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## An RMS for Non-predictably Evolving Applications

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INSTITUT NATIONAL DE RECHERCHE EN INFORMATIQUE ET EN AUTOMATIQUE

# *An RMS for Non-predictably Evolving Applications*

Cristian KLEIN and Christian PÉREZ

**N° 7644 — version 2**

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Domaine 3

A large blue rectangle occupies the lower half of the page. On the left side of this rectangle, there is a large, light grey 'R' logo. To the right of the 'R', the words 'Rapport de recherche' are written in a white, italicized serif font. A horizontal grey brushstroke is positioned below the text.

*Rapport  
de recherche*



## An RMS for Non-predictably Evolving Applications

Cristian KLEIN and Christian PÉREZ

Domaine : Réseaux, systèmes et services, calcul distribué  
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**Abstract:** Non-predictably evolving applications are applications that change their resource requirements during execution. These applications exist, for example, as a result of using adaptive numeric methods, such as adaptive mesh refinement and adaptive particle methods. Increasing interest is being shown to have such applications acquire resources on the fly. However, current HPC Resource Management Systems (RMSs) only allow a static allocation of resources, which cannot be changed after it started. Therefore, non-predictably evolving applications cannot make efficient use of HPC resources, being forced to make an allocation based on their maximum expected requirements.

This paper presents COORMv2, an RMS which supports efficient scheduling of non-predictably evolving applications. An application can make “pre-allocations” to specify its peak resource usage. The application can then dynamically allocate resources as long as the pre-allocation is not outgrown. Resources which are pre-allocated but not used, can be filled by other applications. Results show that the approach is feasible and leads to a more efficient resource usage.

**Key-words:** resource management; supercomputers; clusters; evolving applications; malleability.

## Un gestionnaire de ressources pour les applications évolutives

**Résumé :** Les applications évolutives non-prédictibles sont des applications, dont les besoins en ressources changent en cours d'exécution. Leurs comportements proviennent, par exemple, des méthodes numériques adaptatives, comme le raffinement de maillage adaptatif et les méthodes de particules adaptatives. Il y a un intérêt croissant à ce que ce type d'application acquiert des ressources à la volée. Cependant, les gestionnaires de ressources haute performance (HPC) ne supportent qu'une allocation statique des ressources, qui ne peut donc pas changer après le démarrage de l'application. Par conséquent, les applications évolutives non-prédictibles ne peuvent pas utiliser les ressources HPC de manière efficace, car elles sont forcées de faire une demande de ressources en fonction de leurs pics de besoins.

Cet article présente COORMv2, un gestionnaire de ressources qui permet l'ordonnancement efficace d'applications évolutives non-prédictibles. Une application peut faire des « pré-allocations » pour exprimer ses pics de besoins en ressources. Ensuite, l'application peut dynamiquement allouer de manière sûre des ressources tant que la pré-allocation n'est pas dépassée. Les ressources pré-allouées, mais inutilisées, sont à la disposition des autres applications. Les résultats montrent que l'approche est réalisable et que l'utilisation des ressources est améliorée.

**Mots-clés :** gestion des ressources; supercalculateurs; grappes de calcul; applications évolutives; malléabilité.

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## 1 Introduction

High-Performance Computing (HPC) resources, such as clusters and supercomputers, are managed by a Resource Management System (RMS) which is responsible for multiplexing resources among multiple users. Generally, computing nodes are space-shared, which means that a user gets an exclusive access. Requesting a resource allocation is mostly done using *rigid* jobs: the user requests a number of nodes for a limited duration, then the RMS decides when the allocation is served.

Increased interest has been devoted to giving more flexibility to the RMS, as it has been shown to improve resource utilization [1]. If the RMS can reshape a request, but only before the allocation starts, the job is called *moldable*. Otherwise, if the RMS can change the allocation while it is served, the job is called *malleable*. Taking advantage of moldable jobs often comes for free, as commonly used programming models (e.g., MPI) are already suitable for creating moldable applications. However, writing malleable applications is somewhat more challenging as the application has to be able to reconfigure itself during execution. How to write malleable applications [2, 3] and how to add RMS support for them [4, 5, 6] has been extensively studied.

Improving utilization can be done further by supporting *evolving* applications. These are applications which change their resource requirements during execution as imposed by their internal state. Unlike malleability, the change of the resource allocation is not imposed by the RMS, but by the nature of the computations. Being able to provide applications with more nodes and memory on the fly is considered necessary for achieving exascale computing [7].

We define three types of evolving applications: (i) **fully-predictable**, whose evolution is known at start (e.g., static workflows), (ii) **marginally-predictable** (e.g., non-DAG workflows containing branches), whose evolution can only be predicted within a limited horizon of prediction, and (iii) **non-predictable**, whose evolution cannot be known in advance. Non-predictably evolving applications (NEA) are more-and-more widespread, due to the increased usage of adaptive numeric methods, such as Adaptive Mesh Refinement (AMR) [8] and Adaptive Particle Methods (APM) [9].

Unfortunately, support for evolving applications is insufficient in current RMSs. In batch schedulers, evolving applications are forced from the beginning to allocate enough resources to fulfill their peak requirements. In Clouds, which support dynamic provisioning, large-scale resource requests may be refused with an “out-of-capacity” error, thus, allocating resources on the fly may lead to the application reaching an out of memory condition.

This paper proposes COORMv2 an RMS that enables efficient scheduling of evolving applications, especially non-predicable ones. It allows applications to inform the RMS about their maximum expected resource usage (using **pre-allocations**). Resources which are pre-allocated but unused can be filled by malleable applications.

The main contribution of the paper is three-fold: (i) to devise a model for NEAs based on AMR applications; (ii) to propose COORMv2 an extension to our previous RMS, for efficiently supporting such applications; (iii) to show that the approach is feasible and that it can lead to considerable gains.

The remaining of this paper is organized as follows. Section 2 motivates the work and refines the problem statement by presenting a model of an AMR application. Section 3 introduces COORMv2, a novel RMS which efficiently supports various types of applications as shown in Section 4. Section 5 evaluates the approach and highlights the gains that can be made. Section 6 discusses related work. Finally, Section 7 concludes the paper and opens up perspectives.

## 2 A Model for Non-Predictably Evolving Applications

This section presents a model of a non-predictably evolving application based on observations of AMR applications. First, the evolution of the working set size and the speed-up of the application are modeled. Second, the model is analyzed and the problem statement is refined.

### 2.1 Working Set Evolution Model

Our goal is to devise a model for simulating how the data size evolves during an AMR computation. In order to have a model which is parametrizable, we first devise a “normalized” evolution profile, which is independent of the maximum size of the data and the structure of the computations. The model has

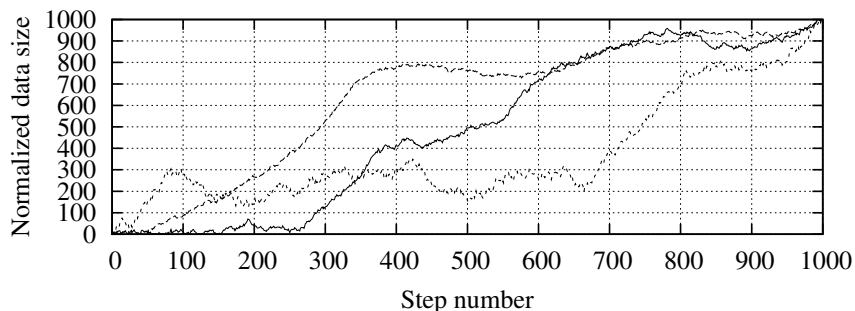


Figure 1: Examples of obtained AMR working set evolutions.

to be simple enough to be easy to analyze and use, but at the same time it should resemble observed behaviors. To this end, we consider that the application is composed of 1000 steps. During step  $i$  the size of the data  $s_i$  is considered constant ( $s_i \in [0, 1000]$ ).

Unfortunately, we have been able to find only a few papers on the evolution of the refined mesh. Most of the papers focus either on providing scalable implementations [10] or showing that applying AMR to a certain problem does not reduce its precision as compared to a uniform mesh [8]. From the few papers we found [11, 12], we extracted the main features of the evolution: (i) it is mostly increasing; (ii) it features regions of sudden increase and regions of constancy; (iii) it features some noise.

Using the above constraints, we derive the following model, that we call the **acceleration-deceleration model**. First, let the evolution of the size of the mesh be characterized by a velocity  $v_i$ , so that  $s_i = s_{i-1} + v_i$ . The application is assumed to be composed of multiple *phases*. Each phase consists of a number of steps uniform randomly distributed in  $[1, 200]$ . Each step  $i$  of an even phases increases  $v_i$  ( $v_i = v_{i-1} + 0.01$ ), while each step  $i$  of an odd phases decreases  $v_i$  ( $v_i = v_{i-1} \times 0.95$ ). Next, a Gaussian noise of  $\mu = 0$  and  $\sigma = 2$  is added. The above values have been chosen so that the profiles resemble the ones found in the cited articles. At the end, the profile is normalized, so that the maximum of the series  $s_i$  is 1000.

To obtain the actual, non-normalized data size profile  $S_i$  at step  $i$ , given the maximum data size  $S_{\max}$ , one can use the following formula:  $S_i = s_i \times S_{\max}$ . Figure 1 shows some examples of data size evolutions returned by the model, which are compatible with those presented in [11, 12].

## 2.2 A Speed-up Model

The next issue is to find a function  $t(n, S)$  that returns the duration of a step, as a function of the number of allocated nodes  $n$  and the size of the data  $S$ . Both  $n$  and  $S$  are assumed constant during a step.

Instead of having a precise model (such as in [13]) which would be applicable to only one AMR application, we aimed at finding a simple formula, which could be fit against existing data. To this end, we chose to use the data presented in [14] as it shows both strong and weak scalability of an AMR application for data sizes which stay constant during one experiment. After trying several functions and verifying how well they could be fit, we found a good one to be:

$$t(n, S) = A \times \frac{S}{n} + B \times n + C \times S + D$$

The terms of this formula can be intuitively explained. Term  $A$  expresses the part of the computation which is perfectly parallelisable. Term  $B$  is the overhead of the parallelization, such as the extra effort to keep track of all the nodes in the system or the extra cost of collective communication. Term  $C$  is the time payed by each nodes per unit of data, the limiting factor for a good weak scalability. Finally,  $D$  is a constant term.

Figure 2 presents the result of logarithmically fitting this formula against actual data. The model fits within an error of less than 15% for any data point. The values of the parameters, used in the rest of the paper, are:  $A = 7.26 \times 10^{-3} \text{ s} \times \text{node} \times \text{MiB}^{-1}$ ,  $B = 1.23 \times 10^{-4} \text{ s} \times \text{node}^{-1}$ ,  $C = 1.13 \times 10^{-6} \text{ s} \times \text{MiB}^{-1}$ ,  $D = 1.38 \text{ s}$ ,  $S_{\max} = 3.16 \text{ TiB}$ .



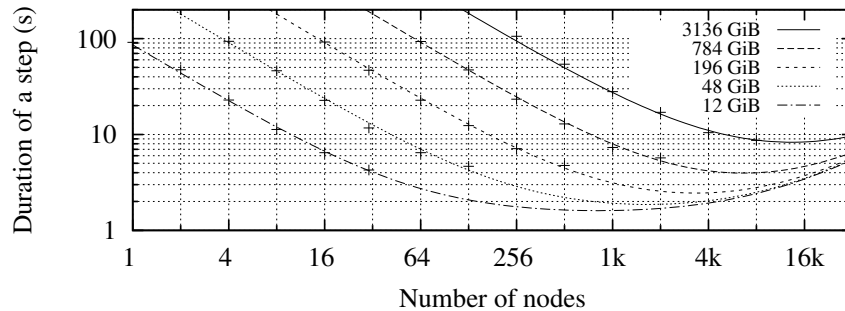


Figure 2: Fitting the AMR speed-up model against the actual data for different mesh sizes.

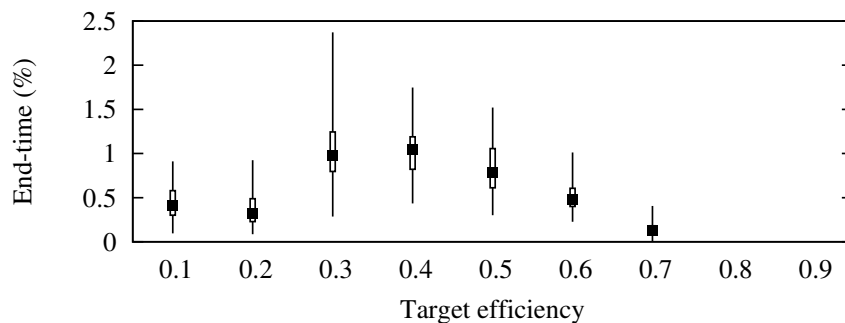


Figure 3: End-time increase when an equivalent static allocation is used instead of a dynamic allocation.

### 2.3 Analysis of the Model

Let us analyze the model and refine the problem statement. Users want to adapt their resource allocation to a target criterion. For example, depending on the computational budget of a scientific project, an application has to run at a given **target efficiency**. This allows scientists to receive the results in a timely fashion, but at the same time control the amount of used resources.

To run the above modeled application at a target efficiency  $e_t$  throughout its whole execution, given the evolution of the data size  $S_i$ , one can compute the number of nodes  $n_i$  that have to be allocated during each step  $i$  of the computation. Let us denote the consumed resource area (node-count  $\times$  duration) in this case  $A(e_t)$ . In practice, while executing the application, one does not need any a priori knowledge of the size of the data, as  $n_i$  only depends on the current  $S_i$ .

However, most HPC resource managers do not support dynamic resource allocations, which forces a user to request a static number of nodes. Let us define the **equivalent static allocation** a number of nodes  $n_{eq}$  which, if assigned to the application during each step, leads to the consumed resource area  $A(e_t)$ . Computing  $n_{eq}$  requires to know all  $S_i$  a priori. Using simulations, we found that  $n_{eq}$  exists for  $e_t < 0.8$ . Of course, with a static allocation, some steps of the application run more efficiently, while others run less efficiently than  $e_t$ . However, interestingly, the end-time of the application increases with at most 2.5% (Figure 3). We deduce that, if users had an *a priori* knowledge of the evolution of the data size, they could allocate resources using a *rigid* job and their needs would be fairly well satisfied.

Unfortunately, the evolution of an AMR application is generally not known a priori, which makes choosing a static allocation difficult. Let us assume that a scientist wants to run her application efficiently. E.g., she wants her application not to run out of memory, but at the same time, she does not want to use 10% more resources than  $A(75\%)$ . Figure 4 shows the range of nodes the scientist should request, depending on the maximum data size  $S_{max}$ . We observe that taking such a decision without knowing the evolution of the application in advance is difficult, in particular, if the behavior is highly unpredictable.

**Ideally**, a distinction should be made between the resources that an evolving application expects to use in the worst case and the resources that it actually uses. The unused resources should be filled by malleable applications, that can free these resources if the evolving application requests them. However, since applications might belong to different users, this cannot be done without RMS support. The next section proposes such an RMS.

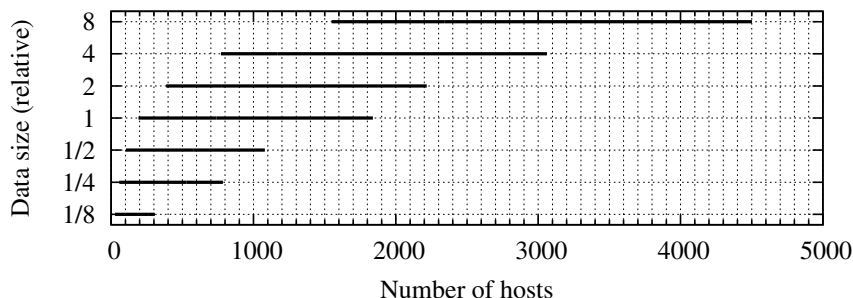


Figure 4: Static allocation choices for a target efficiency of 75%.

### 3 CooRMv2

This section introduces COORMv2, an RMS which allows to efficiently schedule malleable and evolving applications, whether fully-, marginally- or non-predictable. First, it explains the concepts that are used in the system (Section 3.1). Second, an RMS implementation is proposed (Section 3.2). The section concludes by showing an example of interaction between the RMS, a malleable application and an evolving application (Section 3.3).

#### 3.1 Principles

At the core of the RMS-Application interaction are four concepts: requests, request constraints, high-level operations and views. Let us detail each one of them.

##### 3.1.1 Requests

A **request** is a description, sent by applications to the RMS, of the resources an application wants to have allocated. As in usual parallel batch schedulers, a request consists of the number of nodes (node-count), the duration of the allocation and the cluster on which the allocation should take place<sup>1</sup>. It is the RMS that computes a start-time for each request. When the start-time of a request is the current time, node IDs are allocated to the request and the application is notified.

COORMv2 supports the following three request types. **Non-preemptible** requests (also called run-to-completion, default in most RMSs [16]) ask for an allocation that once started cannot be interrupted by the RMS. **Preemptible** requests ask for an allocation that can be interrupted by the RMS, whenever it decides to, similar to OAR’s best-effort jobs [17].

In order to allow a non-predictably evolving application to inform the RMS about its maximum expected resource usage, COORMv2 supports a third request type which we shall call **pre-allocation**. No node IDs are actually associated with the request, the goal of a pre-allocation being to allow the RMS to mark resources for possible future usage. In order to have node IDs allocated, an application has to submit non-preemptible requests inside the pre-allocation. Pre-allocated resources cannot be allocated non-preemptibly to another application, but they can be allocated preemptibly.

Section 4 shows that these types of requests are sufficient to schedule evolving and malleable applications.

##### 3.1.2 Request Constraints

Since COORMv2 deals with applications whose resource allocation can be dynamic, each application is allowed to submit several requests, so as to allow it to express varying resource requirements. However, the application needs to be able to specify some constraints regarding the start-times of the requests relative to each other. To this purpose, each request  $r$  has two more attributes: **relatedTo**—points to an existing request (noted  $r_p$ )—and **relatedHow**—specifies how  $r$  is constrained with respect to  $r_p$ .

COORMv2 defines three possible values for **relatedHow** (Figure 5): **FREE**, **COALLOC**, and **NEXT**. **FREE** means that  $r$  is not constrained and **relatedTo** is ignored. **COALLOC** specifies that  $r$  has to start at the

<sup>1</sup>In practice, separate batch queues are used for each cluster [15].

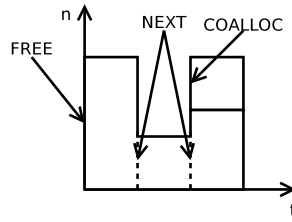


Figure 5: Visual description of request constraints (Section 3.1.2).

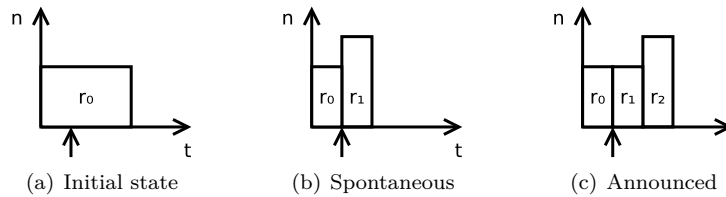


Figure 6: Performing an update.

same time as  $r_p$ . **NEXT** is a special constraint that specifies that  $r$  has to start immediately after  $r_p$ , with  $r$  and  $r_p$  sharing common resources. If  $r$  requests more nodes than  $r_p$ , then the RMS will allow the application to keep the resources allocated as part of  $r_p$  and will send additional node IDs when  $r$  is started. If  $r$  requests fewer nodes than  $r_p$ , then the application has to release node IDs at the end of  $r_p$ .

### 3.1.3 High-Level Operations

Let us now examine how applications can use the request types and constraints to fulfill their need for dynamic resource allocation.

Having defined the above request types and request constraints, the targeted applications only need two low-level operations: **request()** adds a new request into the system, while **done()** immediately terminates a request (i.e., its duration is set to the current time minus the request's start-time) and, for requests constrained with **NEXT**, specifies which node IDs have been released. Using these two operations, an application can perform high-level operations. We shall present two of which are the most relevant: spontaneous update and announced update.

A **spontaneous update** is the operation through which an application immediately requests the allocation of additional resources. It can be performed by calling **request()** with a different node-count, then calling **done()** on the current request. Given the initial request state in Fig. 6(a), Fig. 6(b) shows the outcome of a spontaneous update.

An **announced update** is the operation through which an application announces that it will require additional resources at a future moment of time (i.e., after an **announcement interval** has passed), thus allowing the system (and possible other applications) some time to prepare for the changes of resource allocation. It can be performed by first calling **request()** with a node-count equal to currently allocated number of nodes and a duration equal to the announcement interval, then calling **request()** with a new node-count and, finally, calling **done()** on the current request (see Figure 6(c)).

Note that, in order to guarantee that an update is successful (i.e., the RMS can allocate additionally requested resources), updating non-preemptible requests can only be guaranteed if they can be served from a pre-allocation.

### 3.1.4 Views

For the targeted applications, simply sending requests to the RMS is not enough. Applications need to be able to adapt their requests to the availability of the resources. For example, instead of requesting a large number of nodes which are available only at a future time, a moldable application might want to request fewer nodes to reduce its waiting time, thus reducing its end-time.

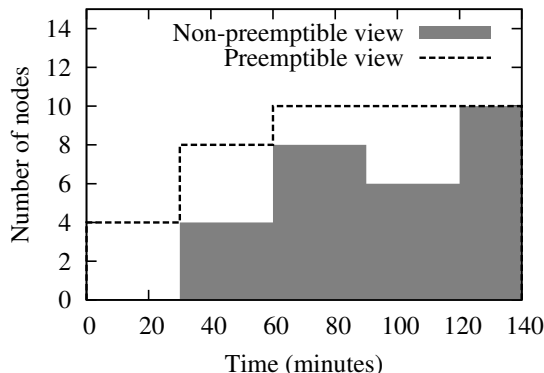


Figure 7: Example of views for one cluster.

To this end, the RMS provides each application a **view** containing the current and future availability of resources. Views should be regarded as the *current information* that the RMS has, but should not be taken as a guarantee. Applications can scan their view and estimate when a request would be served by the RMS. This helps moldable applications as they do not need to emulate the scheduling algorithm of the RMS. When the state of the resources changes, the RMS will push new views to the applications, so that they can update their requests, if necessary.

On a more technical note, a view stores for each cluster a step function, that stores the **cluster availability profile**: the x-axis is the absolute time and the y-axis is the number of available nodes as illustrated in Figure 7.

In CoORMv2, two types of views are sent to each application  $i$ : **non-preemptive** ( $V_{-P}^{(i)}$ ) and **preemptive view** ( $V_P^{(i)}$ ). The former allows applications to estimate when pre-allocations and non-preemptive requests will be served, while the latter allows it to estimate when preemptive requests will be served.

The preemptive view is also used to signal an application, that it has to release some preemptively allocated resources, either immediately or at a future time. In CoORMv2, each application is supposed to cooperate and immediately release node IDs when it is asked to, using the above presented update operation. Otherwise, if a protocol violation is detected, the RMS kills the application's processes and terminates the session with it.

### 3.2 RMS Implementation

This section presents an RMS implementation that we have realized. A CoORMv2 RMS has three tasks: (i) for each application  $i$  compute a non-preemptible ( $V_{-P}^{(i)}$ ) and a preemptible view ( $V_P^{(i)}$ ), (ii) compute the start-time of each request and (iii) start requests and allocate node IDs.

For brevity, only a high-level description of the implementation is given. The RMS runs a scheduling algorithm whenever it receives a **request** or **done** message. In order to coalesce messages coming from multiple applications at the same time and reduce system load, the algorithm is run at most once every **re-scheduling interval**, which is an administrator-chosen parameter. A value for this parameter is given in Section 5.

The scheduling algorithm goes as follows. Applications are sorted in a list based on the time the applications connected to the RMS. First, pre-allocation requests are scheduled using Conservative Back-Filling (CBF) [18]. Next, inside these pre-allocations, non-preemptible requests are scheduled. Non-preemptible requests which cannot be served from pre-allocations are implicitly wrapped in pre-allocations of the same size. The remaining resources are used to schedule preemptible requests.

Regarding preemptive views and the start-time of preemptive requests, they are computed so as to achieve equi-partitioning. However, should an application not use its partition, other applications are allowed to fill it in.

The proposed scheduling algorithm has a linear complexity with respect to the number of requests in the system. We have developed a Python implementation (with more compute-intensive parts in C++)

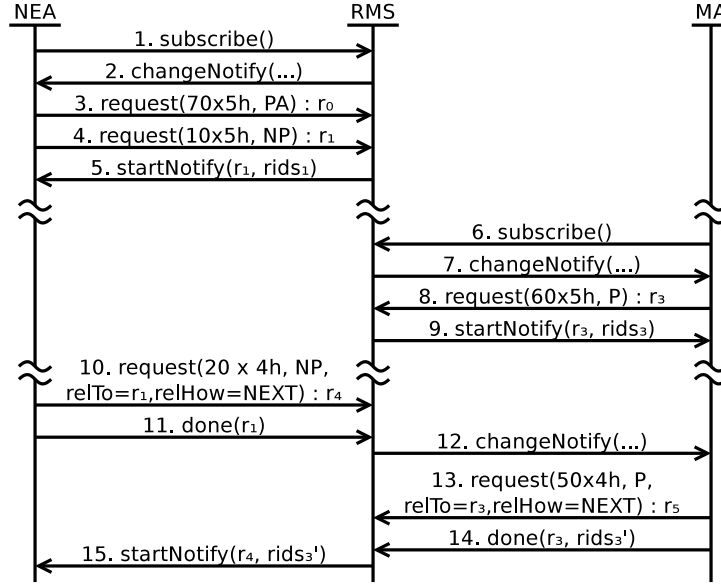


Figure 8: Example of an interaction between the RMS, a Non-predictably Evolving Application and a Malleable Application.

which is able to handle approximately 500 requests/second on a single core of an Intel® Core™2 Duo CPU @ 2.53 GHz.

The above implementation is just one possible implementation and can easily be adapted to other needs. For example, the amount of resources that an application can pre-allocate can be limited, by clipping its non-preemptible view.

### 3.3 Example Interaction

Let us describe the RMS-Application protocol using an example. Assume there is one NEA and one malleable application in the system (see Figure 8). First, the NEA connects to the RMS (step 1). In response, the RMS sends the corresponding views to the application (step 2). The NEA sends a pre-allocation (step 3) and a first non-preemptible request (step 4), to which the RMS will immediately allocate resources (step 5). Similar communication happens between the RMS and the malleable application, except that a preemptible request is sent (step 6–9). As the computation of the NEA progresses, it requires more resources, therefore, it performs a spontaneous update (step 10–11). As a result, the RMS updates the view of the malleable application (step 12), which immediately frees some nodes (step 13–14). Then, the RMS allocates these nodes to the NEA (step 15).

## 4 Application Support

This section evaluates how the COORMv2 architecture supports the types of application presented in Section 1.

A **rigid application** sends a single non-preemptible request of the user-submitted node-count and duration. Since the application does not adapt, it ignores its views.

A **modal application** waits for the RMS to send a non-preemptive view, then runs a resource selection algorithm, which chooses a non-preemptible request. Should the state of the system change before the application starts, the RMS shall keep it informed by sending new views. This allows the application to re-run its selection algorithm and update its request, similarly to COORM [19].

A **malleable application** first sends a non-preemptible request  $r_{min}$  with its minimum requirements. Next, for the extra resources (i.e., the malleable part), the application scans its preemptive view  $V_P$  and sends a preemptible request  $r_{extra}$ , which is COALLOCated with  $r_{min}$ .  $r_{extra}$  can either request a node-count equal to the node-count in  $V_P$ , or it can request fewer nodes. This allows an application to select

only the resources it can actually take advantage of. For example, if the malleable application requires a power-of-two node-count, but 36 nodes are available in its preemptive view, it can request 32 nodes, leaving the other 4 to be filled by another application. During execution, the application monitors  $V_P$  and updates  $r_{extra}$  if necessary.

A **fully-predictably evolving application** sends several non-preemptible requests linked using the NEXT constraint. During its execution, if from one request to another the node-count decreases, it has to call `done` with the node IDs it chooses to free. Otherwise, if the node-count increases, the RMS sends it the new node IDs.

A **non-predictably evolving application** (NEA) first sends a pre-allocation request (whose node-count is discussed below), then sends an initial non-preemptible request. During execution, the application updates the non-preemptible request as the resource requirements change. Since such updates can only be guaranteed as long as they happen inside a pre-allocation, such an application may adopt two strategies: sure execution or probable execution.

The application can opt for a **sure execution**, i.e., uninterrupted run-to-completion, if it knows the maximum node-count ( $n_{max}$ ) it may require. To adopt this strategy, the size of the pre-allocation must be equal to  $n_{max}$ . In the worst case,  $n_{max}$  is the whole machine.

Otherwise, if the application only wants **probable execution**, e.g., because pre-allocating the maximum amount of required resources is impractical, then the application sends a “good-enough” pre-allocation and optimistically assumes never to outgrow it. If at some point the pre-allocation is insufficient, the RMS cannot guarantee that updates will succeed. Therefore, the application has to be able to checkpoint. It can later resume its computations by submitting a new, larger pre-allocation. Note that, in this case, the application might further be delayed as the RMS might have placed it at the end of the waiting queue.

If multiple NEAs enter the system two situations may occur. Either their pre-allocations are small enough to fit inside the system simultaneously, in this case the NEAs are launched at the same time, or their pre-allocations are too large to fit simultaneously, in which case the one that arrived later will be queued after the other. In both cases, the RMS is able to guarantee that whenever one of the NEAs requests an update inside its pre-allocation, it can actually be served. Resources that are pre-allocated to a NEA, but not allocated, cannot be non-preemptively allocated to another application. However, these resources can be filled by the malleable part of other applications. This approach is evaluated in the next section.

## 5 Evaluation

This section evaluates COORMv2. First, the application and resource models are presented. Next, the impact on evolving and malleable applications is analyzed.

The evaluation is based on a discrete-event simulator, which simulates both the COORMv2 RMS and the applications. To write the simulator, we have first written a real-life prototype RMS and synthetic applications. Then, we have replaced remote calls with direct function calls and calls to `sleep()` with simulator events.

### 5.1 Application and Resource Model

As other works which propose scheduling new types of application [6], we shall only focus on the malleable and evolving applications, which can fully take advantage of COORMv2’s features. Therefore, we shall not evaluate our system against a trace of rigid jobs [20] as is commonly done in the community. Nevertheless, as shown in Section 4, the proposed system does support such a usage.

For the evaluation, two applications are used: a non-predictably evolving AMR and a malleable parameter-sweep application. Let us present how the two applications behave with respect to COORMv2.

#### 5.1.1 AMR Application

A synthetic AMR application is considered, which behaves as a non-predictably evolving application with a sure execution (see Section 4). The application knows its speed-up model, but cannot predict how the working set will evolve (see Section 2). Knowing only the current working set size, the application tries to target an efficiency of 75% using spontaneous updates.

The user submits the application by trying to “guess” the node-count  $n_{eq}$  of the equivalent static allocation (defined in Section 2). The application uses this value for its pre-allocation. Inside this pre-allocation, non-preemptible allocations are sent/updated, so as to keep the application running at the target efficiency.

Since the user cannot determine  $n_{eq}$  a priori, her guesses will be different from this optimum. Therefore, we introduce as a simulation parameter the **overcommit factor**, which is defined as the ratio between the node-count that the user has chosen and the best node-count assuming a posteriori knowledge of the application’s behavior.

### 5.1.2 Parameter-Sweep Application (PSA)

Inspired by [21], we consider that this malleable applications is composed of an infinite number of single-node tasks, each of duration  $d_{task}$ . As described in Section 4, the PSA monitors its preemptive view. If more resources are available to it than it has currently allocated, it updates its preemptive request and spawn new processes. If the RMS requires it to release resources immediately, it kills a few tasks then updates its request. The computations done so far are lost. We measure the **PSA waste** which is the number of node-seconds wasted in such a case.

If the RMS is able to inform the PSA in a timely manner that resources will become unavailable, then the PSA waits for some tasks to complete, afterwards it updates its request to release the resources on which the completed tasks ran. No waste occurs in this situation.

### 5.1.3 Resource Model

We assume that resources consist of one single, large homogeneous cluster of  $n$  nodes. The re-scheduling interval of the RMS is set to 1 second, to obtain a very reactive system.

## 5.2 Scheduling with Spontaneous Updates

This experiment evaluates whether CoORMv2 solves the initial problem of efficiently scheduling NEAs.

Two applications enter the system: one AMR and one PSA ( $PSA_1$  with  $d_{task} = 600$  s). Since we want to highlight the advantages that supporting evolving applications in the RMS brings, we shall schedule the AMR application in two ways: **dynamic**, in which the application behaves as described above, and **static**, in which the application is forced to use all the resources it has pre-allocated.

Regarding the resources, the number of nodes  $n$  is chosen so that the pre-allocation of the AMR application can succeed. By observing the behaviour of the application during some preliminary simulations, we concluded that for an overcommit factor of  $\phi$ , having  $n = 1400 \times \phi$  is sufficient.

Figure 9 shows the results of the simulations. Regarding the amount of resources effectively allocated to the AMR (AMR used resources), the figure shows that as the overcommit factor grows, a static allocation forces the application to consume more resources. This happens because, as the user chooses more nodes for the application than optimal, the application runs less efficiently. Moreover, the application is unable to release the resources it uses inefficiently to another application.

In contrast, a dynamic allocation allows the AMR application to cease resources it cannot use efficiently. Therefore, as the overcommit factor grows, a dynamic allocation allows the application to maintain an efficient execution. Note however, that thanks to the pre-allocation, if the resource requirements of the application increase, the application can request new resources and the RMS guarantees their timely allocation. Since, CoORMv2 mandates that preemptible resources be freed immediately, the impact on the AMR application is negligible.

In this experiment, the RMS allocates the resources that are not used by the AMR application to the malleable PSA. However, since the AMR application does spontaneous updates and the RMS cannot inform the PSA in a timely manner that it has to release resources, the PSA has to kill some tasks, thus, computations are wasted (Figure 9 bottom). Nevertheless, we observe that the amount of resources wasted is smaller than the resources which would be used by an inefficiently running AMR application.

The PSA waste first increases as the overcommit factor increases, then stays constant after the overcommit factor is greater than 1. This happens because once the AMR application is provided with a big enough pre-allocation, it does not change the way it allocates resources inside it.

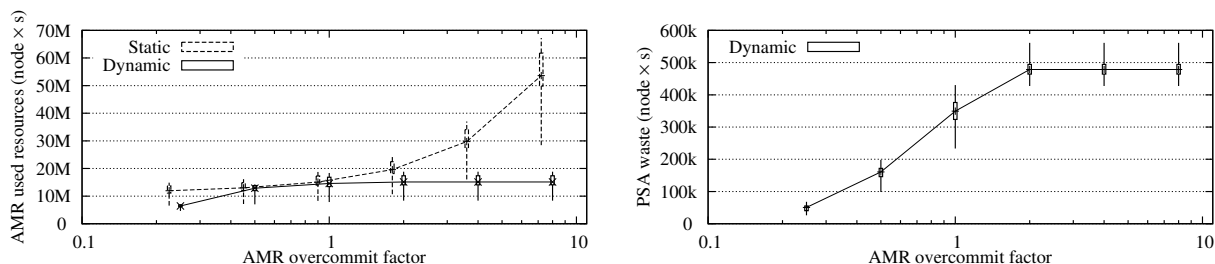


Figure 9: Simulation results with spontaneous updates.

To sum up, this experiment shows that, with proper RMS support, resources can be more efficiently used, if the system contains non-predictably evolving applications. Nevertheless, PSA waste is non-negligible, therefore, the next section evaluates whether using announced updates makes sense to reduce this waste.

### 5.3 Scheduling with Announced Updates

This section evaluates whether using announced updates can improve resource utilization. To this end, the behavior of the AMR application has been modified as follows. A new parameter has been added, the **announce interval**: instead of sending spontaneous updates, the application shall send announced updates (see Section 3.1.3). The node-count in the update is equal to the node-count required at the moment the update was initiated. This means that the AMR receives new nodes later than it would require to maintain its target efficiency. If the announce interval is zero, the AMR behaves as with spontaneous updates. Otherwise, the application behaves like a marginally-predictably evolving application.

For this set of experiments, we have set the overcommit factor to 1. The influence of this parameter has already been studied in the previous section.

Using announced updates instead of spontaneous ones has several consequences. On the negative side, the AMR application is allocated fewer resources than required, thus, its end-time increases<sup>2</sup> (see Figure 10). On the positive side, this informs the system some time ahead that new resources will need to be allocated, thus, it allows other applications more time to adapt.

Figure 10 shows that the PSA waste is decreasing as the announce interval increases. This happens because, in order to free resources, the PSA can gracefully *stop* tasks when they complete, instead of having to *kill* them. Once the announce interval is greater than the task duration  $d_{task}$ , no PSA waste occurs.

Let us discuss the **percent of used resources**, which we define as the resources allocated to applications minus the PSA waste as a percentage of the total resources. Figure 10 shows that announced updates do not generally improve resource utilization. This happens because the PSA cannot make use of resources if the duration of the task is greater than the time the resources are available to it. In other words, the PSA cannot fill resources unused by the AMR if the “holes” are not big enough: these “holes” are either wasted on killed tasks or released to the system. However, the higher the announce interval, the more resources the PSA frees, so that the RMS can either allocate them to another application (see next section), or put them in an energy saving mode.

We observe that the percent of used resources has two peaks, when the announce interval is 300 s and 600 s. In these two cases, a “resonance” occurs between the AMR and the PSA. The “holes” left by the AMR have exactly the size required to fit a PSA task. On the contrary, when the announce interval is just below the duration of the task (i.e., 550 s) the percent of used resources is the lowest, as the PSA has to kill tasks just before they end.

The resource utilisations shown in the graphs are higher than typically found in today’s computing centers, however, it has been shown that these values can easily be obtained using malleable jobs [1].

<sup>2</sup>Instead of sending the currently required node-count in the update, the application could use linear predictions and send a larger announced update. However, such an approach would increase the resource usage. This approach is outside the scope of this article.



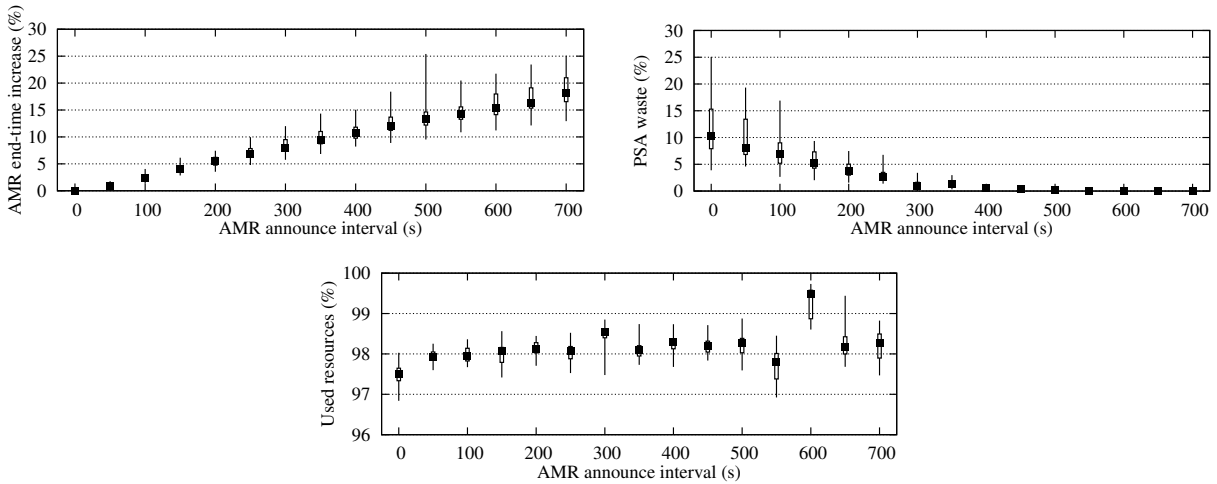


Figure 10: Simulation results with announced updates.

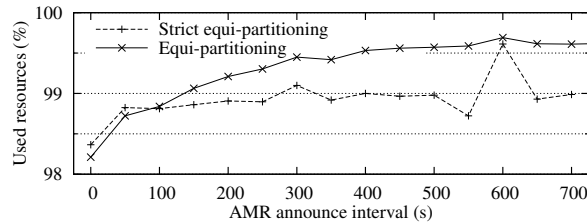


Figure 11: Simulation results for two PSAs.

## 5.4 Efficient Resource Filling

In the previous section, we have observed that while announced updates reduce PSA waste, they do not improve resource utilization. This happens because the PSA’s task duration is greater than the “holes” left by the AMR. In this section, we evaluate whether CoORMv2 is able to allocate such resources to another PSA, with a smaller task duration, in order to improve resource utilization.

To this end, we add another PSA in the system ( $PSA_2$  with  $d_{task} = 60$  s). By default, the RMS does equi-partitioning between the two PSA applications, however, when one of them signals that it cannot use some resources, the other PSA can request them.

To highlight the gain, we compare this experimental setup with an RMS which implements “**strict**” **equi-partitioning**: instead of allowing one PSA to fill the resources that are not requested by the other PSA, the RMS presents both PSAs a preemptible view, which makes them request the same node-count.

Figure 11 shows the percent of used resources. For readability, only medians are shown. Experiments show that CoORMv2 is able to signal  $PSA_2$  that some resources are left unused by  $PSA_1$ . Resource utilization is improved, because  $PSA_2$  is able to request these resources and do useful computations on them.

To sum up, CoORMv2 is able to efficiently deal with the applications it has been designed for: evolving and malleable. On one hand, evolving applications can efficiently deal with their unpredictability by separately specifying what their maximum and what their current resource requirements are. Should evolving applications be able to predict some of their evolution, they can easily export this information into the system. On the other hand, malleable applications are provided with this information and are able to improve resource usage.

## 6 Related Work

To our knowledge, Feitelson [22] was the first to distinguish applications with dynamic resource usage into those that initiate the change themselves (*evolving*) and those that adapt to RMS’s constraints

(*malleable*). Unfortunately, they are often ambiguously called “dynamic” applications in literature [6, 23]. Let us review RMSs which support these types of applications.

## 6.1 Malleable

ReSHAPE [6] is a framework for efficiently resizing iterative applications. After each iteration, applications report performance data to the RMS and the RMS attempts to divide resources, so as to optimize global speed-up. However, ReSHAPE assumes that all iterations of an application are identical and caches performance data. Therefore, applications whose iterations are irregular, such as AMR or APM applications, cannot be efficiently scheduled. Even if performance history were regularly flushed, ReSHAPE targets a specific type of applications, whereas COORMv2 also deals with other types of malleable application.

More general support for malleability can be found in KOALA [21]. Applications declare their minimum resource requirements, then the RMS divides the “extra” resources equally (*equi-partitioning*). The approach is appealing and has been successfully applied to scheduling Parameter-Sweep Applications (PSA) on idle resources. However, the minimum requirements are fixed at submittal and cannot be changed during the execution. Therefore, this solution cannot be used to schedule evolving applications.

The OAR batch scheduler supports low-priority, preemptible jobs called *best-effort*. If there are insufficient resources to serve a normal job, best-effort jobs are killed after a grace period. Best-effort jobs can be used to support malleability [5], therefore, this type of job has inspired COORMv2’s preemptible requests. However, best-effort jobs are killed even if only part of the allocated resources need to be freed. In contrast, COORMv2 allows an application to update its preemptible request and to free only as many resources as needed.

## 6.2 Evolving

In the Cloud Computing context, where consumed resources are paid for, great interest has been shown for applications that dynamically adapt their resource allocation to internal constraints [24]. However, most papers in this field only study how applications should adapt their resource requests, without studying how the RMS should guarantee that these resources can actually be allocated. Indeed, large-scale Cloud deployments can refuse an allocation request with an “out of capacity” error [25].

The Moab Workload Manager supports so-called “dynamic” jobs [23], which are both evolving and malleable: the application can grow/shrink both because its internal load changes and because the RMS asks it to. Moab regularly queries each application what its current load is, then it decides how resources are allocated. This feature has been mainly thought for interactive workloads and is not suitable for batch workloads. For example, if two non-predictably evolving applications arrive at the same time, instead of running them simultaneously, it might be better to run one after the other, so as to guarantee that peak requirements can be met. Also, Moab’s interface does not allow marginally- or fully-predictable applications to present their estimated evolution to the system.

In contrast, COORMv2 allow an application to pre-allocate resources, so that the RMS can guarantee their availability when the application needs them. If two applications potentially require a large amount of resources, they shall be executed one after the other, to guarantee their completion. An application which can predict its evolution can export this information into the system, so as to optimize resource usage.

## 7 Conclusion

This paper presented COORMv2, an RMS architecture which offers a simple interface to support various types of application, among others, malleable and fully-/marginally-/non-predictably evolving. Experiments showed that, if applications take advantage of the RMS’s features, resource utilization can be improved a lot, while guaranteeing that resource allocations are always satisfied.

Future work can be divided in two directions. First, it would be interesting to study how accounting should be done in COORMv2, so as to determine users to efficiently use resources. Second, COORMv2 was designed for managing homogeneous clusters and assumes that the choice of node IDs can be left to

the RMS. However, supercomputers feature a non-homogeneous network [26], therefore, an extension to CoORMv2 should allow network-sensitive applications to optimize their placements on such platforms.

## 8 Acknowledgments

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## A RMS Implementation

This section gives details about the implementation of the RMS, which has been briefly presented in Section 3.2. First, the manipulated data structures are described in detail, next the pseudo-code of the implementation is given.

### A.1 Requests

Requests (defined in Section 3.1.1) stored inside the RMS have two types of attributes: those sent by the application and those set by the RMS. The attributes which are sent by the application are:

- `cid` – the ID of the cluster;
- `n` – the number of nodes;
- `duration` – the duration of the allocation;
- `type` – the type of the request: pre-allocation ( $PA$ ), non-preemptible ( $\neg P$ ) or preemptible ( $P$ );
- `relatedHow` – the type of constraint: `FREE`, `NEXT` or `COALLOC`;
- `relatedTo` – the request to which the start-time is constrained.

While computing a schedule, the RMS sets the following additional request attributes:

- `nalloc` – the number of nodes that will be effectively allocated (see details below);
- `scheduledAt` – the time at which the allocation of this request should start;
- `fixed` – the request is fixed, see Section A.4.1;
- `earliestScheduleAt` – earliest time when the request can be scheduled, see Section A.4.2.

To store information about requests after they started, the RMS sets the following attributes:

- `startedAt` – time when the request has started; if the request has not started yet, e.g., it has just been sent by the application, this attribute is set to `NaN`; `started( $r$ )` returns true if the request has been started.
- `nodeIDs` – the node IDs that have been allocated to this request.

Let us explain the purpose of the `nalloc` attribute. Assume there are two applications in the system: a malleable application  $A$  and an evolving application  $B$ . Let us assume the following scenario.  $A$  scans its preemptive view, finds out that additional resources are available for it and updates its preemptible request. At the same time,  $B$  needs more nodes, so it spontaneously updates its non-preemptible request. The changes induced by the two applications trigger the scheduling algorithm of the RMS. Due to the race between  $A$  and  $B$ , if insufficient resources are available for both applications, then the RMS cannot allocate the requested node-count to  $A$ . Therefore, in order to correctly compute new views and request start-times, `nalloc` stores the number of nodes which  $A$  can be allocated according to the current resource state. When a preemptible request is started, `nalloc` is used to decide how many node IDs to allocate. `nalloc` might be smaller than `n`, which, since preemptible requests are not guaranteed, is allowed by the COORMv2 specifications.

### A.2 Request Constraints

In COORMv2 each application is allowed to send multiple requests, thus the RMS needs to store for each application a **request set**. However, the RMS needs to treat requests of each type differently. Therefore, for each application  $i$ , the RMS stores three separate request sets: the set of pre-allocation requests  $R_{PA}^{(i)}$ , the set of non-preemptible requests  $R_{\neg P}^{(i)}$  and the set of preemptible requests  $R_P^{(i)}$ .

Inside a request set, the requests and their constraints form multiple trees. Indeed, requests which are unconstrained or whose constraints are outside the request set are the roots of distinct trees, while `COALLOC` or `NEXT` constraints determine parent-child relations (see Figure 12). Some of the algorithms that we shall present require navigating the request sets as a tree. Therefore, we define the following functions:

- `roots` :  $R \mapsto R_{\text{roots}}$ , returns the set of root requests in  $R$   
i.e., `roots( $R$ )` =  $\{r \in R, \text{ such that } r.\text{relatedHow} = \text{FREE} \vee r.\text{relatedTo} \notin R\}$
- `children` :  $r, R \mapsto R_{\text{children}}$ , returns the set of child requests of  $r$  which belong to  $R$   
i.e., `children( $r, R$ )` =  $\{r_c \in R, \text{ such that } r_c.\text{relatedTo} = r\}$

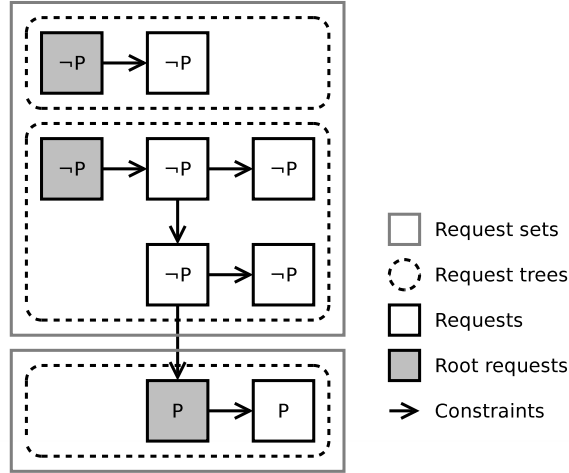


Figure 12: Example of request trees.

### A.3 Views

Views (as defined in Section 3.1.4) map a cluster ID  $\text{cid}$  to a Cluster Availability Profile (CAP), which is a step function: the x-axis represents the absolute time, while the y-axis represents the number of available nodes. The CAPs are stores as a list of duration, node-count pairs. For example,

$$V = \{a : [(3600, 4), (3600, 3)], b : [(\infty, 6)]\}$$

represents that on cluster  $a$ , 4 nodes are available for time  $t \in [0, 3600)$ , 3 nodes are available for time  $t \in [3600, 7200)$  seconds and 0 nodes are available for time  $t \in [7200, \infty)$ . On cluster  $b$ , 6 nodes are always available.

Let us define a few operations on views:

- we note  $V[\text{cid}]$  the step-function which corresponds to  $\text{cid}$  in the view  $V$ ; e.g., for the view above,  $V[a] = [(3600, 4), (3600, 3)]$ ;
- $\text{cap} : t \mapsto n$ , returns the number of nodes  $n$  available at time  $t$ ; e.g.,  $V[a](1800) = 4$ ,  $V[a](3600) = 3$ ,  $V[a](7200) = 0$ ;
- $\cup : V_1, V_2 \mapsto V_R$ , returns the **union** view  $V$  of the views  $V_1$  and  $V_2$ ; i.e.,  $V_1 \cup V_2 = V \Leftrightarrow V[\text{cid}](t) = \max(V_1[\text{cid}](t), V_2[\text{cid}](t)), \forall \text{cid}, t$ ;
- $+$  :  $V_1, V_2 \mapsto V_R$ , returns the **sum** view  $V$  of the views  $V_1$  and  $V_2$ ; i.e.,  $V_1 + V_2 = V \Leftrightarrow V[\text{cid}](t) = V_1[\text{cid}](t) + V_2[\text{cid}](t), \forall \text{cid}, t$ ;
- $-$  :  $V_1, V_2 \mapsto V_R$ , returns the **difference** view  $V$  of the views  $V_1$  and  $V_2$ ; i.e.,  $V_1 - V_2 = V \Leftrightarrow V[\text{cid}](t) = V_1[\text{cid}](t) - V_2[\text{cid}](t), \forall \text{cid}, t$ ;
- $\text{alloc} : V, r \mapsto n$ , returns the node-count that should be allocated to  $r$ , without changing its start-time, limited by the resources available in  $V$ . This function is used to compute  $\mathbf{n}_{\text{alloc}}$ . i.e.,  $\text{alloc}(V, r) = n \Leftrightarrow n = \min(\min_{t \in [r.\text{scheduledAt}, r.\text{scheduledAt} + r.\text{duration})} V[r.\text{cid}](t), r.n)$ ;
- $\text{findHole} : V, r, t_0 \mapsto t_s$ , returns the first time after  $\max(t_0, r.\text{earliestScheduleAt})$  when  $r$  could be started, so that all requested resources can be allocated; i.e., find  $t_s \geq \max(t_0, r.\text{earliestScheduleAt})$ , such that  $\min_{t \in [t_s, t_s + r.\text{duration})} V[r.\text{cid}](t) \geq r.n$

All above operations can be easily implemented by iterating through the list of duration, node-count pairs of the relevant CAPs. Due to their simplicity, the pseudo-code of the above operations is not given.

### A.4 Helper Functions

In order to ease the description of the main scheduling algorithm, three helper functions are defined. Their purpose is to transform a set of requests into a view (called *the generated view*), representing how

resources are being occupied by the input requests. Once a set of requests has been transformed into generated views, the above defined operations on views can be used to compute the resources that are left unused after a set of requests is served. The helper functions are: `toView`, `fit` and `eqSchedule`.

#### A.4.1 `toView()`

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**Algorithm 1:** Implementation of the `toView()` function

---

```

Input:  $R$ , set of requests
          $V_i$ , view of available resources (optional)
Output:  $V_o$ , view generated by requests
         The scheduledAt, n_alloc and fixed attributes of requests are updated

/* Initialization: start with an empty output view, clear fixed flag of requests
   and create an empty queue */
1  $V_o \leftarrow \emptyset$  ;
2 forall the  $r \in R$  do  $r.fixed \leftarrow false$  ;
3  $Q \leftarrow \emptyset$  /* Queue of requests which are to be processed */
   /* First, add started requests to queue */
4 forall the  $r \in R$ , such that started(r) do
5   | enqueue(Q, r) ;

   /* Next, process requests in the queue */
6 while  $Q \neq \emptyset$  do
7   |  $r = dequeue(Q)$  ;
8   | switch  $r.relatedHow$  do
9     | case FREE
10    |   |  $r.scheduledAt \leftarrow r.startedAt$  ;
11    | case NEXT
12    |   |  $r.scheduledAt \leftarrow r.relatedTo.scheduledAt + r.relatedTo.duration$  ;
13    | case COALLOC
14    |   |  $r.scheduledAt \leftarrow r.relatedTo.scheduledAt$  ;
15    | otherwise
16    |   | continue /* Constraint not implemented */
17   | if  $V_i = \emptyset$  then
18     |   |  $r.n_{alloc} = r.n$  ;
19   | else
20     |   |  $r.n_{alloc} = alloc(V_i, r)$  ;
21     |   |  $r.fixed \leftarrow True$  ;
22     |   |  $V_o \leftarrow V_o + \{r.cid : [(r.scheduledAt, 0), (r.duration, r.n_{alloc})]\}$  ;
   /* Enqueue children of this request */
23   | forall the  $r_c \in children(r)$  do
24     |   | enqueue(Q, r) ;

```

---

`toView()` (see Algorithm 1) generates a view representing resources occupied by **fixed requests**, defined as requests which are either started or are constrained to a fixed request. These requests are treated specially, because the RMS cannot choose a start-time for them anymore. Indeed, in order not to violate the COORMv2 protocol and allocate resources to applications according to their requests, the start-times are fixed. As a side effect, `toView()` sets the `scheduledAt`, `fixed` and `n_alloc` attributes of the input requests as needed.

For generating the view of preemptible requests, `toView()` accepts an optional parameter  $V_i$  representing the available resources. If this parameter is given, the generated view uses at most as many resources as available in  $V_i$ . The attribute `n_alloc` of preemptible requests is set according to this limit.

#### A.4.2 `fit()`

`fit()` (see Algorithm 2) generates a view representing resources that are occupied by non-fixed requests. The RMS has the liberty to choose the start-time for these requests, subject to the application-provided constraints.

The main idea of the algorithm is as follows. Each request has an `earliestScheduleAt` attribute, which specifies which is the time that the request can be scheduled the earliest. Initially, this attribute is set to  $t_0$ , which is input to the algorithm (line 3). Then, the algorithm uses a queue of requests it has to process, which is initially filled with all root requests (line 5). Each request is then dequeue (line 7) and, depending on the request's constraint, the `scheduledAt` attribute is computed (lines 14–33). If this attribute is changed, all child requests are queue, so as to recompute their `scheduledAt` attribute (lines 34–35).

In certain cases, the current schedule of the parent request makes it impossible for a child request to be scheduled so as to respect its constraint (lines 22, 31). If this happens, the `earliestScheduleAt` attribute of the parent is updated and the parent is added anew to the queue. This attribute is then used by `findHole` to find a later schedule-time for the parent, which might allow the child to find a valid schedule (lines 15, 21, 30). For preemptible requests, instead of delaying their parent, these requests are shrunken and `nalloc` is set accordingly (lines 19, 28). This behavior is allowed by the COORMv2 specifications.

Eventually, the algorithm converges and the `scheduledAt` attribute of all requests is stable (in worst case, all requests are scheduled at infinity). The `scheduledAt` and `nalloc` attributes of the requests are used to computed the generated view (lines 36–38).

#### A.4.3 `eqSchedule()`

The purpose of this function is to do the equi-partitioning of resources available for preemptible requests. It gets as input the preemptible request set of each application, the view representing the available resources for equi-partitioning and the time after which non-started requests have to be scheduled. It outputs for each application a preemptible view. As a side effect, the `scheduledAt` and `nalloc` attributes of requests are updated.

The pseudo-code is shown in Algorithm 3. It consists of three main parts. First, preliminary occupation views are computed (lines 1–3). These are used to determine time intervals, during which the requested node-count of all applications are constant. Second, for each piece-wise constant resource state (i.e., application resource request and available resources), the number of nodes that can be assigned to each application is determined (lines 4–27). Third, the computed views are used to reschedule the application requests and correctly set the `scheduledAt` and `nalloc` attributes of requests (lines 28–30).

The second part of the algorithm, which operates on a piece-wise constant resource state, works as follows. The system is either in a congested state, i.e., more resources are requested than are available for equi-partitioning, or the system is uncongested. The former situation might occur, due to the following reasons:

- since the last scheduling iteration, the number of resources for equi-partitioning has been reduced,
- a new application has chosen to participate in equi-partitioning,
- an application has decided to increase the requested node-count and use more of its partition.

If any of these situations occur, it is the duty of the RMS to inform malleable applications (by sending them new views), that they have to release some resources. The available resources are distributed equally, until the requests of applications are satisfied (lines 8–18).

In case the system is not congested (during a certain time interval), each application is assigned a view based on the number of resources that other applications leave unused (lines 19–25). However, this should not be smaller that the equi-partition of the application.

The number of equi-partitions is computed as follows (lines 22–23). Applications are either considered active, i.e., they currently request preemptible resources, or inactive. When computing the view of active applications, the number of partitions is equal to the number of active applications in the system. For inactive applications, the number of partitions is equal to the number of active applications in the system plus 1, i.e., the number of partitions if this application were to become active.



**Algorithm 2:** Implementation of the fit function

---

```

Input:  $R$ , set of requests (scheduledAt and fixed must have been set)
           $V_i$ , view of available resources
           $t_0$ , requests have to be scheduled after this time
Output:  $V_o$ , view generated by requests
          The scheduledAt and  $n_{\text{alloc}}$  attributes of non-fixed requests are updated
/* Initialization */
1  $Q \leftarrow \emptyset$  /* Queue of requests which are to be processed */
2 forall the  $r \in R$ , such that  $\neg r.\text{fixed}$  do
3    $r.\text{earliestScheduleAt} \leftarrow t_0$ ; /* No request can be scheduled earlier than  $t_0$  */
4    $r.\text{scheduledAt} \leftarrow \infty$ ; /* In case of error, the request never starts */
/* First, add root requests to queue */
5 forall the  $r \in \text{roots}(R)$  do enqueue( $Q, r$ );
/* Next, deal with each request */
6 while  $Q \neq \emptyset$  do
7    $r \leftarrow \text{dequeue}(Q)$ ;
8   if  $r.\text{fixed}$  then /* If this is a fixed request, just add children to queue */
9     forall the  $r_c \in \text{children}(r)$  do enqueue( $Q, r_c$ );
10    continue;
/* Take a decision for the current request, depending on its constraint */
11    $r_p \leftarrow r.\text{relatedTo}$ ; /* Store parent request to make pseudo-code briefer */
12    $r.n_{\text{alloc}} \leftarrow r.n$ ; /* Set a default value for  $n_{\text{alloc}}$  (will be overwritten later) */
13    $t_{\text{before}} \leftarrow r.\text{scheduledAt}$ ; /* Store the previous value, used to detect changes */
14   switch  $r.\text{relatedHow}$  do
15     case FREE  $r.\text{scheduledAt} = \text{findHole}(V_i, r, 0)$ ;
16     case COALLOC
17       if  $r.\text{type} = P \wedge r_p.\text{type} \in \{PA, \neg P\}$  then
18          $r.\text{scheduledAt} \leftarrow r_p.\text{scheduledAt}$ ;
19          $r.n_{\text{alloc}} = \text{alloc}(V_i, r)$ ;
20       else
21          $r.\text{scheduledAt} = \text{findHole}(V_i, r, r_p.\text{scheduledAt})$ ;
22         if  $r.\text{scheduledAt} \neq r_p.\text{scheduledAt}$  then
23            $r_p.\text{earliestScheduleAt} \leftarrow r.\text{scheduledAt}$ ;
24           enqueue( $Q, r_p$ );
25     case NEXT
26       if  $r.\text{type} = P$  then
27          $r.\text{scheduledAt} \leftarrow r_p.\text{scheduledAt} + r_p.\text{duration}$ ;
28          $r.n_{\text{alloc}} = \text{alloc}(V_i, r)$ ;
29       else
30          $r.\text{scheduledAt} = \text{findHole}(V_i, r, r_p.\text{scheduledAt} + r_p.\text{duration})$ ;
31         if  $r.\text{scheduledAt} \neq r_p.\text{scheduledAt} + r_p.\text{duration}$  then
32            $r_p.\text{earliestScheduleAt} \leftarrow r.\text{scheduledAt} - r_p.\text{duration}$ ;
33           enqueue( $Q, r_p$ );
/* If scheduledAt has changed, reschedule children */
34   if  $t_{\text{before}} \neq r.\text{scheduledAt}$  then
35     forall the  $r_c \in \text{children}(r)$  do enqueue( $Q, r_c$ )
/* Schedule converged, compute generated view */
36  $V_o = \emptyset$ ;
37 forall the  $r \in R$ , such that  $\neg r.\text{fixed}$  do
38    $V_o \leftarrow V_o + \{r.\text{cid} : [(r.\text{scheduledAt}, 0), (r.\text{duration}, r.n_{\text{alloc}})]\}$ ;

```

---

**Algorithm 3:** Implementation of the eqSchedule function

---

```

Input:  $R_P^{(i)}$ , for each application  $i$  ( $i = 1 \dots n_{app}$ ), the set of preemptible requests
           $V_{in}$ , view of available resources for equi-partitioning
           $t_0$ , non-started requests have to be scheduled after this time
Output:  $V_P^{(i)}$ , preemptive view of application  $i$ 
          The scheduledAt and n_allloc attributes of the requests are updated

/* Compute preliminary views of occupied resources */
1 for  $i \leftarrow 1$  to  $n_{app}$  do
2    $V_{occ}^{(i)} \leftarrow \text{toView}(R_P^{(i)}, V_{in})$ ;
3    $V_{occ}^{(i)} \leftarrow V_{occ}^{(i)} - \text{fit}(R_P^{(i)}, V_{in} - V_{occ}^{(i)}, t_0)$ ;
4 forall the  $cid \in \text{clusters}$  do
5   forall the  $t, d \in \text{time interval start-times and durations}$  do
6     /* Store requested and available node-counts during this interval */
7     for  $i \leftarrow 1$  to  $n_{app}$  do  $r^{(i)} \leftarrow V_{occ}^{(i)}(t)$ ;
8      $v_{in} \leftarrow V_{in}(t)$ ;
9     /* Is the system congested during this time interval? */
10    if  $\sum_{i=1}^{n_{app}} r^{(i)} > v_{in}$  then
11      /* Initialize views for this interval */
12      for  $i \leftarrow 1$  to  $n_{app}$  do  $v^{(i)} \leftarrow 0$ ;
13      /* Distribute resources equally until none are left free */
14      while  $v_{in} \neq \emptyset \wedge \exists i, \text{ such that } r^{(i)} \geq 0$  do
15         $n_{partitions} \leftarrow \#\{r^{(i)} > 0\}$ ; /* Compute number of equi-partitions */
16        if  $\exists i, \text{ such that } r^{(i)} = 0$  then  $n_{partitions} \leftarrow n_{partitions} + 1$ ;
17         $v_{eq} \leftarrow \max(v_{in} \div n_{partitions}, 1)$ ; /* Compute size of equi-partitions */
18        for all the  $i, \text{ such that } r^{(i)} \geq 0$  do
19           $v_{in} \leftarrow v_{in} - \min(r^{(i)}, v_{eq})$ ;
20           $r^{(i)} \leftarrow r^{(i)} - v_{eq}$ ;
21           $v^{(i)} \leftarrow v^{(i)} + v_{eq}$ ;
22          if  $v_{in} = 0$  then break;
23      /* The system is not congested during this time interval */
24    else
25      /* Give each application the amount of resources left free by other
26      applications */
27      for all the  $i \leftarrow 1$  to  $n_{app}$  do
28         $v^{(i)} \leftarrow v_{in} - \sum_{i \neq j} r^{(j)}$ ;
29        /* But not less than the equi-partition */
30         $n_{partitions} \leftarrow \#\{r^{(j)} > 0\}$ ;
31        if  $r^{(i)} = 0$  then  $n_{partitions} \leftarrow n_{partitions} + 1$ ;
32         $v_{eq} \leftarrow v_{in} \div n_{partitions}$ ;
33         $v^{(i)} \leftarrow \max(v_{in}, v_{eq})$ ;
34      /* Append values computed for this time interval to application views */
35      for  $i \leftarrow 1$  to  $n_{app}$  do
36        append step  $(d, v^{(i)})$  to  $V_P^{(i)}[cid]$ ;
37
38 /* Reschedule all requests, according to the computed views, so that scheduledAt
39 and n_allloc are set correctly */
40 for  $i \leftarrow 1$  to  $n_{app}$  do
41    $V_{occ}^{(i)} \leftarrow \text{toView}(R_P^{(i)}, V_P^{(i)})$ ;
42    $V_{occ}^{(i)} \leftarrow V_{occ}^{(i)} - \text{fit}(R_P^{(i)}, V_P^{(i)} - V_{occ}^{(i)}, t_0)$ ;

```

---

## A.5 Main Scheduling Algorithm

---

**Algorithm 4:** Main scheduling algorithm – compute views for each application and the start-time of each request

---

**Input:**  $n^{(cid)}$ , number of nodes on cluster  $cid$   
 $R_{PA}^{(i)}, R_{\neg P}^{(i)}, R_P^{(i)}$ , set of  $PA$ ,  $\neg P$  and  $P$  requests of application  $i$  ( $i = 1 \dots n_{app}$ )  
 $now$ , the current time

**Output:**  $V_{\neg P}^{(i)}$ , non-preemptive view presented to application  $i$   
 $V_P^{(i)}$ , preemptive view presented to application  $i$   
updates the `scheduledAt`, `startedAt` and `nalloc` attributes of requests

```

/* Initialize temporary views with all resources */
1  $V_{\neg P} \leftarrow \{cid: [\infty, n^{(cid)}], \forall cid\};$  /* non-preemptible resources */
2  $V_P \leftarrow \{cid: [\infty, n^{(cid)}], \forall cid\};$  /* preemptible resources */
/* Subtract resources allocated to started requests */
3 for  $i \leftarrow 1$  to  $n_{app}$  do
4    $V_{\neg P} \leftarrow V_{\neg P} - \text{toView}(R_{PA}^{(i)});$  /* Subtract pre-allocated resources */
5    $V_P \leftarrow V_P - \text{toView}(R_{\neg P}^{(i)});$  /* Subtract non-preemptibly allocated resources */
/* Compute non-preemptive views and start-times of non-preemptible requests */
6 for  $i \leftarrow 1$  to  $n_{app}$  do
7    $V_{\neg P}^{(i)} \leftarrow \text{toView}(R_{PA}^{(i)}) + V_{\neg P}$ 
/* Compute what this application occupies */
8    $V_{PA}^{occ} = \text{fit}(R_{PA}^{(i)}, V_{\neg P}^{(i)}, now);$ 
9    $V_{\neg P}^{(i)} = \text{fit}(R_{\neg P}^{(i)}, \text{toView}(R_{PA}^{(i)}) + V_{PA}^{occ} - \text{toView}(R_{\neg P}^{(i)}), now);$ 
/* Update views for next application */
10   $V_{\neg P} = V_{\neg P} - V_{PA}^{occ};$ 
11   $V_P \leftarrow V_P - V_{\neg P}^{(i)};$ 
/* Compute preemptive views and start-times of preemptible requests */
12  $V_P^{(1 \dots n_{app})} = \text{eqSchedule}(R_P^{(1 \dots n_{app})}, V_P, now);$ 
/* Start requests, whose start-time is now */
13 forall the  $\neg \text{started}(r)$  and  $r.\text{scheduledAt} \leq now$  do
14    $r.\text{startedAt} \leftarrow now;$ 

```

---

Finally, let us describe the main scheduling algorithm. As stated in Section 3.2, this algorithm is triggered whenever a `request` or `done` message is received from an application. The purpose of this algorithm is to compute views for applications and start-times for requests, given as input the current requests of the applications and the current time.

The proposed pseudo-code is presented in Algorithm 4. Two scratch variables are used,  $V_{\neg P}$  and  $V_P$ , which store two views, representing non-preemptible / preemptible resources that are still available for scheduling. The algorithm works as follows:

1. The scratch variables are initialized to represent all resources (line 1–2);
2. Resources that are already allocated and cannot be preempted, i.e., resources assigned to started preallocations and non-preemptible requests, are subtracted (line 3–5);
3. Preallocations and non-preemptible requests that are not started are scheduled (line 6–11). Non-preemptive views are computed as part of this step;
4. Preemptive views are computed and preemptible requests are scheduled using the previously described `eqSchedule` function (line 12);
5. If any of the computed start-times is the current time, the corresponding requests are started (line 13–14).

For simplicity, the presented scheduling algorithm only allocates non-preemptible requests inside preallocations. The newly computed views are sent immediately to the application.

Let us focus on the `nodeIDs` attribute of requests. This attribute is initialized to an empty set when the request is first submitted to the RMS. Next, if the main scheduling algorithm decided that a request should start, two situations may occur:

1. either enough nodes are free, the `nodeIDs` attribute is immediately assigned `nalloc` node IDs and the application is sent a `startNotify` message;
2. or insufficient nodes are currently free, the RMS waits for an application to release resources. When the application sends the `done` message (as part of an update), the scheduling algorithm is re-run and the `nodeIDs` attribute is reconsidered.

## A.6 Perspectives

The above presented implementation has the following limitations:

- Non-preemptible allocations can only be done inside preallocations.
- The scheduling algorithm does not handle overlapping requests, i.e., requests of the same type, on the same cluster that temporarily overlap.
- Invalid request updates are not handled gracefully. For example, if an application updates a started pre-allocation, so as to request more resources than are available, the RMS is unable to allocate resources to it. The above implementation does not handle these cases well.
- Applications which “steal” resources, i.e., do not release preemptively allocated resources when they are asked to, are not killed.

The above implementation provides a solid foundation and it can easily be extended to address these issues.



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