-critical jobs. Accordingly, a great deal of research conducted in each job categories is presented. If we name a few outstanding works among many schedulers, the traditional HPC schedulers include PBS [21], HTCondor [31], and LSF [57], and the big data schedulers include Google Borg [4], Apache Hadoop YARN [53], and Apache Mesos [22]. Even though our work has similar goals to those of the big data schedulers, our work focuses on how to run time-critical jobs on the existing batch-based HPC platforms while trying to meet the timing requirements of such time-critical jobs. In advanced research on cloud computing, we can classify previous related studies about coping with time-critical jobs in terms of HPC/cloud platforms. There exist roughly three cases. The first case is that time-critical jobs on batch-based HPC platforms are dispatched to the cloud, which is called cloud bursting [12, 19]. The second case is that the cloud provisions on-demand resources for all jobs, both batch and time-critical jobs [13, 33, 55]. Especially Tr-Spark [55] studied checkpointing methods on Spark are studied to evict big data analytics jobs running as secondary background jobs. Lastly, the case of the most recent work closely related to ours is that the central cloud controller dynamically negotiates capacity between on-demand and batch clusters so that time-critical jobs can find required resources on the on-demand cluster without being invasive on batch jobs on the batch cluster [32]. Our work differs from the three cases mentioned above in that we try to make the best use of the existing HPC platforms for batch jobs using sophisticated scheduling algorithms combined with checkpointing and preemption techniques. To the best of our knowledge, there has been no work on analyzing how time-critical jobs’ schedules perform when checkpointing/preemption techniques apply on existing batch-based HPC platforms and appropriate algorithms for such environments are deployed.

In this paper, we tackle this real-time job scheduling problem from a standpoint of general mechanisms based on mathematical formulations and heuristics. In fact, the parallel job scheduling problem whose objective is minimizing makespan is NP-hard [20]. Thus, the production parallel job schedulers and the research studies on parallel job schedulers use heuristics. Following the notation in [20], our problem is $P|\text{pmtn, } r_j|\sum(C_j - r_j)$, which is more complicated problem than NP-hard $P|\text{pmtn}|\sum C_j$, which means a scheduling problem with $P$ identical machines where job preemption is allowed and the objective is to min-
imize the sum of job completion times. Whereas few studies try to compare the heuristics with optimal algorithms, we compare the results of our novel heuristics with optimal solutions of MILP-based formulation.

2.2 Scheduling Real-time and Batch jobs

Although preemptive scheduling is universally used at the operating-system level to multiplex processes on single-processor systems and shared-memory multiprocessors, it is rarely used in parallel job scheduling. Studies of preemptive scheduling schemes have focused on their overheads and their effectiveness in reducing average job turnaround time [10, 14, 26, 28, 34, 44].

Others have studied preemptive scheduling for malleable parallel jobs [14, 37, 42, 56], in which the number of processors used to execute a job is permitted to vary dynamically over time. In practice, parallel jobs submitted to supercomputer centers are generally rigid; that is, the number of processors used to execute a job is fixed. The work most similar to ours is SPRUCE (Special Priority and Urgent Computing Environment) [52], which investigated mechanisms for supporting urgent jobs such as hurricane analysis on HPC resources. The authors define urgent computing jobs as having time-critical needs, such that late results are useless. SPRUCE considered only a basic preemptive scheduling scheme with no checkpointing and assumed that urgent jobs are infrequent. Our work differs in terms of both its job model and the scheduling schemes considered. Our job model assumes that jobs with real-time constraints arrive more frequently and that jobs are not a total failure even if the job timing requirements are missed. We evaluate more sophisticated preemptive scheduling schemes.

2.3 HPC Environments and Simulation

We evaluate the scheduling algorithms using the job logs of Mira [5], which is a IBM Blue Gene/Q supercomputer at Argonne National Laboratory. But without loss of generality, we assume that the proposed approaches apply to other supercomputers.

Mira is a Blue Gene/Q system operated by the Argonne Leadership Computing Facility (ALCF) at Argonne National Laboratory [5]. It was ranked ninth in the 2016 Top500 list, with peak performance at 10,066 TFlop/s. Mira is a 48-rack system, with 786,432 cores. It has a hierarchical structure connected via a 5D torus network. Nodes are grouped into midplanes, each containing 512 nodes; each rack has two midplanes. Partitions on Mira are composed of such midplanes. Thus, jobs on Mira are scheduled to run on partitions that have integer multiples of 512 nodes. The smallest production job on Mira occupies 512 nodes, and the largest occupies 49,152 nodes. The Cobalt [1] batch scheduler used on Mira is an open-source, component-based resource management tool developed at Argonne. It was used as the job scheduler on Intrepid (the supercomputer at ALCF before Mira) and is being used in other Blue Gene systems such as Frost at the National Center for Atmospheric Research [2].

We use the Qsim discrete event simulator [6] as it can simulate all the features supported by the Cobalt scheduler. Job scheduling behavior is triggered by job-submit(Q)/job-start(S)/job-end(E) events. The latest version of Qsim supports three versions of backfilling-based job scheduling policies: first-fit (FF) backfilling, best-fit (BF) backfilling, and shortest-job-first (SJF) backfilling [35]. By design, Qsim supports the simulation of only batch job scheduling. In this study, we extend the Qsim simulator to support real-time job scheduling using a high-priority queue and preemption.

3 Problem Statement

We define real-time and batch jobs, describe metrics used to evaluate scheduling algorithms, and formulate the problem.

3.1 Job Definition

Typically HPC platforms support only batch jobs. To support real-time computing on HPC platforms,
we categorize jobs into either batch jobs or real-time jobs. Here, real-time jobs (RTJs) are the jobs that require immediate service while batch jobs (BJs) require best-effort service. RTJs are also known as low-latency jobs. Each job will have the following attributes: submission time, start time, end time, wall-time, #nodes, and priority (batch or real-time) where submission time is when the job is submitted to a queue, start time is when the job actually started on computing resources, end time is when the job ends, wall time is a user-estimated run time, #nodes is the number of nodes requested by the job. The submission time, walltime, #nodes, and priority are given by a user submitting a job while the start time is determined by the scheduler and the end time will be set when the job is completed.

3.2 Performance Metrics

Commonly used metrics to evaluate parallel job scheduling algorithms are response time/turnaround time of jobs and job slowdown. The response time of a job is the elapsed time after submission until the job ends. The slowdown of a job is a relative measurement of the response time with regard to the run time of the job. We can formally define the slowdown of a job $j$ ($SD_j$) as:

**Definition 1.** $SD_j = \frac{endTime_j - submissionTime_j}{runTime_j}$

In order to limit the influence of very short jobs, we define the bounded slowdown of a job $j$ ($BSD_j$) as

**Definition 2.** $BSD_j = \frac{\text{predictTime}_j + \max(\text{runTime}_j, \text{Bound})}{\max(\text{runTime}_j, 10)} = \frac{(endTime_j - submissionTime_j - runTime_j) + \max(\text{runTime}_j, \text{Bound})}{\max(\text{runTime}_j, \text{Bound})}$

We set the Bound to be 10 minutes.

3.3 The Real-Time Job Scheduling Problem

We assume HPC platforms and the working environment with the following features.

- Jobs submitted to the platform are managed by a central scheduler.
- Jobs upon arrival are run immediately only if there are enough unused resources. Otherwise, the jobs are put in the waiting queue to be scheduled to execute when resources become available.
- All jobs are rigid, which means the number of nodes allocated to a certain job does not change over time.

Our goal is to keep the slowdown of RTJs as close to 1 as possible (in other words, keep the wait time of RTJs as close to 0 as possible). At the same time, we would like to minimize the slowdown (and the wait time) of BJs.

4 Basic Scheduling Techniques

We present and analyze five basic scheduling schemes adapted to accommodate RTJs in addition to the traditional BJs. Ideally, malleability, where the number of nodes of a job can dynamically shrink or expand, can be used to accommodate RTJs by adjusting nodes of running batch jobs. However, the production system such as Mira does not support such functions, and we, therefore, decided not to include malleability as basic techniques. This section is the summary of our previous work\cite{54} to help understand the baseline techniques.

4.1 High-Priority Queue-Based Scheduling

The simplest solution for RTJ scheduling is to use a separate queue for RTJs. RTJs are enqueued in a high-priority queue, whereas BJs are enqueued in a normal queue. The scheduler gives priority to the jobs in the high-priority queue and blocks all the jobs in the normal queue until all the jobs in the high-priority queue are scheduled.
4.2 Preemptive Scheduling with Checkpointing

In the preemptive scheduling schemes, if not enough resources are available to schedule a RTJ, the scheduler selects a partition for the RTJ that maximizes system utilization, preempts any BJs running on this partition, and schedules the RTJ. It then resubmits those preempted BJs to the normal queue for later restart/resume. The overhead introduced by preemption impacts the jobs that are preempted as well as the system utilization.

| Scheme      | Description                        |
|-------------|------------------------------------|
| NO-Cckpt    | No checkpointing                    |
| SYS-Cckpt   | System level checkpointing          |
| APP-Cckpt   | Application/Library level checkpointing |
| JIT-Cckpt   | Just-in-time checkpointing          |

Checkpointing can help reduce the overhead of preemption, but checkpointing does not come for free. Checkpointing’s impact on job runtime and system utilization needs to be accounted for as well. There can be four preemptive scheduling schemes as in Table 1. NO-Cckpt denotes no checkpointing, SYS-Cckpt denotes periodic checkpointing by OS kernel/hardware, APP-Cckpt denotes checkpointing by the application (job) itself, and JIT-Cckpt is checkpointing by the scheduler right before the job is preempted. We define the following terms to capture the overhead introduced by the preemptive scheduling schemes: \( t_{j\,\text{ckpt}} \), \( t_{j\,\text{pre}} \), \( \text{chr}_{j\,\text{ckpt}} \), \( \text{chr}_{j\,\text{pre}} \), \( \#\text{prmtpts}_j \), and \( \text{chr}_{\text{sys\,ckpt}} \), \( \text{chr}_{\text{sys\,pre}} \). Here \( t_{j\,\text{ckpt}} \) and \( t_{j\,\text{pre}} \) are the additional time incurred for job \( j \) due to checkpointing overhead and preemption overhead, respectively; \( \text{chr}_{j\,\text{ckpt}} \) and \( \text{chr}_{j\,\text{pre}} \) are the core-hours lost by the system due to checkpointing overhead and preemption overhead, respectively; and \( \text{chr}_{j\,\text{ckpt}} \) is core-hours lost by job \( j \) due to checkpointing overhead.

**NO-Cckpt:** In NO-Cckpt, no system- or application-level checkpointing occurs. Thus, the preempted jobs have to be restarted from the beginning. Equations 1 - 5 describe the overhead associated with this scheme.

\[
\begin{align*}
    t_{j\,\text{ckpt}} &= 0 \\
    t_{j\,\text{pre}} &= \sum_{i=1}^{\#\text{prmtpts}_j} t_{(j\,\text{pre})_i} \\
    \text{chr}_{\text{sys\,ckpt}} &= 0 \\
    \text{chr}_{\text{sys\,pre}} &= \sum_{k\in\text{batch jobs}} t_{(k\,\text{pre})_k} \times \text{nodes}_k \\
    \text{chr}_{j\,\text{ckpt}} &= 0
\end{align*}
\]

Here, \( \#\text{prmtpts}_j \) is the number of times job \( j \) is preempted, \( t_{(j\,\text{pre})_i} \) is the time that job \( j \) (preempted job) has run in its \( i \)th execution because the job has to start over from the beginning, \( \text{nodes}_j \) is the number of nodes used by job \( j \). **SYS-Cckpt:** This scheme corresponds to the system-level checkpoint support. All BJs are checkpointed periodically by the system (without any application assistance), and the checkpoint data (the process memory including the job context) are written to a parallel file system (PFS) for job restart. Running BJs chosen for preemption are killed immediately, and they are resubmitted to the normal queue. When the preempted BJs get to run again, the system resumes them from the latest checkpoint. The system checkpoint interval (\( \text{ckpIntv}_{\text{sys}} \)) is universal for all running BJs. Equations 6 - 10 describe the overhead incurred by the preempted jobs (in terms of time) and the system (in terms of core-hours).

\[
\begin{align*}
    t_{j\,\text{ckpt}} &= \left\lfloor \frac{t_{j\,\text{runtime}}}{\text{ckpIntv}_{\text{sys}}} \right\rfloor \sum_{i=1}^{\#\text{prmtpts}_j} \frac{\text{ckpData}_{i\,j}}{\text{BW}_{\text{PFS}}} \\
    t_{j\,\text{pre}} &= \sum_{i=1}^{\#\text{prmtpts}_j} \frac{\text{ckpData}_{(j\,\text{pre})_{i\,j}} - \text{ckpTgap}_{i\,j}}{\text{BW}_{\text{PFS}}} \\
    \text{chr}_{j\,\text{ckpt}} &= \sum_{k\in\text{batch jobs}} t_{(k\,\text{pre})_k} \times \text{nodes}_k \\
    \text{chr}_{j\,\text{pre}} &= \sum_{k\in\text{batch jobs}} t_{(k\,\text{pre})_k} \times \text{nodes}_k \\
    \text{chr}_{j\,\text{ckpt}} &= 0
\end{align*}
\]
Here $ckpData^j_i$ is the amount of data to be checkpointed for job $j$ for $i$th checkpoint, and $t^j_{run\_time}$ is the run time of job $j$. $ckpData^j_{latest}$ is the amount of data checkpointed in the most recent checkpoint for job $j$. $BW^{write\_PFS}$ and $BW^{read\_PFS}$ represent the write and read bandwidth of the PFS, respectively. $ckpTgap^j_i$ is the time elapsed between the time job $j$ was checkpointed last and the time job $j$ gets preempted for $i$th preemption.

**APP-CKPT:** This scheme corresponds to application-level checkpointing. Applications checkpoint themselves by storing their execution contexts and recover by using that data when restarted without explicit assistance from the system. The checkpoint interval ($ckpIntv^j_{app}$) and the amount of data checkpointed ($ckpData^j_i$) change based on the application. Equations 11 to 15 describe the overhead incurred by the preempted jobs (in terms of time and core-hours) and the system (in terms of core-hours).

\[
t^j_{ckpt} = \left\lfloor \frac{t^j_{runtime}}{ckpIntv^j_{app}} \right\rfloor \sum_{i=1}^{\#prompts_j} \frac{ckpData^j_i}{BW^{write\_PFS}}
\]  
\[
t^j_{pre} = \sum_{i=1}^{\#prompts_j} \frac{ckpData^j_i}{BW^{read\_PFS}} + ckpTgap^j_i
\]  
\[chrsys_{ckpt} = 0\]
\[chrsys_{pre} = \sum_{k \in \text{batch jobs}} t^k_{pre} \times nodes_k\]
\[chr^j_{ckpt} = t^j_{ckpt} \times nodes^j\]

**JIT-CKPT:** In this scheme, jobs are checkpointed just-in-time (JIT), i.e., right before they get preempted. The premise here is that there is an interaction between the scheduler and the checkpointing module. When the scheduler is about to preempt a job, it informs the appropriate checkpointing module and waits for a checkpoint completion notification before it actually preempts the job. The checkpoint and preemption overhead in this scheme is minimal since there is no need to checkpoint at periodic intervals and there will not be any redundant computation (since checkpoint and preemption happen in tandem). As opposed to the other checkpointing schemes described above, RTJs incur an additional delay (the time taken to do JIT checkpoint) in this scheme. Equations 16 to 20 describe the overhead incurred by the preemption (in terms of time) and the system (in terms of core-hours).

\[
t^j_{ckpt} = \sum_{i=1}^{\#prompts_j} \frac{ckpData^j_i}{BW^{write\_PFS}}
\]  
\[
t^j_{pre} = \sum_{i=1}^{\#prompts_j} \frac{ckpData^j_i}{BW^{read\_PFS}}
\]  
\[chrsys_{ckpt} = \sum_{k \in \text{batch jobs}} t^k_{ckpt} \times nodes_k\]
\[chrsys_{pre} = \sum_{k \in \text{batch jobs}} t^k_{pre} \times nodes_k\]
\[chr^j_{ckpt} = 0\]  

**Summary of the Performance of these Schemes:** We evaluated these schemes using the real-world job logs from Mira. We studied their performance for different percentages of RTJs in the workload. Employing a high-priority queue for RTJ dramatically reduces the slowdown of RTJ (4x or more) when compared with the baseline scheme that treats all jobs equally. However, the absolute values of the average slowdown of RTJs are still around 2. Preemption is required to bring the average slowdown of RTJs close to 1. Surprisingly, both the high-priority queue and preemptive schemes that favor RTJs benefited BJ also when $\% RTJ \leq 30$. Further analyses revealed that in addition to RTJ, narrow (jobs that requested a small number of nodes) and short (jobs with short walltime) BJ also benefited significantly from the schemes that favor RTJ. With preemptive schemes, preemption of wide (jobs that requested a large number of nodes) and long (jobs with long walltime) BJ can help narrow and short BJ (in addition to RTJ) through new backfilling opportunities. With high-priority queue, prioritizing RTJ over BJ (and making wide BJ wait) possibly creates additional backfilling opportunities for narrow and short BJ. But the performance of wide and long jobs suffered, which is likely not acceptable for the HPC centers. Thus, we need sophisticated heuris-
tics that protects these (and all other) classes of BJs from significant degradation in performance. We develop improved heuristics in this work to address this issue. First, we present a MILP formulation of the problem to find the optimal solution for small trace, which then can be used to measure how far off the improved heuristics is from the optimal solution.

5 MILP-based Real-time Scheduling Algorithm

In this section, we mathematically formulate the real-time job scheduling problem as a mixed integer linear programming (MILP). This formulation is used as a baseline for the performance evaluation of our heuristics.

5.1 Overview of problem formulation

The job scheduling problem on modern HPC systems is a multi-dimensional optimization problem. In this study the scheduling problem is a joint optimization problem of improving both RTJ performance ($\Pi_{RTJ}$) and batch job performance ($\Pi_{BJ}$) with system constraints as in Equation (21). Since RTJs and BJs share system resources (i.e. nodes), the performance improvement of one type of jobs, in general, has negative impacts on the other type of jobs. In our actual formulation, for the sake of simplicity, we solve the problem with the objective of maximizing BJs’ performance while guaranteeing RTJs’ performance at least above the predefined threshold. If the formulation fails to solve, the formulation with a looser threshold is tried repeatedly. For example, if the constraint for RTJs’ average slowdown is first set to 1.1 and the formulation fails to solve, that means we cannot find any schedule satisfying 1.1 of RTJs’ average slowdown. Then we should try with a looser constraint such as 1.2. The appropriate RTJs’ average slowdown can be binary searched, e.g., for the interval of 1.1 and 2.0.

$$\max \, \Pi_{RTJ} \text{ and } \Pi_{BJ}$$
subject to job/system constraints

5.1.1 Real-time job performance ($\Pi_{RTJ}$)
The performance of RTJs is the first priority. Here, we use job SD as a performance metric of RTJs. Ideally, all the RTJs should have job SD close to 1.0, and a bigger job SD means worse performance. Thus, the term $\Pi_{RTJ}$ in the objective function is the negative sum of all the costs ($Cost_{RTJ}$) of RTJs as in Equation (22).

$$\Pi_{RTJ} = -\sum_{j \in Job_{RTJ}} Cost_j$$

The cost of a RTJ ($Cost_{RTJ}$) can be generalized as a piecewise function of its job SD as in Equation (23) if we would like to suppress SDs of jobs around a threshold by sharply increasing the costs beyond the threshold.

$$Cost_{RTJ} = \begin{cases} f_s(SD_{RTJ}) & \text{if } 1.0 \leq SD_{RTJ} < SD_{thresh} \\ f_l(SD_{RTJ}) & \text{otherwise} \end{cases}$$

In Equation (23), $f_s$ and $f_l$ are the cost functions used when the RTJ slowdown ($SD_{RTJ}$) is smaller or larger than the job slowdown threshold $SD_{thresh}$, respectively. In this paper, however, we put the objective of minimizing RTJs’ cost as a constraint and define the cost of RTJs as the average of RTJs’ slowdowns where both $f_s(SD_{RTJ})$ and $f_l(SD_{RTJ}) = SD_{RTJ}$.

5.1.2 Batch job performance ($\Pi_{BJ}$)

Based on the checkpoint/preemption scheduling policy, some BJs are checkpointed and will be later restarted if no available resources for RTJs exist due to running BJs. This checkpoint/preemption activity would cause execution overhead to the BJs.

The checkpoint/preemption activity would only generate overhead to BJs. We denote this overhead as $PreemptCost_{BJ}$, and it is represented as a function of checkpoint interval ($Int_{ckp}$), checkpoint data size ($DSize_{ckp}$) and I/O bandwidth ($BW_{ckp}$) for checkpoint data storage as in Equation (24). We adopt only the just-in time checkpoint scheme for our formulation.

$$PreemptCost_{BJ} = g(Int_{ckp}, DSize_{ckp}, BW_{ckp})$$
Like $P_{RTJ}$, $P_{BJ}$ is the negative sum of all the costs ($Cost_{BJ}$) of BJs as in Equation 25. $Cost_{BJ}$ is also the BJ slowdown ($SD_{BJ}$), which factors in $PreemptCost_{BJ}$.

$$P_{BJ} = - \sum_{j \in Job_{BJ}} Cost^j_{BJ} \quad (25)$$

5.1.3 Job/system constraints

As explained in Section 3.3, a job is defined as a tuple of submission time, start time, wall time, run time, job size, and job type (RTJ or BJ). Those attributes of jobs have a relationship among them. For example, start time should be later than submission time. In addition, when a job is scheduled on computing resources, system resource allocation should be considered. For example, only consecutive nodes in terms of network connections can be allocated for a job. Such conditions are imposed as job/system constraints in our formulation.

Besides, regarding big facilities such as Mira at Argonne National Laboratory, the overall system utilization is a critical factor to evaluate the system operating efficiency at the end of every year. In this study, we introduce average productive system utilization ($Util_{productive}$), which is the overall system utilization ($Util_{system}$) subtracted by the utilization caused by checkpoint/preemption overhead ($Util_{overhead}$) as in Equation 26.

$$Util_{productive} = Util_{system} - Util_{overhead} \quad (26)$$

The checkpoint/preemption schemes can decrease the average productive utilization due to overhead incurred by checkpoint data write/retrieval (and the redundant computation from the time last checkpoint was taken to the time the job was preempted). We consider checkpoint/preemption overhead in both our formulation and heuristics such that unnecessary checkpoint/preemption can be avoided to maximize productive system utilization or restricted under some percentage of overall system utilization. The detailed constraints and considerations are described in Section 5.4 and 6.2.

5.2 Machine-dependent features

(IBM BG/Q)

Supercomputers may have different architectures (for example, node configurations) which affects node allocations when scheduling jobs.

In this paper, we target Mira, an IBM BG/Q system at Argonne National Laboratory, for our formulation and experiments, but the results can also be applied to other supercomputer systems. Mira’s various job queues (e.g., prod-capability, prod-short, and prod-long) support different partition sizes, where a partition is a logical boundary of nodes that can be assigned to a job. Due to the restrictions of hardware configurations such as midplane, rack, row, and torus network topology, partition sizes supported are 512, 1024, 2048, 4096, 8192, 12288, 16384, 24576, 32768, and 49152. We define a notion of partition block to track the physical location of a partition. We divide the whole nodes into 512-node blocks which are indexed from partition block 1 to partition block 96 (total number of nodes/512). The partition block number is used for mixed-integer linear programming in the following sections.

The system memory size of a node is 16 GB. The overall bandwidth of parallel file systems of Mira is 240 GB/s, and we assume 90% of bandwidth (216 GB/s) can be used for checkpoint/preemption. Mira has one I/O node, which will do I/O service for compute nodes at 4 GB/s, per each 128 compute nodes.

5.3 Partition-sequence scheduling model

Our formulation of the scheduling problem is based on the notions of partition and sequence. Figure 1 shows how jobs are scheduled on a machine which is represented by a graph with time on x-axis and partition block number on y-axis, for a partition size of 512 nodes. The scale of the y-axis is a multiple of 512, and the maximum value of y-axis equals 96 (x 512) in the case of Mira. The sequence is the order of scheduled jobs on each partition, which means that each partition counts its sequence number as jobs are scheduled on the partition. In Figure 1, J1 through J5 are scheduled. J1, J2, and J4 are scheduled on one
512-nodes whereas $J_3$ and $J_5$ are scheduled on two 512-nodes. The sequence number of a partition block increases only if a job is assigned on the partition. Thus, the 96th partition block has only one sequence, i.e., $s = 1$ for $J_1$. In the case of the second partition block, three jobs are scheduled on the block, which results in sequence numbers ranging from 1 to 3. Note that the $J_5$ is assigned to different sequence numbers (i.e., 2 and 3) of partition block 1 and partition block 2.

![Partition-sequence model for scheduling on parallel machines, especially for Mira.](image)

**Figure 1: Partition-sequence model for scheduling on parallel machines, especially for Mira.**

### 5.4 The offline scheduling problem

Our formulation is for offline scheduling of jobs on the Mira supercomputer, which means all the jobs to be scheduled are known in advance. There is a mix of BJs and RTJs to be scheduled on the Mira supercomputer. In addition, we make a few more assumptions in this paper:

- All the jobs are *rigid*. Thus the number of nodes required for each job is constant and predefined at job submission time. This is consistent with actual job operations in the Mira.
- Regarding batch-job preemption and restart, we assume that BJs can be preempted by RTJs, and will be restarted from the preemption point (with an overhead).
- RTJs cannot be preempted.
- Even though heuristics allow a BJ to be preempted multiple times, in our formulation a BJ can be preempted only once.

We first define notations for the rigorous formulation of the offline scheduling problem. We then formulate the problem as a mixed-integer linear programming (MILP).

#### 5.4.1 Notation

The notations to be used in the job scheduling problem are defined as follows:

- $J$: a total set of jobs, $j \in J = \{1, \ldots, N\}$ where $N$ is the number of jobs.
- $J_R$: a set of RTJs, $j_r \in J_R = \{1, \ldots, N_R\}$ where $N_R$ is the number of RTJs.
- $J_B$: a set of BJs, $j_b \in J_B = \{1, \ldots, N_B\}$ where $N_B$ is the number of BJs.
- $B$: Big number for MILP constraint transformation.
- $P$: a set of machine partitions in unit of 512 nodes, $p \in P = \{1, \ldots, M\}$ where $M$ is the number of partitions in unit of 512 nodes. $M$ equals 96 because the total number of nodes in Mira is 49,152.
- $\text{nodes}_j$: required partition size of job $j \in J$.
- $PB_j$: a set of possible partition blocks for a job $j$. According to $\text{nodes}_j$, $PB_j$ is determined. For example, if $\text{nodes}_j = 1024$, $PB_j = \{1, \ldots, 48\}$.
- $mPartDep[n, blocknr, mapindex]$: a matrix of partition dependency where $n$ is the number of requested nodes in unit of 512 nodes, $pbnr$ is the element of the possible partition block numbers for $n$, and $mapindex$ is the index in the whole node map. For example, if $n$ is $32(=32*512=16384\text{nodes})$, $pbnr$ is in the set...
1, 2, 3 (The total number of nodes in IB BG/Q is 49,152), and mapindex ranges from 1 to 96 regardless of $n$. When $mPartDep[2, 1, 1] = 1$, this means that the partition block number 1 for the partition size of 1024 (=2*512) occupies the first 512-nodes in the system. Likewise, $mPartDep[2, 1, 2]$ would be 1 since 1024 nodes should occupy two 512-nodes. This variable is needed to detect the overlapping of node allocations of different partition sizes.

- **SDRTJ_threshold**: threshold of slowdown of RTJs.
- **$S$**: a set of sequences $s \in S = \{1, ..., T\}$. For example, in Fig. 1, the partition 1 has two sequences comprising $J_3$ and $J_5$ while the partition 2 has three sequences comprising $J_3$, $J_4$, and $J_5$, which makes $T = 3$ in this case.
- **$stSeq_{s,p}$**: start time of sequence $s$ of partition $p$.
- **$subt_j$**: submit time of job $j \in J$.
- **$rt_j$**: runtime of job $j \in J$. not walltime but actual runtime.
- **$st_j$**: start time of job $j \in J$.
- **$rst_j$**: restart time of a BJ $j \in J_B$.
- **$et_j$**: end time of job $j \in J$.
- **$ex_{j,s,p}$**: binary variable for execution of job $j$ on partition $p$.
- **$exPb_{j,pb}$**: binary variable for execution of job $j$ on partition block $pb$.
- **$exRt_{j,s,p}$**: real variable for computation ratio of a BJ across multiple sequences.
- **$exPrmpt_{j}$**: binary variable for the preemption of a BJ $j \in J_B$.
- **$exOvhd_{j,s,p}$**: binary variable for checkpoint overhead of a BJ $j \in J_B$ on the sequence $s \in S$ of the partition $p \in P$.
- **$ovhd_j$**: constant value for checkpoint overhead of a BJ $j$. In the formulation, we simply use Equation 34 to compute the overhead, the time taken to checkpoint or restart the checkpointed job, according to Section 5.2. Recall that one I/O node per 128 compute nodes can write at 4 GB/s and the parallel file system’s maximum I/O throughput is 216 GB/s.

$$ovhd_j = \frac{16 \times \text{nodes}_j}{\min(\frac{\text{nodes}_j}{128} \times 4, 216)} \quad (34)$$

To help understand binary variables, let us take a look at one of the variables. $exR_{j,s,p}$ is a binary variable denoting whether the RTJ $j$ on partition $p \in P$
in the sequence $s$ is executed or not, as in Equation 35. Likewise, $ex_{j,s,p}^B$ is a binary variable for a BJ.

$$ex_{j,s,p}^B = \begin{cases} 1 & \text{if the RTJ } j \text{ is executed on partition } p \\ 0 & \text{otherwise.} \end{cases}$$ (35)

5.4.2 Objective

The objective function in Equation 25 can be translated into minimizing the average SD of BJs as in Equation 36 while constraining the average SD of RTJs to a certain extent. The official definition of job SD is given in Definition 1.

Definition 3. SD of RTJ $j = \frac{(st_j + rt_j) - subt_j}{rt_j}$.

In the case of RTJs, we can expand $et_j$ into $st_j + rt_j$ as in Definition 3 because RTJs cannot be preempted. Constraints are explained in the following sections.

$$\min \sum_{j \in J_B} \frac{et_j - subt_j}{rt_j}$$ (36)

5.4.3 Real-time job slowdown constraint

Equation 37 enforces that the average SD of RTJs is less than or equal to $SDRTJ_{thresh}$.

$$\frac{1}{N_R} \sum_{j \in J_R} \frac{(st_j + rt_j - subt_j)}{rt_j} \leq SDRTJ_{thresh}$$ (37)

5.4.4 Job start/end time constraints

Job start/end time constraints ensure that any precedence requirements of jobs are well observed and start/end times are correctly associated with sequence start times. These constraints get complicated due to preemption of BJs. To model at most once preemption for BJs, a restart time variable for only BJ (i.e., $rst_j$) is introduced. The start/restart time of a job is greater than or equal to the submission time of the job as in Constraint 27. Constraints 28 and 29 ensure that a RTJ’s start time is greater than or equal to a sequence start time if the job is scheduled on that sequence. Constraints 30 and 31 ensure that a BJ’s start/restart time is greater than or equal to a sequence start time if the job is scheduled on that sequence. Figure 2 shows that Constraints 30 and 31 hold for both cases of without preemption and with preemption. Here we provide more details on Constraint 31. In Figure 2(a) the right-side expression becomes $stSeq_{s,p}(= stSeq_{s,p} + B(1 - 3) + 2B - 0B)$, in the first sequence in Figure 2(b) the right-side expression becomes $stSeq_{s,p}(= stSeq_{s,p} + B(2 - 3) + 2B - B)$, and finally in the third sequence in Figure 2(b) the right-side expression becomes $stSeq_{s,p} - B(= stSeq_{s,p} + B(1 - 3) + 2B - B)$, which makes the Constraint 31 always hold true because the start time has nothing to do with the third sequence. Constraints 32 and 33 ensure that a BJ’s end time is greater than or equal to the BJ’s start/restart time.

5.4.5 Sequence constraints

Sequence constraints are related to the timing of sequences (i.e., sequence start times) and how jobs are scheduled on sequences. Constraint 38 ensures that the start time of the first sequence in any partition is 0. Constraint 39 ensures that the start time of a sequence is less than or equal to the start time of the next sequence. Constraint 40 and 41 ensure that if a RTJ is scheduled on the sequence $s$, the end time of the job should be less than the start time of sequence $s + 1$, because RTJs cannot be preempted. Constraints 42 – 44 ensure that if a BJ is scheduled on the sequence $s$, the end time of the BJ composed of the run time and the preemption overhead should be less than the start time of the next sequence $s + 1$. 

Figure 2: Start constraint for a BJ: (a) without and (b) with preemption.
Constraints \([43]\) and \([44]\) are more complicated: as with Constraints \([30]\) and \([31]\), they must allow for both the BJs that get preempted and the BJs that do not get preempted, as shown in Figure 2.

\[
\begin{align*}
\text{stSeq}_{q,p} &= 0, \quad p \in P, \quad \text{stSeq}_{q,p} \leq \text{stSeq}_{q+1,p}, \quad s \in S\setminus T, \quad p \in P, \\
\text{stSeq}_{q,p} &\leq \text{stSeq}_{q+1,p}, \quad s \in S\setminus T, \quad p \in P, \\
(st_{j} + rt_{j})ex_{j,s,p}^{R} &\leq \text{stSeq}_{q+1,p}, \quad j \in J_{R}, \quad s \in S\setminus T, \quad p \in P.
\end{align*}
\]

Constraints \([30]\) and \([31]\) put limits on the execution time of BJs and RTJs. Constraints \([43]\) and \([44]\) are more complicated: as with Constraints \([38]\) and \([39]\), they must allow for both the BJs that get preempted and the BJs that do not get preempted, as shown in Figure 2.

\[
\begin{align*}
\sum_{s \in S, pb \in PB_{j}, \, p \in P} (mPartDep[s_{\frac{\text{nodes}}{512}}, pb, p] &\quad j \in J_{R}) \quad \text{Constraint 45}, \\
\sum_{s, pb \in P} \times (\text{ex}_{j,s,p}^{R} \text{exPb}_{j,pb}) &\quad j \in J_{R} \quad \text{Constraint 46}, \\
\sum_{s \in S, pb \in P} (mPartDep[s_{\frac{\text{nodes}}{512}}, pb, p] &\quad j \in J_{B} \quad \text{Constraint 47}, \\
\sum_{s \in S, pb \in P} \times (\text{ex}_{j,s,p}^{B} \text{exPb}_{j,pb}) &\quad j \in J_{B} \quad \text{Constraint 48}, \\
\sum_{s \in S, p \in P} \sum_{j \in J_{R}} (\text{ex}_{j,s,p}^{R}) &\quad s \in S, \quad p \in P \quad \text{Constraint 49}, \\
\sum_{s \in S, p \in P} \sum_{j \in J_{B}} (\text{ex}_{j,s,p}^{R}) &\quad s \in S, \quad p \in P \quad \text{Constraint 50}.
\end{align*}
\]

5.4.6 Job assignment constraints

A job is assigned to a partition block at some point of time. A BJ can be preempted whereas a RTJ can not be preempted. Thus, a preempted BJ is assigned to the same partition block at two different sequences. Our formulation allows for only one preemption, so as to avoid more complicated decision variables and additional constraints.

Constraint \([45]\) ensures that the number of nodes assigned to a job \(j\) is same as the requested number of nodes. Constraint \([46]\) ensures that a RTJ occupies the requested number of nodes. Constraints \([47]\) and \([48]\) ensures that a BJ occupies the requested number of nodes. Constraint \([49]\) ensures that at most one job can run at a certain sequence on any partition. Constraint \([50]\) ensures that a RTJ can run on a certain partition at most one time throughout all sequences.

5.4.7 Preemption constraints for batch jobs

We allow for at most one preemption for a BJ, and also take into account the overhead of preemption/restart. Constraint \([51]\) ensures that the partial execution ratio of a BJ is greater than or equal to the threshold, which is 0.1 in this equation. Constraint \([52]\) enforces that the number of preemptions across partitions are the same. Constraint \([53]\) ensures that the number of allocated partitions matches the request number of nodes, for both with and without preemption. Constraint \([54]\) matches batch ratios with scheduled sequences on partitions.
\[
\frac{ex_j^{B,p}}{10} \leq exRt_j^{B,s,p} \leq ex_j^{B,s,p}, \quad j \in J_B, s \in S, \quad (51)
\]

\[
\sum_{s \in S} ex_j^{B,s,p} = exPrmpt_j^{B} + 1, \quad j \in J_B, p \in P \quad (52)
\]

if \[
\sum_{s \in S} ex_j^{B,s,p} > 0,
\]

\[
\sum_{s \in S, \ p \in P} exRt_j^{B,s,p} = \left\lceil \frac{\text{nodes}_j}{512} \right\rceil (exPrmpt_j^{B} + 1), \quad j \in J_B \quad (53)
\]

\[
\sum_{s \in S} (exRt_j^{B,s,p} \times ex_j^{B,s,p}) = 1 \ or \ 0, \quad j \in J_B, p \in P \quad (54)
\]

### 5.4.8 Additional constraints for partitions (specific to IBM BG/Q)

Only one partition block among possible partition blocks depending on \( \text{nodes}_j \) is assigned to a job. This constraint can be formulated as follows.

\[
\sum_{pb \in PB_j} exPb_{j,pb} = 1, \forall j \in J \quad (55)
\]

### 5.4.9 Transformation of formulation

Some constraints in the formulation such as Constraint (53) need a transformation to be regular equations or inequalities. We use Big M method [9] for this purpose, and one constraint can be split into one or more equations and inequalities. For example, an if-then-else statement can be split into two or more equations and inequalities. Also for quadratic terms such as a multiplication of binary variable(b) and a real variable(r) can be solved by introducing a new variable \( z(=b \times r) \) with inequalities. We do not show the complete transformations due to the space limitation.

### 5.5 Complexity Analysis

The time complexities of linear programming problems depend on the number of variables and constraints whereas the time complexities of mixed integer linear programming problems also depend on the number of integer variables. As described in Section 5.4.1 the maximum number of a certain type of variable (i.e. \( ex_j^{B,s,p} \)) among all variables is \( N \times M \times T \) where \( N \) is the number of jobs, \( M \) is the number of partitions, and \( T \) is the number of sequences. The thing making it worse to compute the optimal solution in a reasonable time is those variables that are binary. Table 2 shows the number of binary variables after preprocessing the problem and run times of solving formulations when using IBM CPLEX [3] as the problem size is growing. We ran these sample experiments on a 32-core machine. We can see the run time grows exponentially with the size of the problem, and it takes up to 12 hours when the number of jobs is seven, and the partition size and the sequence size are 16 and 5, respectively. Thus, we evaluate our heuristics with our formulation when the number of jobs is seven. The details are described in Section 7.

### 6 Novel Scheduling Heuristic

As summarized in Section 4 our previous work [54] showed that simple as well as some sophisticated heuristics to support RTJs can be detrimental to certain classes of batch jobs. Here we build on that work to develop a new heuristic that addresses the issues with the heuristics described in Section 4. To develop our scheduling heuristic, we made the additional changes to the modified Cobalt scheduling heuristic in [54] as follows.

- Split jobs into a low priority and a high priority queue to give preferential treatment to jobs that our scheduler deems as high priority.
• Created a weighted cost scheduling algorithm for high priority queue jobs.

6.1 Estimated Slowdown

Before going into more details of the scheduling heuristic, it is essential to understand the primary metric used for the heuristic’s decision-making process: estimated slowdown. A job submitted to an HPC system has a walltime, which is a user submitted time for a job that corresponds to the maximum possible runtime for the job. The actual runtime, which is the time that the job actually runs in the HPC system and can only be computed after the job completes.

When scheduling jobs, our heuristic computes a job’s estimated slowdown and then uses this value to make decisions. For jobs that haven’t started running yet, we define the estimated slowdown (ESD) of a job as below.

\[
\text{ESD} = \frac{\text{job.wallTime} + \text{currentTime} - \text{job.submitTime}}{\text{job.wallTime}}
\]  

(56)

For jobs that are currently running, we define ESD as

\[
\text{ESD} = \frac{\text{job.estimatedEndTime} - \text{job.submitTime}}{\text{job.wallTime}}
\]

(57)

where estimatedEndTime of a job is computed as follows.

\[
\text{job.estimatedEndTime} = \text{job.wallTime} + \text{currentTime} - \text{job.runningTime}
\]

(58)

Thus, a job’s ESD is a way of estimating what a job’s slowdown would be if the job were to (start now, if not started already, and) run for completion.

Note that the equation for the ESD is different from the BSD (bounded slowdown) equation that is used to evaluate the performance of the scheduling algorithms. The equation for ESD uses a job’s walltime instead of runtime since in the real world we don’t know a job’s actual runtime until after it completes, and thus we use the job’s walltime as a substitute.

6.2 Heuristic Details

We use two queues: one low priority and one high priority. The low priority queue contains BJs and also RTJs below a configurable RTJ slowdown threshold; these jobs cannot preempt any currently running jobs. The high priority queue contains all other RTJs; these jobs can preempt running BJs under certain conditions.

We note that the high priority queue in this scheme is different from the high-priority queue scheme in [54]. The high priority queue in this scheme only has RTJs that have reached a slowdown threshold, while he high-priority queue scheme in [54] contains all RTJs. We use a weighted cost job scheduling (WCJS) algorithm for scheduling jobs in high priority queue, which is discussed in the next section. The complete algorithm is shown in Algorithm 1.

6.3 Weighted Cost Job Scheduling Algorithm

At each iteration of the scheduler, our scheduling heuristic separates all available jobs (i.e., jobs that are ready to be run but are not currently running) into the two queues. BJs are automatically placed in the low priority queue. For RTJs, an estimated slowdown value is computed and jobs with values below the threshold are placed in the low priority queue,
Algorithm 2: Weighted Cost Job Scheduling

Input: A job, $job$, in the high priority queue

1. partitions ← getPartitionsBySize($job$.nodes)
2. for $p$ in partitions do
3.   if $p$.available = True then
4.     runJob($job$, $p$)
5.   return

6. possiblePartitions ← []
7. for $p$ in partitions do
8.   if $p$.preemptRealtime() = True then
9.     continue;
10.  else if $p$.preemptBiggerJob() = True then
11.    continue;
12.  else if $p$.preemptThreshold() = True then
13.    continue;
14.    possiblePartitions.add($p$)
15. bestPartition ← None
16. bestScore ← $\infty$
17. for $p$ in possiblePartitions do
18.    totalScore ← 0
19.    for childJob in $p$.getChildJobs() do
20.      score ← childJob.nodes
21.      score ← score × childJob.slowdownFactor()
22.      score ← score × childJob.checkpointFactor()
23.      score ← score × childJob.timeRemainingFactor()
24.      totalScore ← totalScore + score
25.    if totalScore < bestScore then
26.      bestPartition ← $p$
27.      bestScore ← totalScore
28. runJob($job$, bestPartition)

while the remainder are placed in the high priority queue.

Next, the scheduler attempts to schedule the quenched jobs. Our algorithm only schedules low priority queue jobs if the high priority queue is empty. Otherwise, the algorithm schedules the high priority queue jobs. For low priority queue jobs, our scheduling heuristic scores the jobs based on wall-time, queuetime, and number of nodes and then uses these scores to sort the jobs in the queue. Then for each job in the newly sorted queue, the heuristic looks for an available partition for the job to run on, and if a matching partition is found, it runs the job.

When scheduling high priority queue jobs, our heuristic uses a custom weighted cost job scheduling algorithm that has the ability to preempt currently running BJIs that meet certain criteria. Thus, only RTJs with an estimated slowdown value above a certain threshold can preempt jobs in the system, and BJIs can never preempt other jobs.

When a job is placed in the high priority queue, the weighted cost scheduling algorithm tries to identify the best partition in the system for high priority queue jobs to run in. For this, the algorithm takes all partitions that are of the right size for the job, i.e., the smallest partitions that are still bigger or equivalent in size to the job. For example, a 1000 node job would want a 1024 node partition.

As shown in Algorithm 2 lines 1-5, if there is an appropriately sized partition that is available (no job is running on the partition), then there is no need to preempt a running job, and the job is run on this partition. Otherwise, it identifies all eligible partitions. Eligible partitions are the ones that

1. Do not have any RTJs running.
2. Do not have any jobs bigger than the preempting job.
3. Do not have BJIs that have a slowdown that exceeds a certain threshold based on the job’s size and walltime.

Accordingly, the justification for these criteria are as follows – preempting RTJs will incur additional delays to them and thus will make them as non
real-time; preemting Bigger (in terms of number of nodes) BJs will have a hard time getting back in after being preempted; Preemting BJs that already have a high slowdown value could result in unreasonably high slowdowns for them.

It is important to note that partitions are organized in a parent-child hierarchical structure based on the topology of the supercomputer. A parent partition is a superset of any of its child partitions. For example, 1024-nodes partition is composed of two 512-nodes children partitions. You can only run a job on the parent partition if you preempt all of the child partitions’ jobs. Thus, for all of the correctly sized partition it is necessary to check their child partitions for criteria 1 and 3, and their parent partitions for criteria 2. As long as one partition in the system meets the criteria, then the job will be run right away. If not, the job waits in the queue until a valid partition becomes available.

Next, the algorithm (lines 17-27) computes a weighted cost value for all partitions that meet the criteria. The cost is calculated by summing together scores for all of the jobs in the partition that would be preempted by the new job. The score for each preempted job consists of the number of nodes for the preempted job multiplied by three different factors, each of which has a different weight. The three factors are the slowdown of the preempted jobs, the last checkpoint time of the preempted jobs (if the experiment is using an interval checkpointing scheme), and the percentage of time remaining for the preempted jobs.

Accordingly, the rationale for these factors are preempting jobs with high slowdown values is bad for performance, preempting jobs that checkpointed recently is better than preempting jobs that are not checkpointed recently, and we want to avoid preempting jobs that are almost done. Although these factors and their weights appear somewhat arbitrary, they are the result of extensive testing done to determine which factors and weights produce the best results. Once this weighted cost is computed for all available partitions, the partition with the lowest cost is selected, all jobs running in the partition are preempted, and the new job is run.

7 Simulation-based Evaluation

In this section, we present the detailed methodology for a simulation-based evaluation and the evaluation results. We also compare the results of heuristics with those of MILP-based formulation to evaluate the performance and possible improvement of heuristics.

7.1 Experimental Setup

7.1.1 Job Categories

To understand simulation results better, we divided the jobs into four categories: two classes for the number of nodes (narrow and wide) and two classes for the runtime (short and long). The criteria used for classification is as follows:

- Narrow: number of nodes used is in the range [512, 4096] inclusive (note that the number of nodes allocated on Mira is a multiple of 512).
- Wide: number of nodes used is in the range [4608, 49152] inclusive.
- Short: jobs with runtime ≤ 120 minutes.
- Long: jobs with runtime > 120 minutes.

Consequently, there are four job categories – narrow-short, narrow-long, wide-short, and wide-long.

7.1.2 Workload Trace

\[
\text{jobSize}_{\text{normalized}} = \frac{\text{jobSize}_\text{original} \times \text{Mira.node.count}}{CEA.Curie.node.count}
\]

7.1.3 Job Variation

1. Default: we randomly choose R% (RTJ percentage) of jobs in the experimental trace log, and set them as RTJs, with the rest (100 – R)% as BJs.

2. 90 minute walltime threshold: same as the default method except that we only allow jobs in the trace log with a runtime of less than 90 minutes to be RTJs. This method is designed to reflect situations in which RTJs have similar to
characteristics to BJs except that they are by nature shorting running jobs with a higher slowdown sensitivity.

3. APS Log Jobs: all jobs in the original trace log are BJs. We generate RTJs for the experiment by using log data taken from the APS (Advanced Photon Source), which a particle accelerator at Argonne National Lab. The log used contains the jobs run to process data for one of the research stations at APS. Running APS jobs on the Mira supercomputer one was of the primary motivators for this research and so it made sense to use this data to simulate RTJs on the Mira system. However, the APS log data is incomplete, and it only contains job runtimes or job sizes. To use the APS log data as RTJs in our experiments, we randomly select a number of jobs from the log (based on the number of jobs in the batch log being used, and the % of RTJs for the experiment)

7.1.4 Checkpointing Methods

To evaluate our scheduling heuristic discussed above, we implemented three different checkpointing methods: application checkpointing with 5% overhead (APP-CKPT-5%), application checkpointing with 10% overhead (APP-CKPT-10%), and just in time checkpointing (JIT-CKPT).

The application checkpointing method is based on the idea that a job’s total checkpointing overhead should be less than some percentage of the job’s entire runtime. For implementing this, the scheduler computes the time to checkpoint each job and then uses this value to calculate the number of times each job can be checkpointed so that the total checkpointing overhead is less than or equal to a certain percentage (either 5% or 10%) of the walltime (as we don’t know the actual runtime of a job before the job completes). The scheduler, then evenly distributes that number of checkpoints throughout the walltime of the job. For example, if the checkpoint overhead is 10%, a 120-minute job that takes 5 minutes to checkpoint can be checkpointed two times without exceeding the checkpoint overhead limit (12 minutes). In this case, the job will checkpoint every 40 minutes of runtime.

7.1.5 Performance metrics for evaluation

We analyze the performance of various scheduling algorithms in terms of slowdown and turnaround time of the jobs. To establish the baseline for future comparison, we first capture the performance of batch scheduling algorithm employed at Mira by running both RTJs and BJs as BJs on the Qsim simulator.

7.2 Scheduling Heuristic Simulation Results

We illustrate our results with a series of figures, which contain the simulation performance results for one week-long trace. Due to space constraints, we do not include the results for another week-long trace; we note that the trends for the other log were similar to that of the trends for the trace presented here. There are five figures for results. Fig. 3 contains results for all jobs, and Fig. 4 through 7 contain results for each of the four job categories, narrow-short, narrow-long, wide-short, wide-long respectively.

In all figures, the top and bottom row contains a boxplot for the bounded slowdown values and the turnaround times respectively. Each row is divided into two columns, with the left column showing the results for real-time jobs and the right column showing the results for BJs. Each subplot contains 16 different boxplots in groups of 4. The four groups of boxplots correspond to the four different % of RTJs simulated. Within each group is four boxplots which correspond to the four different checkpoint heuristics evaluated. The four different checkpoint heuristics are color-coded as indicated in the legend at the top of each figure, and the coloring is consistent across all subplots and figures. As a result, the x-axes, indicating the % of RTJs, are the same for all plots, but y-axes, indicating either the slowdown or turnaround time, are different for each subplot.

The bottom and top whiskers of the boxplots correspond to the 5% and 95% values respectively. The bottom, middle and top lines of the boxes for the boxplots correspond to the 25%, 50% (median) and 75% values. The dots of the boxplots represent the
average value. For both metrics provided, slowdown and turnaround time, lower values are better. The lowest possible slowdown value for all jobs would be 1 since this would mean that a job does not have to wait at all. The lowest possible turnaround time value for a job is the job’s runtime and thus is job dependent. We decided to present the results in the form of boxplots since we felt it necessary to show not only the average results from the simulation but also the range of values, especially, the upper range or maximum values. We chose to put the whiskers at 5% and 95% in an attempt to prevent outliers from skewing the results. However, there are many cases in the figures in which it is difficult to see all lines of a boxplot, in particular, the bottom whisker, 25% line and 50% line. In these cases, we felt that these values were all negligibly small enough relative to the other values in the plot that this loss of granularity was okay since it enables showing the upper range of values.

We first discuss the high-level trends that are evident in all jobs as shown in Fig. 3 before we move on to discussing the trends and unusual behaviors in the job category figures. To start with, RTJ slowdown values and turnaround times are across all figures lower than BJ values. Our custom scheduling heuristics perform better compared to the baseline for RTJs, but they perform worse for the BJs. This is to be expected, since the performance improvements experience by the RTJs with our scheduling heuristics come to some extent at the expense of the BJs’ performance. However, since there are so many more BJs than RTJs, the ratio of performance variation is much higher for the RTJs than it is for the BJs. I.e., the RTJs’ performance improvement is much larger than BJs’ performance decline.

When comparing our three scheduling heuristics, we found that APP-CKPT-5% performed better than APP-CKPT-10% for both the cases of the median value and the 95% value. This implies that the time saved with the extra checkpoints in APP-CKPT-10% does not make up for all of extra overhead involved in doing those extra checkpoints compared to the APP-CKPT-5%, which has only half the number of check-
points. Similarly, we found that the JIT-CKPT performed better than the APP-CKPT-5% in terms of both the median value and the 95% value. Like the previous comparison, this implies that it is better to checkpoint only when needed as in the JIT-CKPT heuristic instead of periodically checkpointing as in the APP-CKPT-5% heuristic. This is likely because the overhead cost of periodically checkpointing in the APP-CKPT-5% heuristic outweighs any performance benefits of periodically checkpointing. There are a few cases in the figures where the 95% value performance for the APP-CKPT-5% is actually better than that for the JIT-CKPT. However, these cases are only for the RTJs, and are likely caused by the RTJs having to wait until the JIT checkpointing of BJs is completed before starting to run.

Figure 4: Average slowdown and turnaround time — narrow-short

The trends are unclear when comparing the performance for the different percentages of RTJs. In Fig. 3 when % RTJs increases, the performance decreases for BJs, but there is not any clear performance difference for RTJs. The performance decline experienced by the BJs corresponds with the fact that having more RTJs in the system means that more jobs have higher priority and can preempt the BJs in the system. This explanation also explains the near constant performance seen by the RTJs since even as % RTJs increases, the extra RTJs have the same high priority as the rest of the RTJs. However, unlike the different checkpoint heuristics, the goal of testing with different % RTJs is less about determining which % RTJs has the best performance and more about how high of % RTJs that the scheduler can handle will still delivery adequate performance for both job types.

Next, we evaluate the results of different job categories. There are significant performance variations in terms of slowdown and turnaround time between the four different job categories for both BJs and RTJs. These trends are evident not only in our scheduling heuristics but also in the baseline heuristic, implying that the performance variations are the result of the underlying nature of the jobs and not artifacts of our scheduling heuristics.

It is important to note that when comparing job performance between the different job categories, the slowdown is a more natural metric than turnaround time since slowdown is normalized to a job’s runtime, while turnaround time is not. Thus, the performance variations seen in turnaround time across job categories is mainly due to the different job lengths.

Fig. 4 through 7 show that narrow-long jobs have the best slowdown performance in terms of both the median and 95% values. Narrow-long RTJs using the JIT-CKPT heuristic have near-real-time median slowdown values (1.08 when there are 10% RTJs), and narrow-long BJs using the same heuristic have

Figure 5: Average slowdown and turnaround time — narrow-long

| Job Category | Slowdown Median | Slowdown 95% | Turnaround Time Median | Turnaround Time 95% |
|--------------|-----------------|-------------|------------------------|---------------------|
| BJs (baseline) | 1.20            | 1.50        | 100                    | 150                 |
| APP-CKPT-5%  | 1.15            | 1.45        | 90                     | 140                 |
| JIT-CKPT     | 1.08            | 1.38        | 80                     | 130                 |

Figure 6: Average slowdown and turnaround time — narrow-long
Figure 6: Average slowdown and turnaround time — wide-short

Figure 7: Average slowdown and turnaround time — wide-long

similar performance to the baseline heuristic (∼1.40). It makes sense that narrow jobs would perform better than wide jobs since it is much easier for the scheduler to accommodate and find space for the narrow jobs, thus allowing them to run sooner and have lower slowdowns.

Narrow-short RTJs have a similar median performance to the narrow-long jobs since they benefit from their smaller job size as well. However, they have significantly worse 95% performance, which is likely caused by the higher variation between walltime and runtime for the narrow-short jobs. There are a number of narrow-short RTJs with runtimes that are proportionally much shorter than their walltimes. Since the slowdown threshold for RTJs is based on walltime, a job may end up with a higher slowdown value than we expect it to. For example, a job with a walltime of 60 minutes that only runs for 10 minutes, might wait for 12 minutes in the scheduler since we think this will give it a slowdown of 1.2; however, due to its short runtime its actual slowdown will be 2.2 even though it only waited for 12 minutes. Thus, even though these jobs have relatively short wait times in the scheduler queue, their short runtimes cause them to have much higher slowdowns compared to the rest of the narrow-short RTJs. Narrow-long RTJs are less affected by this slowdown skewing since they have longer walltimes and therefore lower proportional variation between walltime and runtime. Another factor for the large value for 95% performance is the checkpointing time involved in JIT-CKPT when a batch job needed to be checkpointed and preempted before a RTJ can be run. Especially in the case of extra short RTJs, this checkpointing time can cause a significant increase in waittime and thus resulting slowdown value.

Narrow-short BJs have worse median performance compared to narrow-long BJs which we also expect is due to the shorter nature of the narrow-short jobs which causes them to be more affected by wait-times even if those wait-times are well within an acceptable range for standard HPC uses.

Wide-long RTJs also have a similar performance to the narrow RTJs for our scheduling heuristics. However, the median performance gap between the baseline and the heuristics for wide-long RTJs is higher compared to narrow RTJs, which means our scheduling heuristic offers wide-long RTJs a relatively bigger performance increase compared to the narrow jobs.

Wide-short jobs are the outliers when it comes to performance. This is best demonstrated by the significantly high slowdown values in Fig. 6(a) and (b) compared to the other job categories. However, these higher slowdowns are represented in the baseline heuristic as well as our scheduling heuristic,
which implies that they are due to the differing characteristics of the jobs themselves and not our scheduling heuristic. In fact, as mentioned above, the wide-short RTJs experience vastly improved performance with our scheduling heuristics compared to the baseline. One obvious question that this raises is why are the wide-short jobs slowdown values so much higher compared to the other job categories. We hypothesize that similar to the performance difference experienced between the narrow-short and narrow-long jobs mentioned above, the wide-short jobs are much more sensitive to wait times than the wide-long jobs due to their shorter runtimes. This issue is further compounded by the fact that since they are wide jobs, it is much harder for the scheduler to find space for them, which causes them to wait significantly longer in the queue compared to narrow-short jobs.

Though again, because performance variation is experienced in the baseline as well as our scheduling heuristic, our primary goal is not to get all job categories to have the same performance. Instead, our goal is to have our scheduling heuristics give RTJs the best performance possible while still ensuring BJs have comparable performance to their baseline benchmark for each job category.

One abnormality in the wide-short category is that the JIT-CKPT heuristic has a higher 95% slowdown value for RTJs than the APP-CKPT-5% heuristic for the 10% RTJs case. Since there are so few jobs of this category in the simulation, this is the result of a small number of wide-long RTJs (3) with significantly higher slowdowns values that skew the 95% value. These higher slowdowns are likely the result of the simulation randomly selecting some wide-long jobs with a large difference between their walltimes and runtimes to be RTJs, which as discussed for the narrow-short jobs can cause higher slowdown values than expected by the scheduler. In addition, since these jobs have such short runtimes, any time required to checkpoint and then preempt running batch jobs in order to run these RTJs can have a large impact on the RTJs’ slowdown values, even though the checkpointing times are not actually that long.

The average simulation values follow many of the same trends as the median. The average values are higher than the median values (as shown in the plots by the average dot being above the median line in nearly all of the box plots). This is likely the result of there being a number of large outlier values that make the average value higher than the median value; this also corresponds with the high top whiskers seen for many of the boxplots. Regarding average values, the JIT-CKPT still performs the best among the three custom scheduling heuristics in nearly all of the different simulation configurations. JIT-CKPT performs better than the baseline heuristic for RTJs and performs worse for BJs; however, as is the case for the median values, the performance degradation for the BJs is much smaller than the performance improvement seen by the RTJs.

Take for example the simulations using JIT-CKPT and 10% RTJs, which we consider as a very reasonable scenario for practical realization (It is relatively easier to convince the HPC administrators to support a small percentage of RTJs) The results show that across all the categories, the JIT-CKPT significantly reduces RTJs slowdown by 35% (from 1.94 in the baseline to 1.25), while only increasing BJs slowdown by 10% (from 2.26 to 2.51). Furthermore, when broken into the four job categories, 3 of the categories have a BJs slowdown increase under 10%. Narrow-short jobs are the only category that doesn’t, and in this case, the BJs slowdown values go from 1.68 to 1.94 which we argue is still a reasonable slowdown value for these types of jobs. All four categories experience significant improvement in slowdown performance for RTJs ranging from 20% for narrow-short jobs, since the baseline value was already very low, to 60% for wide-long jobs (from 3.0 to 1.2), to 80% for wide-narrow jobs (from 24.40 to 5.06). Thus, the categories that have the highest slowdown values for RTJs are also the categories that experience the largest performance improvements. One unusual data point to point out is that in the wide-short figure (Fig. 6), the average RTJ slowdown value for APP-CKPT-10% with 5% RTJs is higher than even the top whisker. This is likely simply due to a very small number of data points (5), and thus it only takes one large value to bring the average much higher than the boxplots.

For the sake of space, we don’t discuss in detail the average turnaround time performance details; how-
ever, as shown in the figures the trends and relative performance variations are similar to those experienced by the average slowdown values.

There may exist batch jobs which are unable to checkpoint. In such cases, the changes in the heuristic would be minimal since the heuristic can handle such un-checkpointable workloads as non-preemptible batch jobs, which will worsen the slowdowns of real-time jobs depending on the percentage of un-checkpointable workloads.

7.3 Comparison with MILP-based formulation

To evaluate the performance of our heuristic, the Weighted Cost Job Scheduling Algorithm, against the near-optimal scheduling, we compare with our optimal offline scheduling formulation for small problem sizes. Recall that the MILP-based formulation has limitations in scheduling large problem sizes. The major differences of the optimal formulation from the WCJS algorithm are:

- The formulation obtains the optimal solution.
- The formulation schedules jobs given in advance (i.e., offline scheduling) while the WCJS schedules jobs in an online fashion. The offline scheduling definitely shows better performance than the online scheduling.
- The formulation permits at most one preemption of a BJ whereas the WCJS has no limitation on that.
- The formulation allows a BJ to preempt other BJs whereas the WCJS allow only RTJs to preempt BJs.
- The formulation strictly restrict the upper limit of SD of RTJ to $SD_{RTJ_{thresh}}(=1.2)$.

We randomly generated 20 job logs with 5 BJs and 2 RTJs where the size of the available nodes is 8096 nodes, and accordingly, the requested node size of jobs are also randomly chosen in the set of {512, 1024, 2048, 4096, 8192}. Table 3 shows the comparison of the formulation and WCJS heuristic results. The WCJS heuristic with JIT-CKPT shows 69% and 38% worse than the optimal formulation in terms of BJ and RTJ slowdowns, respectively. This suggests that there are still opportunities for improvement for the WCJS such as taking multiple jobs in wait queues into account when scheduling.

8 Conclusion

We evaluate how existing HPC platforms can accommodate real-time jobs in this paper. We first present the results of applying existing basic techniques to this problem and show mathematical formulations as mixed-integer linear programming to compute near-optimal solutions. We then propose the weighted-cost job scheduling heuristic for practical deployment to overcome the high time complexity of mixed-integer linear programming. The results show that with 10% real-time job percentages, just-in-time checkpointing method combined with our heuristic could improve the slowdowns of real-time jobs by 35% while limiting the increase of the slowdowns of batch jobs to 10%. Based on the comparison results with mixed-integer linear programming, we believe there is still a room for improvement. Our results are promising for existing HPC platforms to accommodate real-time workflow applications, the newly emerging applications if the platforms support checkpointing methods and the scheduler algorithms deploy our proposed heuristics.

Acknowledgment

We thank the Argonne Leadership Computing Facility at Argonne National Laboratory for providing the Mira trace log used in this study.
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