RCA: A Resourceful Coordination Approach for Multilevel Scheduling

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Abstract

HPC users aim to improve their execution times without particular regard for increasing system utilization. On the contrary, HPC operators favor increasing the number of executed applications per time unit and increasing system utilization. This difference in the preferences promotes the following operational model. Applications execute on exclusively-allocated computing resources for a specific time, and applications are assumed to utilize the allocated resources efficiently. In many cases, this operational model is inefficient, i.e., applications may not fully utilize their allocated resources. This inefficiency results in increasing application execution time and decreasing system utilization. In this work, we propose a resourceful coordination approach (RCA) that enables the cooperation between, currently independent, batch- and application-level schedulers. RCA enables application schedulers to share their allocated but idle computing resources with other applications through the batch system. The effective system performance (ESP) benchmark is used to assess the proposed approach. The results show that RCA increased system utilization up to 12.6% and decreased system makespan by the same percent without affecting applications' performance.

Keywords: Dynamic load balancing; Self-scheduling; System utilization; System makespan; Slurm; SimGrid
1 Introduction

Modern HPC systems exhibit parallelism at various hardware levels (node, socket, core, vector unit, etc.). The efficient utilization of these levels of parallelism becomes more challenging with the increase of the degree of parallelism within each level. When a large-scale HPC system wastes only 1% to 10% of its computing cycles, it wastes energy that could support a small city [1]. In practice, HPC users aim to improve their execution times without particular regard for increasing the HPC system utilization. This leads to the following operational model: applications execute on a set of exclusively-allocated computing resources for a certain time (space policy), and applications are assumed to utilize the allocated resources efficiently via efficient domain decomposition and work assignment (balanced execution).

Dynamic resource allocation (DRA) plays a significant role in increasing the usage efficiency of HPC systems [2, 3]. A batch system, also known as a resource and job management system (RJMS), is the middleware responsible for resource allocation (RA) and for managing job execution on the allocated resources [4]. A batch system supports DRA if it implements scheduling policies that can increase or decrease the number of allocated resources of a given job. A job is an instance of an application that requires a certain amount of computational resources to execute on. Evolving jobs can request more or fewer resources than their current allocation based on the evolution of their computational load during the execution [5, 6]. Malleable jobs need to adapt to new resource allocations smoothly [5]. In practice, production RJMS systems, such as Slurm [7] and Torque [8], support static resource allocation (SRA), where the number of the allocated resources is defined before the job execution and cannot subsequently be changed. Certain research efforts have extended production RJMS to support malleability [9, 10].

Node sharing can also significantly improve system utilization via the simultaneous execution of multiple applications on the same computing node [11]. The main challenge to achieve efficient node sharing is to identify applications that do not share the same set of resources. Node sharing is much easier to implement than DRA. Node sharing does not require any changes or support from applications and/or their underlying programming paradigms. Early research efforts introduced the PARbench which is a benchmark that assesses the performance impact of running multiple jobs in a multiprogramming environment [12, 13]. The results showed that the performance impact varies from being significant to be minor based on the configuration of the system and the job requirements. This large variation makes node sharing not a common approach in practice, i.e., HPC users mainly have performance concerns that may arise from sharing node-level resources.

The current work introduces a resourceful coordination approach (RCA) to increase system utilization via coordination between batch and application schedulers. RCA enables cooperation between the currently independent batch and application schedulers. It enables application schedulers to share their allocated but idle computing resources with other applications through the...
batch system. The proposed resourceful coordination approach is not an explicit dynamic resource allocation nor a node sharing approach but a unique approach that leverages the advantages of both of these approaches. It offers an efficient idle resource sharing without shrink or expansion operations on the application side.

To implement RCA a Slurm-based simulator [11] is employed as a batch scheduling framework together with a SimGrid-based simulator [14] as an application scheduling framework. Both SimGrid-based and Slurm-based simulators have been shown to be realistic in terms of the close agreement between results obtained natively via direct experiments on HPC systems and results obtained via simulation [11, 14].

To assess the usefulness of RCA, we employ the effective system performance benchmark (ESP) [15], and instantiate it with two workloads. The computational load of the first workload is represented by a computationally-intensive parallel application called parallel spin-image algorithm (PSIA) [16] form computer vision, while the second workload is represented by a well-known parallel kernel, the Mandelbrot set [17]. For each job, three application-level scheduling techniques, called static [18], guided self-scheduling [19], and adaptive factoring [20], are used to balance applications’ execution on their assigned resources. The experimental results showed that RCA increased system utilization up to 12.6% and decreased the system makespan by the same percent without affecting applications’ performance.

This work makes the following contributions: (1) Introduces RCA as a cooperation approach between batch and application-level schedulers. (2) Converts a Slurm-based simulator [11] into an event-based simulator to evaluate the proposed approach. This extension yields deterministic and reproducible results. (3) Enables simulations of HPC workloads at fine (tasks within applications) and coarse (jobs within a workload) scales. To gain additional in-depth insights into the system and applications performance, we visualize the simulation events collected at both batch- and application-level by converting them to an OTF2-based trace that is compatible with trace visualization tools, such as Vampir [21].

The significance of the present work is that RCA allows static RA to overcome the low system utilization, while avoiding the overhead of traditional DRA. The implementation extensions introduced in the Slurm simulator, convert it into an event-based simulator. This conversion is critical for simulations of high performance computing systems, as it delivers deterministic and results.

The remainder of the paper is organized as follows. Section 2 provides the background on batch- and application-level scheduling. The most relevant research efforts are surveyed and reviewed in Section 2. The proposed resourceful coordination approach (RCA) is presented in Section 3, with details about the extensions introduced to existing batch and application simulators. In Section 4 the evaluation methodology and results are presented and discussed. The paper concludes and outlines directions for future work in Section 5.
2 Background and Related Work

**Background.** RJMS employ various batch scheduling techniques, such as the first-come-first-serve (FCFS) which schedules next the job with the earliest arrival time. In practice, HPC system administrators employ a simple configuration of FCFS with backfilling (BF) \[22\]. Backfilling is a supporting scheduling technique that helps to increase system utilization by executing small jobs (which request a small number of computing resources) when there are insufficient available computing resources to assign to the highest priority jobs in the queue.

At the application level, we consider three application level scheduling techniques: static (STATIC) \[18\], guided self-scheduling (GSS) \[19\], and adaptive factoring (AF) \[20\]. STATIC \[18\], also known as straightforward parallelization, assigns each computing resource a chunk of loop iterations (or tasks) equal to $\lceil \frac{N}{P} \rceil$, where $N$ and $P$ are the total number of loop iterations and the total number of computing resources, respectively. GSS is a dynamic self-scheduling technique that uses a non-linear function to self-schedule a decreasing chunk sizes. At every scheduling step, GSS divides the remaining loop iterations by the total number of processing elements. AF \[20\] is an adaptive self-scheduling technique that is based on the factoring (FAC) technique \[23\]. FAC requires prior knowledge of the mean $\mu$ and the standard deviation $\sigma$ of the loop iterations execution times. Unlike FAC, AF learns both $\mu$ and $\sigma$ for each computing resource during applications’ execution to ensure full adaptivity to all factors that cause load imbalance.

**Related Work.** A notable research effort implemented an elastic execution framework for MPI applications \[9\]. The framework introduced certain extensions to the MPI standard and to the Slurm RJMS. These extensions permit dynamic change of the number of processes of a given application in a way that addresses several challenges of the original dynamic process support of the MPI standard. The extensions included four new MPI functions. The elastic framework requires application scientists to use the new MPI functions to support application malleability.

This elastic MPI framework has the same goal as RCA. However, RCA shifts the responsibility of releasing or requesting computing resource to the application scheduler rather than the application code itself. Moreover, in RCA, allowing one application to share idle computing resources with others does not require shrinking operation at the side of that application. This keeps the overhead low.

The dynamic resource ownership management (DROM) is a recent research effort that allows RJMS to address the efficient resource usage challenge \[24\]. Compared to the elastic MPI framework \[9\], the DROM APIs provide effortless malleability for RJMS that requires no change in applications’ source codes. The DROM APIs exploit the finest level of parallelism to support application malleability, i.e., changing the number of the threads assigned to a computing resource to create a new room for other applications on the same computing resource. One may use the DROM APIs with load balancing libraries similar to LeWI \[25\] (LeWI is a runtime library that uses standard mechanisms, such as OMPT \[26\] to monitor application execution.). LeWI can enhance application...
performance and increase resource utilization of individual computing nodes.

The DROM APIs and the LeWI library are similar to RCA in the current work in the sense that we address the challenge of efficient resource usage, while our target is to enable cooperation between the scheduling of different applications via batch systems. For instance, waiting or running applications (need more computing resources) may communicate their needs to the RJMS, which requests other MPI-based applications to stop scheduling any workload on the required computing resources for a certain period of time. In this scenario, the schedulers of different applications cooperate with each others through the RJMS. When an application scheduler decides not to schedule any workload on a certain process, the process can be entirely suspended by the operating system and their computing resource can be used by other applications.

Other research efforts that are relevant to the present work include the recent advancements in the Slurm Simulator \cite{27}. There are two distinctive versions of the Slurm Simulator Slurm V1 \cite{28,29,30} and Slurm V2 \cite{31,11}. Slurm V2 is extensively simplified compared to Slurm V1, i.e, Slurm V2 serializes the code on a single process, called sim_controller. Such a simplification can been seen as a disadvantage because the simulator loses certain features, e.g., plugins that are used inside a Slurm node. However, the same simplification can also be seen as an advantage when the target simulation scenarios do not use nor depend on these feature. This yields a clear code that is easier to extend, maintain, and debug. Slurm V2 comes with a detailed documentation on how to reuse and extend. Therefore, the present work uses and extends Slurm V2. RCA is independent of the simulator and the same extensions can also be implemented in Slurm V1.

3 Resourceful Coordination Approach for Multilevel Scheduling

The resourceful coordination approach (RCA) requires information exchange between batch and application level schedulers: (1) From the application schedulers to the batch scheduler. The application schedulers report the status of their free computing resources and the remaining amount of work. (2) From the batch scheduler to the application schedulers. The batch scheduler can take advantage of knowing the execution history of certain applications and can benefit from additional hints that the user may provide, such as expected applications’ execution time, communication/computation ratio, etc. The information exchange allows the batch scheduler to reuse computing resources as soon as they become idle, and there are no more tasks from the job that can be assigned to them. User hints allow the batch scheduler to identify applications that experience minimal performance degradation when they exclude a specific number of their allocated resources. The exclusion means that the application schedulers will not schedule further tasks on the excluded resource. This exclusion differs from shrinking the resource allocation of malleable jobs. In RCA, the application still owns the
temporarily relinquished computing resource, but it allows other applications
use it. RCA allows application schedulers to accept or reject resource exclusion
requests from the batch scheduler.

Figure 1 illustrates three executing applications (App1, App2, App3) and
two queued applications (App4 and App5). First-come-first-serve (FCFS) is
employed at the batch-level to schedule the five jobs. App4 has higher priority
than App5. App4 requests four computing resources and only two resources
are available: R9 and R10. However, the batch system cannot start App4 due
to insufficient free resources. In this case, existing batch scheduling systems
would leave App4 waiting in the queue and R9 and R10 idle until one of the
executing applications finish. In contrast, in RCA, the batch system receives
information from application schedulers during applications’ execution. App1
and App3 report that R4 and R7 became free. R4 and R7 can be reassigned to
other applications through the batch system. The information from App1 and
App3 may be reported at different times. Once the batch system receives these
two reports, and if App4 is still in the queue, the batch system can assign R4,
R9, R10, and R7 to App4 which can then begin execution.

The batch system can identify (based on applications’ execution history) ap-
lications that can relinquish certain resources without performance degradations.

Figure 1: Proposed resourceful coordination approach (RCA) in which applica-
tions (e.g., App1, App4) cooperate by yielding idle resources (e.g., R4) through
the batch system.

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In the example illustrated in Figure 1, the batch system identified App2 as such an application. The application scheduler of App2 rejected the request and did not release any resources. In RCA, the batch scheduler does not control the ALS decisions. Application schedulers can reject the release of resource requests. Accepting or rejecting batch requests can be seen as a higher level of cooperation than reporting resource idle time that can be enabled or disabled based on users’ preferences. Moreover, the batch system leaves the decision regarding which resource to be freed to the application scheduler.

RCA separates concerns between BLS and ALS. BLS provides the required number of resources to waiting jobs, while ALS decides which resource(s) is (are) ready to be released right away. This separation eliminates BLS’ need to employ techniques that extrapolate and predict future resource requirements for executing applications. ALS schedulers always have information about the remaining computational workload. With RCA, this information can easily be shared with BLS.

Design details: At batch-level scheduling, the current work employs the widely used Slurm simulator [27]. We extend one of the latest versions of the Slurm simulator [11] to support RCA, modifications being listed in Listing 1.

Listing 1: Batch-level scheduling

```c
slurm_sim_controller(){
  read_slurm_sim_configuration(sim_config);
  extract_als_configuration(als_config);
  sim_read_job_trace(trace_head);
  synchronize_with_app_simulator(als_config);
  while True do
    run_scheduling_round();
    update_SimGrid_simulation_clock();
    if no_jobs_to_submit() then
      if no_running_apps() then
        collect_simulation_trace();
        end_app_simulator();
        exit();
      sim_submit_jobs();
      sim_process_finished_jobs();
      sim_cancel_jobs();
      sim_schedule();
      sim_run_priority_decay();
      schedule_plugin_run_once();
      sim_sinfo();
    sim_squeue();
  }
}
```

Listing 1, Line 2 shows the new code we added to allow the Slurm simulator
to read ALS information, such as the ALS scheduling method. Line 3 represents the modified code that extends the Slurm simulator to accept workloads in the standard workload format (SWF) \[32\]. This modification enables the simulation of various workloads from production HPC systems that are available in the public workload archive \[32\]. Lines 4 to 12 represent new added code that connects the SimGrid-based simulator with the Slurm simulator. Hence, the SimGrid-based simulator works as an *internal clock* for the Slurm simulator. SimGrid simulations are event-based simulations, and consequently, the simulation time is only advanced by the occurrence of simulation events. In our approach, the simulation time is advanced only when scheduling events happen at either the batch- or application-level. Lines 13 to 16 represent certain functions of the original Slurm simulator \[11\] that we extended to produce or consume scheduling events of the SimGrid-based simulator.

The communication between the two simulators employs a shared data structure called \textit{all_apps}, which holds all information about jobs’ execution (Line 1 in Listing 2). Scheduling events, such as starting a job on a specific set of resources, are produced by the Slurm-based simulator and stored in the \textit{all_apps} data structure. Also, scheduling events, such as job completion, are produced by the SimGrid-based simulator and are stored in the \textit{all_apps} data structure. Each simulator consumes the events produced by the other simulator.

At application-level scheduling, the present work designs and extends an accurate SimGrid-based simulator \[14\] that is used to simulate applications’ executions with various DLS techniques by *simultaneously* simulating the execution of several applications running on the same simulated HPC platform. The intention behind this difference is to let the simulator account for application interference. Earlier research efforts \[33, 14\] focused on the study of applications’ performance under various scheduling techniques. In contrast, the current work relaxes the assumption of applications executing on separate sets of resources during their entire execution, thereby increasing the realism of the simulation.

Listing 2 shows a single scheduling round of our extended SimGrid-based simulator. A scheduling round refers to a scanning procedure where all simulated applications and their assigned resources are examined to identify the idle resources and to self-schedule the remaining work. Listing 2 illustrates the logic of the function \textit{run_scheduling_round()} of Listing 1.

For native Slurm RJMS, the BLS-ALS communication can be implemented via remote procedure call (RPC) similar to the communication between the Slurm daemons (slurmct1 and slurmd). The Slurm daemons periodically exchange messages to monitor resources’ status. These small messages have minimal impact on the performance of the running application. The BLS-ALS communication are not periodic and they are occasionally sent. For instance, BLS-ALS communication messages are sent when the originating entity is not executing any workload. The BLS-ALS communication messages in that sense will not degrade applications’ performance.
Listing 2: Application-level scheduling

```
run_scheduling_round(){
    foreach app in all_apps do
        unscheduled = check_unscheduled_tasks(app);
        hosts = get_free_hosts(app);
        foreach host in hosts do
            if unscheduled > 0 then
                scheduling_method= scheduling_method(app);
                tasks=chunk_size(app, scheduling_method);
                schedule_tasks(host, tasks);
                unscheduled = unscheduled - tasks;
            release_host(host,app);
    }
/*scheduling round in SimGrid*/
```

4 Experimental Design and Evaluation

**Experimental design:** In all experiments reported herein, a simulated platform with 256 compute hosts is used. A fully-connected network topology is used to connect all hosts. The network fabric is assumed InfiniBand like with link bandwidth and latency of 50 Gbps and 500 ns, respectively.

The effective system performance (ESP) [15] benchmark is used to evaluate the usefulness of the proposed approach. ESP gives a description of batch workloads that can be used to assess batch systems’ performance. The description includes guidelines regarding the total number of jobs, estimated job execution time, number of requested resources per job, and job arrival times [15, 3, 4]. Table 1 illustrates the characteristics of the ESP system benchmark, which consists of 230 jobs divided into 14 job categories. Jobs of different categories require various numbers of computing resources, from 3.12% to 100% of the available computing resources. For instance, one job in Category A requires 8 computing resources (3.12% of the entire system), while one job in Category Z requires 256 computing resources (the entire system).

Another essential factor in the ESP system benchmark is the job arrival time. The ESP designers suggested a job arrival scheme in which Category Z jobs arrive in such a way that they divide the arrival timeline into 3 parts [15]. This means that jobs arrive during the batch execution. This arrival pattern prevents the batch scheduler from knowing the entire workload before the execution, which would be unrealistic. Figure 2 shows the job submission time for each job of the ESP. Once a full-size job (Job of Category Z) is submitted, no other jobs are submitted for a specific amount of time that is equal to 10% of the ESP workload makespan.

ESP jobs are synthetic and can be represented by various applications [15]. Here, we exemplify the ESP system benchmark with the PSIA and Mandelbrot applications. We generate and use two different workloads of the ESP system.
### Table 1. Characteristics of the two implemented versions of the ESP system benchmark: ESP-PSIA and ESP-Mandelbrot.

| Category ID | Requested Hosts | Total Jobs | ESP-PSIA #images | ESP-Mandelbrot #iterations |
|-------------|-----------------|------------|------------------|---------------------------|
| A           | 8               | 75         | 32 K             | 0.635 M                   |
| B           | 16              | 9          | 76.5 K           | 1.2 M                     |
| C           | 128             | 3          | 800 K            | 15 M                      |
| D           | 64              | 3          | 582 K            | 8.5 M                     |
| E           | 128             | 3          | 595 K            | 8.8 M                     |
| F           | 16              | 9          | 440 K            | 6.5 M                     |
| G           | 32              | 6          | 635 K            | 1 M                       |
| H           | 40              | 6          | 630 K            | 10 M                      |
| I           | 8               | 24         | 170 K            | 3.35 M                    |
| J           | 16              | 24         | 174.5 K          | 2.75 M                    |
| K           | 24              | 15         | 172.6 K          | 2.85 M                    |
| L           | 32              | 36         | 172.5 K          | 2.725 M                   |
| M           | 64              | 15         | 176.5 K          | 2.65 M                    |
| Z           | 256             | 2          | 375 K            | 5.25 M                    |

A benchmark called ESP-PSIA and ESP-Mandelbrot. PSIA and Mandelbrot are chosen to represent two extremes of interest for testing our approach: a balanced execution (PSIA) and a highly load imbalanced execution (Mandelbrot). Moreover, individual research efforts [14, 35] proposed an accurate and verified representation of the computational workload of both applications in SimGrid. A mixed workload that comprises both applications is planned as immediate future work.

PSIA [16] is a computationally-intensive application from computer vision.
Figure 3: Load imbalance profile of the jobs within the ESP-PSIA and ESP-Mandelbrot workloads. The ratio max/mean indicates the degree of balanced execution for each job $J_x^i$, where $x$ is a job category (see Table 1) and $i$ ranges according to the size of each job category. Values that are close to 1 denote a balanced execution.
that consists of a large loop that dominates the entire execution. Loop iterations in PSIA have different computational loads and require efficient loop scheduling to achieve a balanced execution of these iterations. Various dynamic scheduling techniques can achieve a balanced execution for PSIA. Consequently, there are few differences in computing resource finishing times that execute the PSIA application. Such times are important in this work as they represent idle resources that can be relinquished. The Mandelbrot set is a well-known mathematical kernel. It contains a set of irregular and independent loops and has been used to evaluate DLS techniques in the literature [36, 37].

The last two columns of Table 1 show the characteristics of the two versions of the ESP system benchmark workload that contain PSIA and Mandelbrot jobs. Various input parameters control the execution of PSIA and Mandelbrot [16, 17]. One parameter for each application is changed to let the applications meet the job execution category of the ESP [3]. For PSIA, #images indicates the total number of generated spin-images. For Mandelbrot, #iterations indicates the maximum number of iterations per pixel. The two parameters are chosen because they had a linear relation to the application execution time. Therefore, it is more precise to estimate their initial values that meet the job execution category.

Figure 3 shows the load imbalance profile of the two versions of the ESP system benchmark: ESP-PSIA and ESP-Mandelbrot. The metric \( \frac{\text{max/mean}}{\text{mean}} \) denotes the ratio between the finishing time of the latest computing resource and the average finishing time of all computing resources that execute a certain job. When the ratio \( \frac{\text{max/mean}}{\text{mean}} \) of a certain job is very close to one, the job has a balanced load execution on its allocated resources.

**Experimental Evaluation and Discussion:** System utilization (SU) is an important metric that indicates the efficiency of batch scheduling techniques. We calculate SU as shown in Eq. (1) where \( T_k \) is the time that a computing resource \( k \) spent executing jobs, \( P \) is the total number the computing resources, and \( T_{\text{batch}} \) denotes the system makespan measured as the total execution time of the entire batch, i.e., \( T_{\text{batch}} = T_j - T_i \), where \( T_i \) is the time when the first job starts execution and \( T_j \) is the time when the last job in the batch completes execution. System utilization ranges from 0% to 100%. Higher values of system utilization indicate better system performance.

\[
SU = \frac{\sum_{k=0}^{P-1} T_k}{P \times T_{\text{batch}}} \times 100 \tag{1}
\]

Figure 4 shows the system utilization over batch execution time for the ESP-PSIA with and without the proposed approach. When our resourceful

| BLS workload            | BLS technique | ALS technique |
|-------------------------|--------------|---------------|
| ESP PSIA-based          | FCFS with BF | STATIC/ FAC/ AF |
| ESP Mandelbrot-based    |              |               |

Table 2. Details of the factorial experimental design for the performance evaluation of the proposed approach
scheduling approach is not enabled in the simulation, the makespan of the ESP-PSIA using STATIC, GSS, and AF is 13,000, 12,875, and 12,875 seconds, respectively (see Figure 4a). This corresponds to the increase in the system utilization in Figure 4a; the GSS and AF curves are slightly higher than the STATIC curve.

Figure 4b shows that the system makespan improved with our resourceful scheduling approach. For instance, the system makespan for ESP-PSIA with STATIC is 12,965 instead of 13,000 seconds. For GSS and AF the improvement is not impressive. As mentioned earlier, ESP-PSIA is an extreme case of a highly balanced execution. This means that the differences in resource finishing times that execute the PSIA application are minimal. In this case, RCA has limited advantage. One can still notice that the gap in system utilization when using STATIC, GSS, and FAC with RCA (see Figure 4b) is slightly smaller than the gap in Figure 4a that is without RCA.

![Figure 4: System utilization of ESP-PSIA](image)

For ESP-Mandelbrot, Figure 5 shows that RCA increased the average system utilization when the jobs used STATIC from 71.2% to 83.82%. When jobs are executed using GSS and AF, RCA is only able to increase the average system utilization by 0.5% and 0.05%, respectively. This is because AF can achieve a highly balanced execution of all jobs. By enabling our resourceful scheduling approach, the system makespan of the ESP-Mandelbrot using STATIC is reduced from 11,020 to 8,840 seconds (see Figures 5a and 5b).

When all jobs are highly load balanced, our approach offers slight improvements in terms of increasing system utilization. However, the slight improvements in system utilization are of high value for HPC operators as they translate into efficient power consumption [1]. Future work will explore the relation between RCA and the power consumption efficiency.
Because of the new feature we added to the Slurm simulator [31], we are also able to visualize the execution trace of the workload at coarse- and fine-grain scales. The left side of Figure 6a shows the entire ESP-Mandelbrot execution trace in which STATIC is used at the ALS, FCFS+BF is used at the BLS, and the proposed resourceful ordination approach is not enabled. The right side of Figure 6a is a horizontal zoom into the timeline of the execution trace between 415–550 seconds. Zooming this close helps to understand the poor system utilization, i.e., why jobs J8, J9, J10, and J11 wait for the latest computing resources of job J7 to become free.

Figure 6b shows the execution trace of the same scenario (STATIC at ALS and FCFS+BS at BLS) with the proposed resourceful coordination approach enabled. At the coarse-grain time scale (left side), the intensity of the green color (busy computing resources) is higher in Figure 6b than Figure 6a. The total system makespan is shorter in Figure 6b than Figure 6a by 1,413 seconds. On the right side of Figure 6b (horizontal zoom from 415 to 550 seconds), due to the usage of the proposed resourceful coordination approach, jobs J8, J9, J10, and J11 started earlier than in Figure 6a. This reduces the idle times of the computing resource and increases the overall system utilization.

Jobs J8, J9, J10, and J11 in Figure 6b are assigned to non-contiguous hosts compared to their resource allocation in Figure 6a. In practice, such a non-contiguous resource allocation may cause performance degradation for communication-intensive applications. The applications PSIA and Mandelbrot used in the current work are computationally-intensive. Therefore, such a non-contiguous allocation bears no effect on their simulated performance. Future work will include further analysis of the performance advantages and disadvantages of RCA in the case of mixed types of applications (computation-,
Figure 6: Visualization (obtained using Vampir [21]) of the execution trace of the ESP-Mandelbrot workload. STATIC is used at the ALS, while FCFS+BF is used at the BLS. White spaces indicate idle computing resources, while colors denote executing jobs. The short timeline on the right side of each sub-figure is a zoom into a certain time interval of the timeline on the left side.
5 Conclusion and Future Work

The present work proposed a resourceful coordination approach (RCA) that allows application schedulers to cooperate by involving the batch scheduler. We implemented the proposed approach in a two-level simulation using realistic and well-known simulators (a Slurm-based simulator \[31\] and a SimGrid-based simulator \[14\]). The effective system performance (ESP) benchmark was used to assess the proposed approach by instantiating it with the parallel spin-image generation and the Mandelbrot set.

Our proposed RCA increased the entire system utilization by 12.6% and decreased the system makespan by the same percent when applications suffered from severe load imbalance. When application execution was balanced, e.g., when employing AF for ESP-Mandelbrot, RCA increased the entire system utilization by 0.5% as there were few idle system resources to exploit. These improvements at the system level are important to eliminate unnecessary system waste, and consequently, unnecessary energy waste, which instead could be used to support small cities \[1\]. The present work also shows that for long-executing HPC applications, exploiting computing resources’ idle times (in the order of a few seconds) can significantly improve the entire system utilization. Prior to this work, it was commonly accepted that short computing resource idle times should be filled by Big Data workloads \[38\]. The current work highlighted the potential of exploring such idle times also for HPC workloads.

Our extensions to the Slurm-simulator \[31\] enabled the visual analysis of the workload execution at coarse- and fine-grain temporal resolutions using Vampir \[21\]. The visual analysis showed that using our approach idle resources were exploited efficiently, while jobs were not assigned to contiguous computing resources. Such a non-contiguous resource allocation may cause performance degradation for communication-intensive applications which were not in the scope of the present work but planned as future work.

Future work also includes porting our changes to the latest source code of Slurm. This porting will enable RCA assessment in a real production environment, including more HPC applications. Communication between the application schedulers and the batch system requires standardization. Several APIs offer such communication \[24, 9\] and will be evaluated in future work. Since our approach does not depend on a specific RJMS, we plan to explore the integration of RCA approach into modern and future RJMS, such as Flux \[39\]. Extend RCA to include information exchange about other computing resources, such as GPUs and co-processors, is also planned for the future.
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