



**HAL**  
open science

## Scheduling tasks sharing files from distributed repositories

Arnaud Giersch, Yves Robert, Frédéric Vivien

► **To cite this version:**

Arnaud Giersch, Yves Robert, Frédéric Vivien. Scheduling tasks sharing files from distributed repositories. [Research Report] RR-4976, LIP RR-2003-49, INRIA, LIP. 2003. inria-00071602

**HAL Id: inria-00071602**

**<https://inria.hal.science/inria-00071602>**

Submitted on 23 May 2006

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

*Scheduling tasks sharing files from distributed  
repositories*

Arnaud Giersch, Yves Robert, Frédéric Vivien

**No 4976**

October 2003

THÈME 1



*Rapport  
de recherche*



## Scheduling tasks sharing files from distributed repositories

Arnaud Giersch, Yves Robert, Frédéric Vivien

Thème 1 — Réseaux et systèmes  
Projet ReMaP

Rapport de recherche n°4976 — October 2003 — 38 Conclusionfigure.188 pages

**Abstract:** This paper is devoted to scheduling a large collection of independent tasks onto a large distributed heterogeneous platform, which is composed of a set of servers. Each server is a processor cluster equipped with a file repository. The tasks to be scheduled depend upon (input) files which initially reside on the server repositories. A given file may well be shared by several tasks. For each task, the problem is to decide on which server to execute it, and to transfer the required files (those which the task depends upon) to that server repository. The objective is to find a task allocation, and to schedule the induced communications, so as to minimize the total execution time. The contribution of this paper is twofold. On the theoretical side, we establish complexity results that assess the difficulty of the problem. On the practical side, we design several new heuristics, including an extension of the *min-min* heuristic to the decentralized framework, and several lower cost heuristics, which we compare through extensive simulations.

**Key-words:** Scheduling, heterogeneous clusters, grid, independent tasks, file-sharing, heuristics.

*(Résumé : tsvp)*

This text is also available as a research report of the Laboratoire de l'Informatique du Parallélisme  
<http://www.ens-lyon.fr/LIP>.

## Ordonnancement de tâches partageant des fichiers provenant d'entrepôts de données distribués

**Résumé :** Dans cet article, nous nous intéressons à l'ordonnancement d'un grand nombre de tâches indépendantes sur une plate-forme hétérogène distribuée composée d'un ensemble de serveurs. Chaque serveur est une grappe de processeurs doté d'un entrepôt de données. Les tâches à ordonnancer dépendent de fichiers (d'entrée) qui sont initialement stockés dans les entrepôts. Un fichier donné peut être partagé par plusieurs tâches. Pour chaque tâche, notre problème est de décider sur quel serveur l'exécuter, et de transférer les fichiers nécessaires (ceux dont dépend la tâche) vers l'entrepôt de ce serveur. L'objectif est de trouver une allocation des tâches, et un ordonnancement des communications induites, qui minimisent le temps total d'exécution. La contribution de cet article est double. Sur le plan théorique, nous établissons de nouveaux résultats de complexité qui caractérisent la difficulté du problème. Sur le plan pratique, nous proposons plusieurs nouvelles heuristiques, dont une extension de l'heuristique *min-min* aux plates-formes distribuées, et des heuristiques de moindre coût, que nous comparons grâce à des simulations.

**Mots-clé :** Ordonnancement, grappes hétérogènes, grilles de calcul, tâches indépendantes, partage de fichiers, heuristiques.

## 1 Introduction

In this paper, we are interested in scheduling independent tasks onto collections of heterogeneous clusters. These independent tasks depend upon files (corresponding to input data, for example), and difficulty arises from the fact that some files may well be shared by several tasks. Initially, the files are distributed among several server repositories. Because of the computations, some files must be replicated and sent to other servers: before a task can be executed by a server, a copy of each file that the task depends upon must be made available on that server. For each task, we have to decide which server will execute it, and to orchestrate all the file transfers, so that the total execution time is kept minimum.

This paper is a follow-on of two series of work, by Casanova, Legrand, Zagorodnov, and Berman [3, 4] on one hand, and by Giersch, Robert, and Vivien [8, 9] on the other hand. In [3, 4], Casanova et al. target the scheduling of tasks in APST, the AppLeS Parameter Sweep Template [1]. APST is a grid-based environment whose aim is to facilitate the mapping of application to heterogeneous platforms. Typically, an APST application consists of a *large* number of independent tasks, with possible input data sharing (see [4, 3] for a detailed description of a real-world application). By *large* we mean that the number of tasks is usually at least one order of magnitude larger than the number of available computing resources. When deploying an APST application, the intuitive idea is to map tasks that depend upon the same files onto the same computational resource, so as to minimize communication requirements. Casanova et al. have considered three heuristics designed for completely independent tasks (no input file sharing) that were proposed in [10]. They have modified these three heuristics (originally called *min-min*, *max-min*, and *sufferage* in [10]) to adapt them to the additional constraint that input files are shared between tasks.

As pointed out, the number of tasks to schedule is expected to be very large, and special attention should be devoted to keeping the cost of the scheduling heuristics reasonably low. In [8, 9], Giersch et al. have introduced several new heuristics, which are shown to perform as efficiently as the best heuristics in [3, 4] although their cost is an order of magnitude lower.

However, all the previous references restrict to a very special case of the scheduling problem: they assume the existence of a master processor, which serves as the repository for all files. The role of the master is to distribute the files to the processors, so that they can execute the tasks. The objective for the master is to select which file to send to which slave, and in which order, so as to minimize the total execution time. This master-slave paradigm has a fundamental limitation: communications from the master may well become the true bottleneck of the overall scheduling scheme.

In this paper, we deal with the most general instance of the scheduling problem: we assume a fully decentralized system, where several servers, with different computing capabilities, are linked through an interconnection network. To each server is associated a (local) data repository. Initially, the files are stored in one or several of these repositories (some files may be replicated). After having decided that server  $S_i$  will execute task  $T_j$ , the input files for  $T_j$  that are not already available in  $S_i$  local repository will be sent through the network. Several file transfers may occur in parallel along disjoint routes.

The contribution of this paper is twofold. On the theoretical side, we establish a complexity result that assesses the difficulty of the problem. On the practical side, we design several heuristics. The first heuristic is the extension of the `min-min` heuristic to the decentralized framework. This extension turns out to be surprisingly difficult, and we detail both the problems encountered, and the solution that was provided. The next heuristics aim at retaining the good performances of the `min-min` variants while reducing the computational cost by an order of magnitude.

The rest of the paper is organized as follows. The next section (Section 2) is devoted to the precise and formal specification of our scheduling problem, which we denote as TSFDR (*Tasks Sharing Files from Distributed Repositories*). Next, in Section 3, we establish a complexity result, namely the NP-completeness of the very specific instance of the problem where all files have the same size, all tasks have negligible (zero) cost, and all communication links have identical bandwidth. After this theoretical result, we move to the design of polynomial heuristics. In Section 4, we start with the implementation of the `min-min` heuristic. We detail the difficulties linked to the routing (Section 4.2) and to the ordering of the communications (Section 4.3); then, in Section 4.4, we design an algorithm to schedule a set of communications whose target destination is the same server, a crucial step in the implementation of the `min-min` heuristic (Section 4.5). In Section 5 we deal with the design of low-cost polynomial-time heuristics to solve the TSFDR problem. We report some experimental data in Section 6. Finally, we state some concluding remarks in Section 7.

## 2 Framework

In this section, we formally state the optimization problem to be solved. We also work out a toy example.

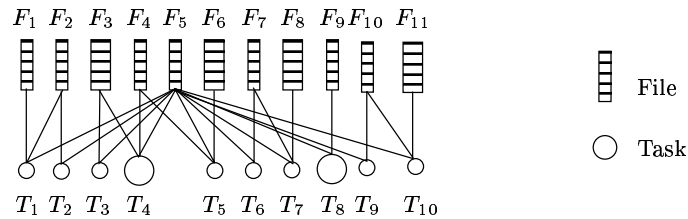


Figure 1: Bipartite graph gathering the relations between the files and the tasks.

### 2.1 Tasks and files

The problem is to schedule a set of  $n$  tasks  $\mathcal{T} = \{T_1, T_2, \dots, T_n\}$ . These tasks have different sizes: the weight of task  $T_j$  is  $t_j$ ,  $1 \leq j \leq n$ . There are no dependence constraints between the tasks, so they can be viewed as independent (a task never takes as input the result of the computation of another task).

However, the execution of each task depends upon one or several files, and a given file may be shared by several tasks. Altogether, there are  $m$  files in the set  $\mathcal{F} = \{F_1, F_2, \dots, F_m\}$ . The size of file  $F_i$  is  $f_i$ ,  $1 \leq i \leq m$ . We use a bipartite graph  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$  to represent the relations between files and tasks. The set of nodes in the graph  $\mathcal{G}$  is  $\mathcal{V} = \mathcal{F} \cup \mathcal{T}$ , and there is an edge  $e_{i,j} : F_i \rightarrow T_j$  in  $\mathcal{E}$  if and only if task  $T_j$  depends on file  $F_i$ . Intuitively, files  $F_i$  such that  $e_{i,j} \in \mathcal{E}$  contain data needed as input for the execution of task  $T_j$ . The processor that will have to execute task  $T_j$  will need to receive all the files  $F_i$  such that  $e_{i,j} \in \mathcal{E}$  before it can start the execution of  $T_j$ . See Figure 1 for a small example, with  $m = 11$  files and  $n = 10$  tasks. For instance, task  $T_1$  depends upon files  $F_1$ ,  $F_2$ , and  $F_5$ , and file  $F_5$  is an input to all tasks  $T_1$  to  $T_{10}$ .

To summarize, the bipartite graph  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ , where each node in  $V = \mathcal{F} \cup \mathcal{T}$  is weighted by  $f_i$  or  $t_j$ , and where edges in  $\mathcal{E}$  represent the relations between the files and the tasks, gathers all the information on the application.

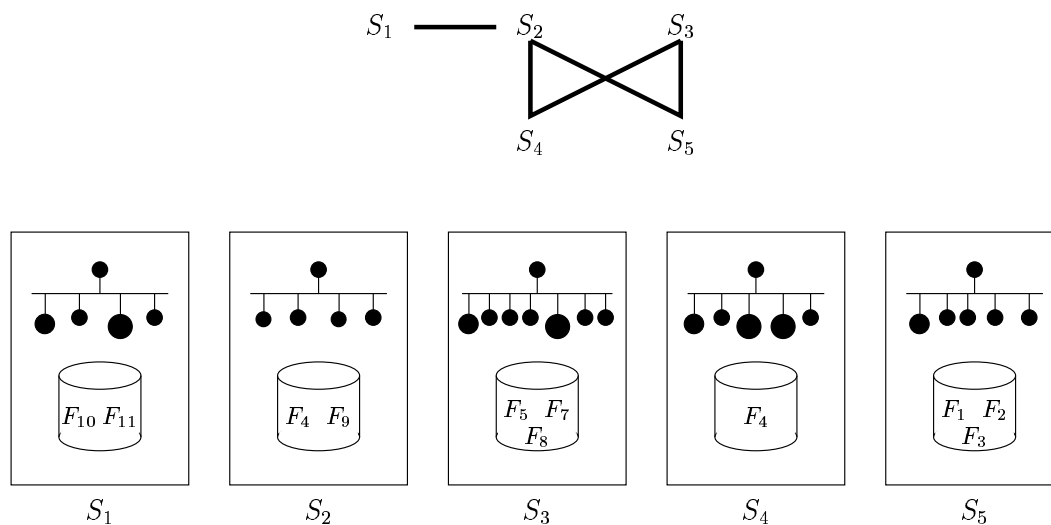


Figure 2: Platform graph, with the initial distribution of files to the server repositories.

## 2.2 Platform graph

The tasks are scheduled and executed on an heterogeneous platform composed of a set of *servers*, which are linked through a platform graph  $\mathcal{P} = (\mathcal{S}, \mathcal{L})$ . Each node in  $\mathcal{S} = \{S_1, \dots, S_s\}$  is a server, and each link  $l_{i,j} \in \mathcal{L}$  represents a communication link from server  $S_i$  to server  $S_j$ . We assume that the graph  $\mathcal{P}$  is connected, i.e. that there is a path between any server pair. By default, we assume that all links are bidirectional, hence  $\mathcal{P}$  is undirected, but we could easily deal with oriented links.



Each server  $S_i = (R_i, C_i)$  is composed of a local repository  $R_i$ , associated to a local computational cluster  $C_i$ . The files needed by the computations (the tasks) are stored in the repositories. We assume that a file may be duplicated, and thus simultaneously stored on several repositories. We make no restriction on the possibility of duplicating the files, which means that each repository is large enough to hold a copy of all the files. See Figure 2 for an example of platform.

For a cluster to be able to process a task, the corresponding repository must contain all the files that the task depends upon. With the previous notations: for cluster  $C_i$  to be able to process task  $T_j$ , repository  $R_i$  must hold all files  $F_k$  such that  $e_{k,j} \in \mathcal{E}$ . Therefore, before  $C_i$  can start the execution of  $T_j$ , the server  $S_i$  must have received from the other server repositories all the files that  $T_j$  depends upon, and which were not already stored in  $R_i$ . For communications, we use the one-port model: at any given time-step, there are at most two communications involving a given server, one sent and the other received.

As for the cost of communications, consider first the case of adjacent servers in the platform graph. Suppose that server  $S_i$  sends the file  $F_j$  (stored in its repository  $R_i$ ) to another server  $S_k$ , to which it is directly linked by the network link  $l_{i,k} = l$ . We denote by  $b_l$  the bandwidth of the link  $l$ , so that  $f_j/b_l$  time-units are required to send the file. Next, for communications involving distant servers, we use a store-and-forward model: we route the file from one server to the next one, leaving a copy of the file in the repository of each intermediate server. The cost is the sum of the costs of the adjacent communications. Leaving copies of transferred files on intermediate servers multiplies the number of potential sources for each file and is likely to accelerate the processing of the next tasks, hence the store-and-forward model seems quite well-suited to our problem.

Finally, we suppose that when the necessary files are on a server repository, they are available for free on its cluster. In other words, we assume no communication time between a cluster and its associated repository: the cost of intra-cluster messages is expected to be an order of magnitude lower than that of inter-cluster ones. We also assume that the only communication costs are due to the communication of files. Indeed, we consider no migration cost for assigning a task to a cluster. In another model, one could imagine that the code of a task originally lies on a repository and that it should also be sent to the repository linked to the cluster the task is assigned to. This model can easily be embedded in ours as one only need to add to our bipartite graph of relations between files and tasks some “virtual files” representing the task codes.

As for computation costs, each cluster  $C_i$  is composed of heterogeneous processors. More precisely,  $C_i$  gathers  $c_i$  processors  $C_{i,k}$ ,  $1 \leq k \leq c_i$ . The speed of processor  $C_{i,k}$  is  $s_{i,k}$ , meaning that  $t_j/s_{i,k}$  time-units are needed to execute task  $T_j$  on  $C_{i,k}$ . A coarser approach is to view cluster  $C_i$  as a single computational resource of cumulative speed  $\sum_{k=1}^{c_i} s_{i,k}$ . We easily model the situation where a given server is composed of a single repository but has no computational capability: simply create a (fake) cluster of null speed.

### 2.3 Objective function

The objective is to minimize the total execution time. The execution is terminated when the last task has been completed. The schedule must decide which tasks will be executed by each processor of each cluster, and when. It must also decide the ordering in which the necessary files are sent from server repositories to server repositories. We stress three important points:

- Some files may well be sent several times, so that several clusters can independently process tasks that depend upon these files.
- A file sent to some repository remains available for the rest of the schedule; so, if two tasks depending on the same file are scheduled on the same cluster, the file must only be sent once.
- Initially, a file is available on one or several well-identified servers. But when routing a file from one of these servers to another one, a copy is left on each intermediate server repository. Hence all the intermediate servers, in addition to the server which was the final destination of the file in the communication, become potential sources for the file.

We let  $\text{TSFDR}(\mathcal{G}, \mathcal{P})$  (Tasks Sharing Files from Distributed Repositories) denote the optimization problem to be solved.

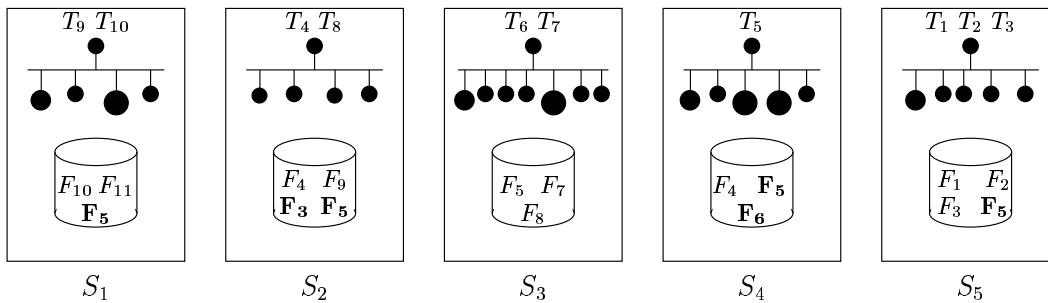


Figure 3: Platform graph, with task assigned to servers, and the final location of the files. Duplicated files are shown in bold.

### 2.4 Working out the example

Consider the example presented in Figures 1 (application graph) and 2 (platform graph). On Figure 2, we have also indicated the initial file distribution on the servers. Assume that the task mapping was decided to be the following, as illustrated on Figure 3:

- Server  $S_1$  executes tasks  $T_9$  and  $T_{10}$

- Server  $S_2$  executes tasks  $T_4$  and  $T_8$
- Server  $S_3$  executes tasks  $T_6$  and  $T_7$
- Server  $S_4$  executes task  $T_5$
- Server  $S_5$  executes tasks  $T_1$ ,  $T_2$ , and  $T_3$ .

We do not discuss here how to determine such a mapping, although we point out that this is a difficult procedure, as shown later in the paper. Instead, we focus on the communications that are required by the mapping. Here is the list of the files needed by each server:

- Server  $S_1$  needs files  $F_5$  and  $F_{10}$  for  $T_9$ , and files  $F_5$ ,  $F_{10}$  and  $F_{11}$  for  $T_{10}$
- Server  $S_2$  needs files  $F_3$ ,  $F_4$  and  $F_5$  for  $T_4$ , and files  $F_5$  and  $F_9$  for  $T_8$
- Server  $S_3$  needs files  $F_5$  and  $F_7$  for  $T_6$ , and files  $F_5$ ,  $F_7$  and  $F_8$  for  $T_7$
- Server  $S_4$  needs files  $F_4$ ,  $F_5$ , and  $F_6$  for  $T_5$
- Server  $S_5$  needs files  $F_1$ ,  $F_2$ , and  $F_5$  for  $T_1$ , files  $F_2$  and  $F_5$  for  $T_2$ , and files  $F_3$  and  $F_5$  for  $T_3$ .

Initially,  $S_1$  holds  $F_{10}$  and  $F_{11}$  in its repository, so it needs to receive only file  $F_5$ . Note that  $S_1$  needs to receive  $F_5$  only once, even though it executes two tasks that depend upon this file. In fact, because each task depends upon  $F_5$ , each server except  $S_3$  needs to receive  $F_5$ . In addition to  $F_5$ ,  $S_2$  needs to receive file  $F_3$ ;  $S_3$  does not need any extra file;  $S_4$  needs  $F_4$ ,  $F_5$ , and  $F_6$ , while  $S_5$  only needs  $F_5$ .

Since  $S_3$  is the only source for  $F_5$ , we have to decide an ordering for scheduling the transfers to the other processors. There are two routes from  $S_3$  to  $S_2$  in the platform, through  $S_4$  or through  $S_5$ , and we have to decide which one to use. Also, we have to (try) to schedule independent computations in parallel: for instance the transfer of  $F_5$  from  $S_3$  to  $S_5$  and the transfer of  $F_4$  from  $S_2$  to  $S_4$  can take place in parallel. We come back to the different scenarios for routing and communication scheduling in Section 4.

### 3 Complexity

Most scheduling problems are known to be difficult [12, 5], and the TSFDR optimization problem is no exception. Heterogeneity may come from several sources: files or tasks can have different weights, while clusters or links can have different speeds. Simple versions of these weighted problems already are difficult. For instance the decision problem associated to the instance with no files and two single-processor clusters of equal speed already is NP-complete: in that case, TSFDR reduces to the scheduling of independent tasks on a two-processor machine, which itself reduces to the 2-PARTITION problem [7] as the tasks have different weights. Conversely, mapping equal-size files and equal-size tasks on a single

server platform with two heterogeneous processors and two links of different bandwidths is NP-hard too [9].

The aim of this section is to prove that the simple fact of deciding where to move the files so as to execute the tasks is a difficult combinatorial problem, even in the un-weighted version where all files have same size and all communication links have same bandwidth. We even assume that all tasks have zero weight, or equivalently that all clusters have infinite speed. We then have a mapping problem: we have to map the tasks to the clusters and to gather each required set of files (that are input of a task) on a server repository, with the objective to minimize the number of communications steps. All communications have unit-time, but independent communications, i.e. involving distinct senders and distinct receivers, may well take place in parallel. Formally, we state the decision problem associated to this very particular instance of TSFDR as follows:

**Definition 1 (TSFDR-Move-Dec( $\mathcal{G}, \mathcal{P}, K$ )).** *Given a bipartite application graph  $\mathcal{G} = (\mathcal{F} \cup \mathcal{T}, \mathcal{E})$ , a platform graph  $\mathcal{P} = (\mathcal{S}, \mathcal{L})$ , assuming:*

- *uniform file sizes ( $f_i = 1$ ),*
- *homogeneous interconnection network ( $b_i = 1$ ),*
- *zero processing time ( $t_i = 0$  or  $s_j = +\infty$ ),*

*and given a time bound  $K$ , is it possible to schedule all tasks within  $K$  time-steps?*

**Theorem 1.** *TSFDR-Move-Dec( $\mathcal{G}, \mathcal{P}, K$ ) is NP-complete.*

*Proof.* Obviously, TSFDR-Move-Dec( $\mathcal{G}, \mathcal{P}, K$ ) belongs to NP. To prove its completeness, we use a reduction from the well-known MINCUT problem, which is NP-complete [7]. More precisely we use a restriction of the MINCUT problem where each vertex has a large degree, but we show that this restriction, which we denote as MINCUTLARGEDEGREE, remains NP-complete:

**Definition 2 (MinCutLargeDegree( $\mathcal{H}, B$ )).** *Given a non-oriented graph  $\mathcal{H} = (V, E)$ , with an even number of vertices, and a bound  $B$ ,  $1 \leq B \leq |V|$ , and assuming that each vertex has a degree at least  $B + 1$ , is there a partition  $V = V_1 \cup V_2$  with  $|V_1| = |V_2| = |V|/2$ , such that the number of crossing edges does not exceed  $B$ :  $|\{e = (u, v) \in E, u \in V_1, v \in V_2\}| \leq B$ ?*

**Lemma 1.** *MINCUTLARGEDEGREE( $\mathcal{H}, B$ ) is NP-complete.*

*Proof.* Obviously, MINCUTLARGEDEGREE( $\mathcal{H}, B$ ) still belongs to NP. To prove its completeness, we use a reduction from the original MINCUT problem: consider an arbitrary instance  $\mathcal{I}_1$  of MINCUT: given a graph  $H' = (V', E')$ , where  $|V'|$  is even, and a bound  $B'$ , is there a partition  $V' = V'_1 \cup V'_2$  with  $|V'_1| = |V'_2| = |V'|/2$ , such that  $|\{e = (u, v) \in E' | u \in V'_1, v \in V'_2\}| \leq B'$ ? To construct an instance  $\mathcal{I}_2$  of MINCUTLARGEDEGREE, we expand each vertex  $v \in V'$  so as to form a “private” clique of size  $B' + 2$ , so that each vertex has a degree at least  $B' + 1$ . The edges of the cliques are the only ones added. Formally,  $V = \{v_{i,k}, 1 \leq i \leq |V'|, 0 \leq k \leq B' + 1\}$ , and  $E = \{(v_{i,0}, v_{j,0}) | (v_i, v_j) \in E'\} \cup \{(v_{i,k}, v_{i,k'}) | 0 \leq k \neq k' \leq B' + 1, 1 \leq i \leq |V'|\}$ . Intuitively,  $v_{i,0}$  corresponds to the original vertex  $v_i \in V'$

and  $v_{i,j}$ ,  $j \geq 1$ , is a new vertex (in the clique). Finally, we let  $B' = B$ . Clearly, the size of  $\mathcal{I}_2$  is polynomial in the size of  $\mathcal{I}_1$ .

Assume first that  $\mathcal{I}_1$  has a solution, i.e. an equal-size partition  $V' = V'_1 \cup V'_2$  with no more than  $B'$  crossing edges. We let  $V_1 = \{v_{i,k} | 0 \leq k \leq B+1, v_i \in V_1\}$ , and we let the other vertices in  $V_2$ . This leads to an equal-size partition of  $V$ . The number of crossing edges is the same, because each clique has been mapped on the same side of the partition, and there are no other edges involving new vertices. Hence a solution to  $\mathcal{I}_2$ .

Conversely, assume that  $\mathcal{I}_2$  has a solution, i.e. an equal-size partition  $V = V_1 \cup V_2$  with no more than  $B$  crossing edges. We claim that each clique has been mapped on the same side of the partition. Otherwise, for a given index  $i$ , we would have  $b$  vertices  $v_{i,k} \in V_1$  and  $B+2-b$  vertices  $v_{i,k} \in V_2$ , with  $1 \leq b \leq B+1$ . But there are  $b(B+2-b) > B$  crossing edges linking these vertices, a contradiction. Now we easily derive the solution to  $\mathcal{I}_1$ :  $V'_1$  is the set of vertices  $v_i$  such that  $v_{i,0} \in V_1$ , and similarly for  $V_2$ .  $V_1$  and  $V_2$  are of equal size, and each clique is mapped on the same set, so  $V_1$  and  $V_2$  have the same number of cliques, hence  $V'_1$  and  $V'_2$  have same cardinal. Finally, all crossing edges are between cliques, hence their number is the same in the partition  $V = V_1 \cup V_2$  as in the partition  $V' = V'_1 \cup V'_2$ , hence the result.  $\square$

We now return to the proof of the completeness of  $\text{TSSFDR-MOVE-DEC}(\mathcal{G}, \mathcal{P}, K)$ . We start from an arbitrary instance  $\mathcal{I}_1$  of  $\text{MINCUTLARGEDEGREE}$ : given a graph  $H = (V, E)$ , where  $|V|$  is even, and a bound  $B$ ,  $1 \leq B \leq |V|$ , and assuming that each vertex has a degree at least  $B+1$ , is there a partition  $V = V_1 \cup V_2$  with  $|V_1| = |V_2| = |V|/2$ , such that  $|\{e = (u, v) \in E | u \in V_1, v \in V_2\}| \leq B$ ? Let  $|V| = 2p$ , and (without loss of generality) assume that  $p \geq 3$  and  $B \leq p-1$ . See Figure 4 for an illustration with  $p = 4$  and  $B = 2$ .

We construct the following instance  $\mathcal{I}_2$  of  $\text{TSSF2DR-MOVE-DEC}(\mathcal{G}, \mathcal{P}, K)$ . To each  $v_i \in V$  we associate a file  $f_i \in \mathcal{F}$ . We also introduce a collection of new files:

- $(p+1)B$  files  $x_{i,j}$ ,  $1 \leq i \leq B, 1 \leq j \leq p+1$ ,
- $(p-2)B$  files  $y_{i,j}$ ,  $1 \leq i \leq B, 1 \leq j \leq p-2$ ,
- and  $p+1$  files  $z_i$ ,  $1 \leq i \leq p+1$ ,

so that there is a total of  $m = 3p+1 + B(2p-1)$  files in  $\mathcal{F}$ .

As for tasks, there are as many tasks as edges in the original graph  $H$ , plus  $B$  additional tasks, so that  $\mathcal{T}$  comprises  $n = |E| + B$  tasks. More specifically, we create a task  $T_{i,j}$  for each edge  $e = (v_i, v_j) \in E$ , and we add  $B$  tasks denoted as  $T'_i$ ,  $1 \leq i \leq B$ . The relations between tasks and files are defined as follows. First, if  $(v_i, v_j) \in E$ , there are two edges in  $\mathcal{E}$ , one from file  $f_i$  to task  $T_{i,j}$ , and the other from  $f_j$  to  $T_{i,j}$ . The files  $f_i$  and  $f_j$  are not the only inputs of task  $T_{i,j}$ , which also depends upon all files  $z_k$ . In other words, we add  $(p+1)|E|$  edges  $(z_k, T_{i,j})$  in  $\mathcal{E}$ . Then, the last  $B$  tasks  $T'_i$  all have  $2p-1$  input files: given  $i$ , there is an edge from each  $x_{i,j}$  and from each  $y_{i,j}$  to  $T'_i$ . In summary, there are  $(p+3)|E| + (2p-1)B$  edges in  $\mathcal{E}$ . See Figure 5 for an illustration.

There remains to describe the platform graph  $\mathcal{P}$ . There are  $2p+2B+2$  servers in  $\mathcal{P}$ , which we denote  $F_i$ , for  $1 \leq i \leq 2p$ ,  $X_i$  and  $Y_i$ , for  $1 \leq i \leq B$ , and  $W_1$  and  $W_2$ . There is a

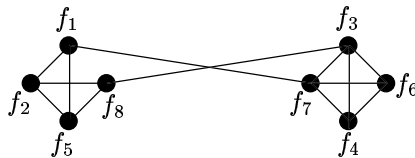


Figure 4: The original graph in the MINCUTLARGEDEGREE instance.

communication link from each  $F_i$  to  $W_1$ , to  $W_2$ , and to each  $X_j$ , which amounts to  $2p(B+2)$  links. There are  $B$  additional links, namely from  $Y_i$  to  $X_i$ , hence a total of  $2p(B+2)+B$  links in  $\mathcal{P}$ . See Figure 6 for an illustration. The initial distribution of files to server repositories is the following:

- file  $f_i$  is stored in  $F_i$ , for  $1 \leq i \leq 2p$ ,
- files  $x_{i,j}$ ,  $1 \leq j \leq p+1$ , are stored in  $X_i$ , for  $1 \leq i \leq B$ ,
- files  $y_{i,j}$ ,  $1 \leq j \leq p-2$ , are stored in  $Y_i$ , for  $1 \leq i \leq B$ ,
- and files  $z_k$ ,  $1 \leq k \leq p+1$ , are duplicated  $B+2$  times, to be stored in  $W_1$ , in  $W_2$ , and in each  $X_i$ ,  $1 \leq i \leq B$ .

Finally, we let  $K = p$  for the scheduling bound. This completes the description of  $\mathcal{I}_2$ , whose size is clearly polynomial in the size of  $\mathcal{I}_1$ . As specified in the problem, all files have unit size, all communication links have unit bandwidth, and computation is infinitely fast.

Now we have to show that  $\mathcal{I}_2$  admits a solution if and only if  $\mathcal{I}_1$  has one. Assume first that  $\mathcal{I}_1$  has a solution, i.e. that there is a partition  $V = V_1 \cup V_2$  with  $|V_1| = |V_2| = p$ , such that  $b = |\{e = (u, v) \in E \mid u \in V_1, v \in V_2\}| \leq B$ . We decide to compute task  $T'_{i,j}$  in server  $X_i$ . For each edge  $(v_i, v_j) \in E$  such that both  $v_i$  and  $v_j$  belong to  $V_1$ , we execute task  $T'_{i,j}$  in server  $W_1$ . We make a similar decision if both  $v_i$  and  $v_j$  belong to  $V_2$ , then executing the task in  $W_2$ . There remains  $b$  tasks to allocate, those corresponding to crossing edges. Since  $b \leq B$ , we assign one of these tasks to each of the first  $X_i$  servers,  $1 \leq i \leq b$ . This allocation implies  $B(p-2) + 2p + 2b$  communications, namely  $p-2$  for each task  $T'_{i,j}$ , one for each file  $f_i$  to either  $W_1$  or  $W_2$ , and two for each crossing edge. We have to orchestrate these communications within  $K = p$  time-steps, without violating any one-port constraint. Intuitively,  $W_1$  receives  $p$  files  $f_i$ , where  $v_i \in V_1$ , and similarly for  $W_2$ : these  $2p$  messages are independent and can be scheduled at any time-step. Each  $X_i$  receives  $p-2$  files  $y_{i,j}$  from  $Y_i$ , so it has two time-slots left, exactly what is needed to receive the two files needed to execute one crossing edge task. Each server  $F_i$  sends its file  $f_i$  at most  $B+1$  times, one time to one of the two  $W$  servers, and as many times as  $v_i$  is an incident vertex to a crossing edge. Rather than describing the schedule by extension, which would be cumbersome, we resort to the big artillery: we build a bipartite graph with senders on one side (the  $F$  and  $Y$  servers), receivers on the other side (the  $X$  and  $W$  servers), and we insert one edge for each communication to be scheduled. As  $B+1 \leq p$ , the maximal degree of each node in

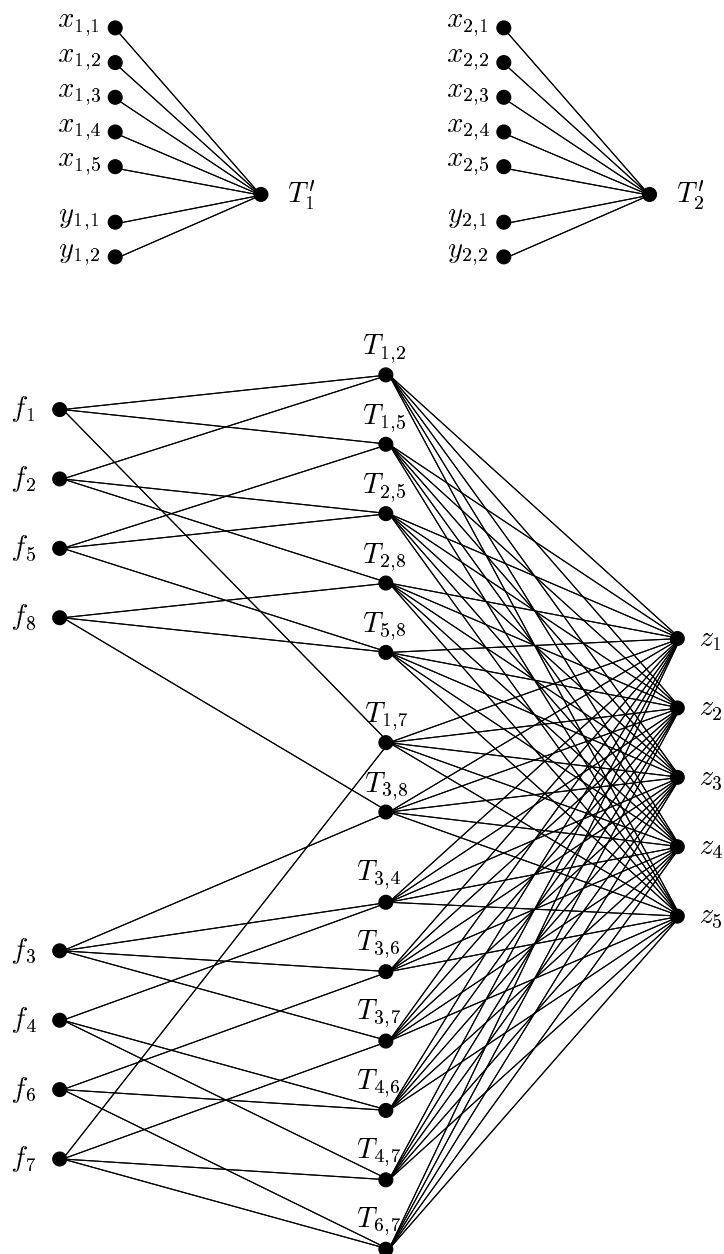


Figure 5: The bipartite application graph used in the reduction.

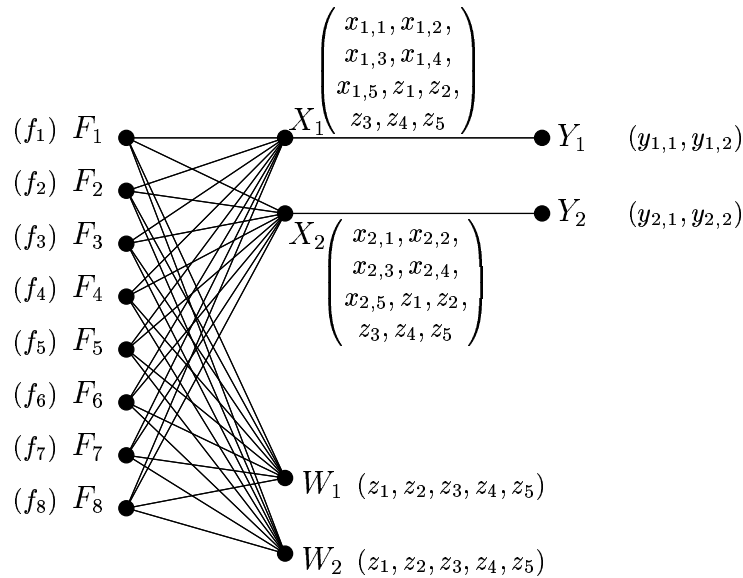


Figure 6: The platform graph used in the reduction.

the graph does not exceed  $p$ . König's edge coloring theorem [11, chapter 20] ensures that we can partition all the edges into  $p$  disjoint matchings, and we implement one matching (which by definition involves independent communications) per time-step.

Overall, we obtain a valid scheduling to execute all tasks within  $p$  time-steps, hence a solution to  $\mathcal{I}_2$ .

Assume now that  $\mathcal{I}_2$  has a solution. We proceed in several steps:

1. Necessarily, server  $X_i$  executes task  $T'_i$ . Otherwise, if another server would execute it, the  $p+1$  files  $x_{i,j}$  (for all  $j$ ) which reside in (the repository of)  $X_i$  should be transferred to the other server; since  $X_i$  is the only source for these files, this would require  $p+1$  outgoing messages from  $X_i$ , which is impossible within  $p$  steps.
2. With the same reasoning, a server labeled  $F$  or  $Y$  cannot execute any of the tasks  $T_{i,j}$ , because these tasks depend upon the  $p+1$  files  $z_k$  whose sources lie in the servers labeled  $X$ , and in  $W_1$  and  $W_2$ .
3. Because  $X_i$  executes  $T'_i$ , it must receive the  $p-2$  files  $y_{i,j}$  (for all  $j$ ), whose only source is server  $Y_i$ . Hence  $X_i$  can receive at most two other files during the  $p$  steps of the schedule. As a consequence,  $X_i$  can execute at most one task  $T_{j,k}$ , if it indeed receive the two missing files.
4. How many files  $f_i$  have been received by  $W_1$  and  $W_2$ ? Let  $V_1$  denotes the set of the files  $f_i$  sent by the  $F$  servers to  $W_1$ , and  $V_2$  those sent to  $W_2$ . We do not know yet



whether some files have been sent to both  $W_1$  and  $W_2$ . But assume for a while that a given file  $f_i$  has neither been sent to  $W_1$  nor to  $W_2$ . All the tasks  $T_{i,j}$ , where  $(i,j) \in E$ , must have been executed elsewhere. The only candidates are servers labeled  $X$ . But there are  $B$  of them, and each can execute at most one such task, while the degree of  $v_i$  in  $H$  is at least  $B + 1$ , a contradiction.

5. Therefore, each file  $f_i$  has been sent either to  $W_1$  or to  $W_2$  (or both). But there is a total of  $2p$  files to send to two servers within  $p$  time-steps: each server can receive at most  $p$  files. So no file has been sent twice. We conclude that  $V_1$  and  $V_2$  form a partition of  $V$ , with  $|V_1| = |V_2| = p$ .
6. There remains to show that there are no more than  $B$  edges crossing the partition  $V = V_1 \cup V_2$ . But these crossing edges correspond to tasks that can only be executed by the  $X$  servers, hence the result.

Finally, we have characterized the solution to  $\mathcal{I}_1$ . □

## 4 Extending the min-min scheme to distributed repositories

As the TSFDR scheduling problem is NP-complete, we look for polynomial heuristics to solve it. Considering the work of Casanova et al. [3, 4] for master-slave systems with a single server, we start by adapting the min-min scheme. During this study, we will justify some of our assumptions and simplifications concerning the communication model. Later, in Section 5, we introduce several new heuristics, whose main characteristic is a lower computational complexity than that of the min-min scheme.

This section is organized as follows. We recall the basic principle of the min-min heuristic in Section 4.1. We detail the difficulties linked to the routing in Section 4.2, and those related to the ordering of the communications in Section 4.3. Then, in Section 4.4, we design an algorithm to schedule a set of communications whose target destination is the same server, a crucial step when allocating a new task to a server in the implementation. We outline the final design of the min-min heuristic in Section 4.5.

### 4.1 Principle of the min-min scheme

The principle of the min-min scheme is quite simple:

- While there remain tasks to be scheduled do
  1. for each processor  $C_{i,j}$  in the system and each task  $T_k$  that remains to be scheduled, evaluate the minimum completion time of  $T_k$  if mapped on  $C_{i,j}$ ;
  2. pick a couple  $(C_{i,j}, T_k)$  whose minimum completion time is minimal, and schedule the task  $T_k$  on the processor  $C_{i,j}$ .

The problem with this heuristic is to evaluate the Minimum Completion Time (MCT). When trying to schedule a task on a given processor, one has to take into account which required files already reside in the corresponding repository, and which should be routed through the network of servers. It is straightforward to determine which communications should take place. However, the scheduling of these communications is NP-complete in the general case, as discussed below.

Once we have decided how to schedule the communications, there only remains to evaluate the computation time. We heuristically decide to view a whole cluster as a single processor whose processing power is the sum of the processing powers of the cluster processors (the coarse-grain approach alluded to in Section 2.2). The start date for the execution of the new task is set as the latest date between (1) the arrival of the last of the necessary files and (2) the end of the (coarse evaluation of the) computation of the tasks assigned so far to the cluster. With this simplified coarse-grain view for computations, the only problem we are left with is the scheduling of the communications.

## 4.2 Complexity of scheduling communications with free routing

We deal with the situation where all communications have the same destination (namely the server that will execute the task). In the 1-port model, if the routing in the platform graph is not fixed, then this simple scheduling problem already is NP-hard. We first formally define the decision problem and then prove its NP-completeness:

**Definition 3.**  $\text{COMMSCHEDFREEROUTE}(\mathcal{P}, \mathcal{M}, D, T)$ : Given a platform graph  $\mathcal{P} = (\mathcal{S}, \mathcal{L})$ , a finite set  $\mathcal{M}$  of communications of same destination  $D$ , and a time bound  $T$ , is there a valid scheduling of the communications whose makespan is not greater than  $T$ ? Each element of  $\mathcal{M}$  is a couple  $(S_i, s)$  representing the communication of a file of size  $s$ , from the server  $S_i$  to the destination server  $D$ .

**Theorem 2.**  $\text{COMMSCHEDFREEROUTE}(\mathcal{P}, \mathcal{M}, D, T)$  is NP-complete.

*Proof.* Obviously,  $\text{COMMSCHEDFREEROUTE}(\mathcal{P}, \mathcal{M}, D, T)$  belongs to NP. To prove its completeness, we use a reduction from 2-PARTITION, which is NP-complete [7]. Consider an arbitrary instance  $\{a_1, a_2, \dots, a_n\}$  of 2-PARTITION, where the  $a_i$  are strictly positive integers: is there a subset  $I$  of  $\{1, \dots, n\}$  such that  $\sum_{i \in I} a_i = \sum_{i \notin I} a_i$ ?

From this instance of 2-PARTITION, we build the platform  $\mathcal{P} = (\mathcal{S}, \mathcal{L})$  represented in Figure 7. In this platform, there are  $n + 5$  servers:

- $A_1, \dots, A_n$ : the server  $A_i$  stores a file  $F_i$  of size  $a_i$ .
- $X_l$  and  $X_r$ : from each of the  $n$  servers  $A_1, \dots, A_n$ , there is a link of bandwidth 1 to the server  $X_l$  and one to the server  $X_r$ .
- $Y_l$  and  $Y_r$ : there is a link of bandwidth  $\frac{1}{2N}$  from the server  $X_l$  to the server  $Y_l$ , and one from  $X_r$  to  $Y_r$ , where  $N = \sum_{1 \leq i \leq n} a_i$ .
- $D$ : there is a link of bandwidth 1 from the servers  $Y_l$  and  $Y_r$  to the server  $D$ .

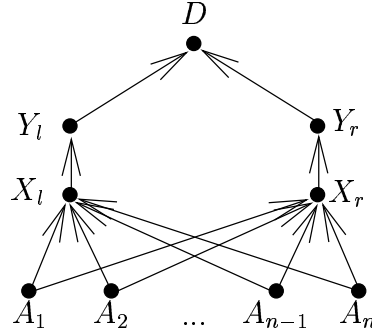


Figure 7: Graph used in the reduction from 2-PARTITION to COMMSCHEDFREEROUTE.

The set,  $\mathcal{M}$ , of communications is defined by communications from the  $A$  servers to  $D$ :  $\mathcal{M} = \{(A_i, a_i)\}_{1 \leq i \leq n}$ . The time bound is  $T = N^2 + N + \min_{1 \leq i \leq n} a_i$ . Clearly the size of the constructed instance of COMMSCHEDFREEROUTE is polynomial in the size of the original instance of 2-PARTITION.

Assume that the original instance of 2-PARTITION admits a solution: let  $(\mathcal{I}_1, \mathcal{I}_2)$  be a partition of  $\{1, \dots, n\}$  such that  $\sum_{i \in \mathcal{I}_1} a_i = \sum_{i \in \mathcal{I}_2} a_i = \frac{N}{2}$ . Without loss of generality, suppose that  $\mathcal{I}_1$  contains an element  $a_j$  which is minimal:  $a_j = \min_{1 \leq i \leq n} a_i$ . We derive a scheduling for the instance COMMSCHEDFREEROUTE as follows:

1. At date 0,  $A_j$  sends its file of size  $a_j$  to  $X_l$ , which is received at date  $a_j$ .
2. Between dates 0 and  $\frac{N}{2}$ , the servers corresponding to  $\mathcal{I}_2$  ( $\{A_i\}_{i \in \mathcal{I}_2}$ ) send their files, in any order, to  $X_r$ .
3. Between dates  $a_j$  and  $a_j + 2Na_j$ ,  $X_l$  sends the file received from  $A_j$  to  $Y_l$ .
4. Between dates  $a_j$  and  $\frac{N}{2}$ , the servers  $\{A_i\}_{i \in \mathcal{I}_1, i \neq j}$  send their files, in any order, to  $X_l$ .
5. From  $a_j + 2Na_j$  to  $a_j + 2N\frac{N}{2}$ ,  $X_l$  sends to  $Y_l$ , in any order, the files received from the servers in  $\{A_i\}_{i \in \mathcal{I}_1, i \neq j}$ .
6. Between dates  $\frac{N}{2}$  and  $\frac{N}{2} + 2N\frac{N}{2}$ ,  $X_r$  sends to  $Y_r$ , in any order, the files received from the servers corresponding in  $\mathcal{I}_2$ .
7. From  $a_j + 2N\frac{N}{2}$  to  $a_j + 2N\frac{N}{2} + \frac{N}{2}$ ,  $Y_l$  sends, in any order, all the files that it holds to  $D$ .
8. From  $a_j + 2N\frac{N}{2} + \frac{N}{2}$  to  $a_j + 2N\frac{N}{2} + N$ ,  $Y_r$  sends, in any order, all the files that it holds to  $D$ .

Therefore, we have derived a valid scheduling that matches the time bound, hence a solution to the COMMSCHEDFREEROUTE instance.

Reciprocally, assume that the COMMSCHEDFREEROUTE instance admits a solution, hence a valid scheduling satisfying the time bound  $T$ . Then, the communication originating from any  $A_i$  must go either through  $X_l$  or  $X_r$ . We define as  $\mathcal{I}_1$  (respectively  $\mathcal{I}_2$ ) the  $A_i$  servers whose files are sent to  $D$  through  $X_l$  (resp.  $X_r$ ). Thus,  $\mathcal{I}_1$  and  $\mathcal{I}_2$  defines a partition of  $\{1, \dots, n\}$ . Suppose this is not a solution to 2-PARTITION. Then, without loss of generality,  $\sum_{i \in \mathcal{I}_1} a_i > \sum_{i \in \mathcal{I}_2} a_i$  and thus  $\sum_{i \in \mathcal{I}_1} a_i > \frac{N}{2}$ . Thus,  $\sum_{i \in \mathcal{I}_1} a_i \geq 1 + \frac{N}{2}$ . Then, the time needed by  $X_l$  to send to  $Y_l$  all the files it received from the  $A_i$ 's is equal to  $2N \cdot (\sum_{i \in \mathcal{I}_1} a_i) \geq 2N \frac{N}{2} + 2N > \min_{1 \leq i \leq n} a_i + 2N \frac{N}{2} + N = T$ , which is absurd.  $\square$

Theorem 2 shows that scheduling the communications is NP-complete as soon as we have the freedom to chose the route followed by the files. Therefore we assume that the routing from one server to another is fixed. Note that this is a realistic assumption in practice, because the routing is usually decided by table lookup. Between each pair of servers, if multiple routes are available, we decide to chose one among all the routes of maximal bandwidth. Furthermore, we decide the whole routing to be coherent: if  $S$  is the first server in the route from a server  $R$  to a server  $T$ , then the route from  $R$  to  $T$  is made of the physical link between  $R$  and  $S$  and of the route from  $S$  to  $T$ .

### 4.3 Complexity of communication scheduling with respect to an history

When trying to schedule the communications required for a task  $T_k$ , one must take into account the communications scheduled for the tasks previously scheduled. In other words, when trying to schedule the communications for a new task, one must take into account that the communication links are already used at certain time slots due to previously scheduled communications. Even with our hypothesis of a fixed routing, this leads to an NP-complete problem, as we now show:

**Definition 4.** COMMSCHEDWITHHISTORY( $\mathcal{P}, \mathcal{M}, D, \mathcal{H}, T$ ): Given a platform graph  $\mathcal{P} = (\mathcal{S}, \mathcal{L})$ , a finite set  $\mathcal{M}$  of communications of same destination  $D$ , an history  $\mathcal{H}$  specifying for any communication link at which time-slots it is unavailable due to previously scheduled communications, and a time bound  $T$ , is there a valid scheduling of the communications whose makespan is not greater than  $T$ ?

**Theorem 3.** Problem COMMSCHEDWITHHISTORY( $\mathcal{P}, \mathcal{M}, D, \mathcal{H}, T$ ) is NP-complete.

*Proof.* Obviously, COMMSCHEDWITHHISTORY( $\mathcal{P}, \mathcal{M}, D, \mathcal{H}, T$ ) belongs to NP. To prove its completeness, we use a straightforward reduction from 2-PARTITION. Consider an arbitrary instance  $\{a_1, a_2, \dots, a_n\}$  of 2-PARTITION with  $\sum_{1 \leq i \leq n} a_i = N$ . From this instance, we build a simple platform composed of two servers linked by a single communication link which is available at any time  $t$  in  $[0, \frac{N}{2}] \cup [1 + \frac{N}{2}, \dots, \infty[$ . We let  $T = N + 1$ . Then, one can easily see that there is a solution for the instance 2-PARTITION if and only if there is a solution to the corresponding instance of COMMSCHEDWITHHISTORY. To reach this result, we make the assumption that communications are never preempted, i.e. that a file is sent in one time and is not cut in several sub-pieces which would be sent at different non contiguous times.  $\square$

As a consequence of this result, we (heuristically) decide not to interleave previously scheduled communications with next communications to be scheduled. Therefore, a new communication will always be scheduled *after* any communication already scheduled on the same link.

#### 4.4 Communication scheduling algorithm

Because of the two complexity results above, we have decided so far:

1. that the routing of communications is fixed;
2. that new communications are always scheduled after communications using the same links.

Under these hypotheses, we are able to design a greedy algorithm to schedule the communications required to send the necessary files to the server which we want to assign the new task to. In the following, we call

- *transfer* the communication, through the network of servers, of a file from the source server (which stores the file in its repository) to the destination server (where we attempt to schedule the new task);
- *local communications* the communications between neighbor servers; therefore, a transfer is potentially made up of several local communications.

In order (i) to avoid contentions and (ii) to enforce the one-port model, we would *a priori* need to memorize the availability dates of the links, in addition to the availability dates, in emission and in reception, of the servers. In fact, we do not need to store any data for the links: for each server  $S$ , its availability date in emission, denoted as  $d_{out}(S)$ , is equal to the maximum of the availability date of its outgoing communication links. The same holds true for its availability date  $d_{in}(S)$  in reception. In addition to the availability dates of the servers, we also need to store the arrival date of a file on an intermediate server (between the source and the destination of a transfer).

Algorithm 1 presents our greedy algorithm: on each intermediate server we schedule the local communications as soon as possible, the intermediate servers being considered in decreasing distance from the destination of transfers.

Of course, the algorithm does not always compute the optimal solution. The general problem is most likely NP-complete, due to its similarity with the flow-shop problem [7]. Here is a simple example where the algorithm fails to return the optimal solution. Consider two files  $F_1$  and  $F_2$ , of sizes  $f_1 = 2$  and  $f_2 = 4$ , to be routed from server  $A$  to server  $D$  via server  $B$ . The bandwidth of the link from  $A$  to  $B$  is 1, that of the link from  $B$  to  $D$  is 0.5. The availability dates of  $F_1$  in server  $A$  is  $t = 1$  while that of  $F_2$  is  $t = 0$ . The greedy algorithm will route  $F_2$  before  $F_1$  on each link, starting at  $t = 0$ : the sending of  $F_2$  terminates at  $t = 4$  in  $B$  and at  $t = 12$  in  $D$ ;  $F_1$  follows at  $t = 6$  in  $B$  and  $t = 16$  in  $D$ . However, routing  $F_1$  first is better, even though we cannot start before  $t = 1$ :  $F_1$  reaches  $B$  at  $t = 3$  and  $D$  at  $t = 7$ , while  $F_2$  reaches  $B$  at  $t = 7$  and  $D$  at  $t = 15$ .

**Algorithm 1** Schedule a set of transfers of same destination  $D$ 


---

```

1: from the platform graph  $\mathcal{P}$ , extract the tree  $\mathcal{T}$  of the transfers to  $D$ .
2: for each server  $S$  in  $\mathcal{T}$  do
3:   compute the depth of  $S$  (starting from 0 for  $D$ )
4:   for each server  $S$  source of a transfer of a file  $F_i$  do
5:     add to the set of communications to be scheduled, the sending of file  $F_i$  from  $S$  to
       father( $S$ ) with start date  $d_{out}(S)$ 
6:   for  $h = \text{height}(\mathcal{T}) - 1$  downto 0 do
7:     for each server  $S$  of depth  $h$  do
8:       while there remains to schedule some local communications do
9:         take any local communication  $c$  of file  $F_i$  from  $R$  to  $S$  of earliest start date  $d$ 
10:         $start \leftarrow \max\{d, d_{out}(R), d_{in}(S)\}$ 
11:         $end \leftarrow start + f_i/b_{R \rightarrow S}$ 
12:        schedule  $c$  between dates  $start$  and  $end$ 
13:         $d_{out}(R) \leftarrow end$ 
14:         $d_{in}(S) \leftarrow end$ 
15:        if  $S \neq D$  then
16:          add to the set of communications to be scheduled, the sending of file  $F_i$  from
              $S$  to father( $S$ ) with start date  $end$ 

```

---

**Complexity**

If we denote by  $n_t$  the number of transfers and by  $h$  the height of the communication tree, the complexity of the algorithm is  $O(n_t \cdot h + n_t \log n_t)$ . Indeed, one does need to sort the file availability dates on the tree leaves. However, each intermediate servers receives sorted lists from each of its sons in the tree, and merging these lists costs at most  $O(n_t)$  on each on the  $h - 2$  heights concerned.

More specifically, if we denote by

- $\Delta T$  the maximum degree of a task, i.e. the maximum number of files that a task depends upon;
- $\Delta \mathcal{P}$  the diameter of the platform graph;

the complexity of this algorithm is in  $O(\Delta T \cdot \Delta \mathcal{P} + \Delta T \log(\Delta T))$ .

**4.5 Outline of the whole min-min scheme**

Algorithm 2 presents our implementation of the min-min scheme on distributed repositories. The complexity of the whole heuristic is

$$O(n^2 s (\Delta T \cdot \Delta \mathcal{P} + \Delta T \log(\Delta T)) + n \max_{1 \leq i \leq s} c_i).$$

The last term comes from scheduling the tasks on the clusters. Indeed, once the communications are scheduled, we have for each task the availability date of the files which it depends upon at a cost  $O(|\mathcal{E}|)$ . On each cluster, we greedily schedule the tasks on the available processors. Among the tasks of lowest availability date, we take the largest one and schedule it on the processor on which it will have the minimum completion time (taking into account the date at which this processor will be available, knowing which tasks were already scheduled on it). The complexity of this task scheduling is  $O(n \max_{1 \leq i \leq s} c_i)$ .

We remark that going from systems with a single repository, as in [9], to systems with several repositories, the complexity increases by a factor  $(\Delta T \cdot \Delta \mathcal{P} + \Delta T \log(\Delta T))$ , corresponding to the cost of the communication scheduling algorithm. In the meantime, the number of processors was replaced by the number of servers. This is because of our simplified view of the problem: in the decision phase, we see each cluster  $C_j$  as a single computational resource of cumulative speed  $\sum_{k=1}^{c_j} s_{j,k}$ .

---

**Algorithm 2** Outline of the whole min-min scheme
 

---

```

1: while there remains tasks to be scheduled do
2:   for each remaining task  $T_i$  do
3:     for each server  $S_j$  do
4:       use Algorithm 1 to compute the date  $t$  at which all the files required for the
         execution of  $T_i$  will be available on  $S_j$ 
5:       evaluate the minimum completion time of  $T_i$  on  $S_j$  knowing  $t$  (as computed above)
         and considering the cluster  $C_j$  as a single processor
6:     pick a couple  $(S_j, T_i)$  whose minimum completion time is minimal
7:     map  $T_i$  on the cluster  $C_j$ 
8:     use Algorithm 1 to schedule the communications needed by the execution of  $T_i$  on  $S_j$ 
9:     schedule task  $T_i$  on the processor  $C_{j,k}$ ,  $1 \leq k \leq c_k$ , which provides the minimum
         completion time

```

---

#### 4.6 Variant of the min-min scheme

Our framework promotes file duplication. When a given server  $S$  requires a file  $F$  for the execution of some task  $T$ , the file may be available on several servers. A static policy would be to transfer the file from the server originally storing it, or more precisely from the closest server (in terms of communication time) that originally stored it, in the case of an initial duplication of the file. This naive scheme has the advantages of its simplicity: it is cheap and does not require to memorize file transfers. A more dynamic policy would be to choose, as the source of transfer, the closest server among the ones holding the file at the time where we consider the communication. We call this policy *closest*. Hopefully, such a policy can decrease communication costs. But it requires to dynamically update a list of possible sources for each file. Each time the *closest* policy is used, it induces a complexity increase of  $O(s\Delta T)$ , hence an overall complexity increase of  $O(n^2 s^2 \Delta T)$  in the heuristic.

Of course, a third policy would be to invoke Algorithm 1 on all possible sets of transfer sources and to choose the best solution. Knowing the complexity of min-min heuristics, such an expensive policy is not realistic.

In the rest of this paper, we denote by min-min the heuristic following the first policy, and by min-min+closest the heuristic following the second policy.

## 5 Heuristics of lower complexity

As appealing as the min-min scheme could be because of the quality of the scheduling that it produces [3, 9], its computational cost is huge and may forbid its use. Therefore, we aim at designing heuristics which are an order of magnitude faster, while trying to preserve the quality of the scheduling produced.

Our heuristics are based on a *cost* function which tries to estimate the completion time of the execution a given task on a given server. We have designed two types of heuristics: static ones where costs are estimated once and for all; and dynamic ones where costs are reevaluated as mapping and scheduling decisions are being made.

### 5.1 Static heuristics

Algorithm 3 presents the structure of our first static heuristic. Step by step, we describe its different parts, and we explain our design choices.

---

**Algorithm 3** Structure of the `static1` heuristic

---

```

1: for each task  $T_i$  do
2:   for each server  $S_j$  do
3:     compute the cost  $a(T_i, S_j)$ 
4:   map  $T_i$  on a server  $S(T_i)$  such that  $a(T_i, S(T_i)) = \min_{1 \leq j \leq s} a(T_i, S_j)$ 
5:   for each task  $T_i$ , in increasing order of the costs  $a(T_i, S(T_i))$  do
6:     use Algorithm 1 to schedule the communications needed by the execution of  $T_i$  on  $S(T_i)$ 
7:   for each server  $S_j$  do
8:     greedily schedule the tasks mapped on  $S_j$ 

```

---

#### The cost function

In our fully static heuristics, the cost of a task  $T_i$  on a server  $S_j$  is defined as an evaluation of the minimum completion time of  $T_i$  on  $S_j$ . Following what has been previously done for the min-min heuristic, the minimum completion time is defined as the sum of the time needed to send the required files to  $S_j$ , as computed by Algorithm 1, plus the time needed by the



cluster  $C_j$  to process the task, when the cluster is seen as a single computational resource:

$$a(T_i, S_j) = \text{Time-Algo-1} \{ \text{comm}(\text{source}(F_k, S_j), S_j, F_k) \mid e_{k,i} \in \mathcal{E}, F_k \notin R_j \} + \frac{t_i}{\sum_{1 \leq l \leq c_j} s_{j,l}} \quad (1)$$

where

- $\text{source}(F_k, S_j)$  denotes the server which initially stores  $F_k$ ; in fact, since there may be several sources for  $F_k$ , we use the one closest to  $S_j$  (in terms of communication time);
- $\text{comm}(S, S', F)$  denotes the time to transfer file  $F$  from  $S$  to  $S'$ .

The overall complexity of the evaluation of the costs is  $O(ns\Delta T \cdot \Delta \mathcal{P})$ . We even speed-up these evaluations by approximating the time needed to send all the necessary files. Instead of using the precise but costly Algorithm 1, we use the simple formula:

$$Op_{e_{k,i} \in \mathcal{E}, F_k \notin R_j} \text{comm}(\text{source}(F_k, S_j), S_j, F_k), \quad (2)$$

where  $Op$  can design either the “sum” operator (over-approximation by sequentialization of all the communications) or the “max” operator (under-approximation by considering all the communications to take place in parallel). If we precompute once and for all the cost of sending an elementary file between any two servers, which requires  $O(s^3)$  operations, the overall complexity of the evaluation of the costs drops to  $O(n|\mathcal{E}| + s^3)$  with our approximations.

### Task scheduling

To schedule the communications, we use Algorithm 1, the source of the file transfers being chosen according to the *closest* policy defined in section 4.6.

Once the communications are scheduled, we have for each task the availability date of the files which it depends upon at a cost  $O(|\mathcal{E}|)$ , and we proceed as explained in Section 4.5 for the min-min heuristic, with a cost  $O(n \max_{1 \leq i \leq s} c_i)$ .

### Overall complexity

In the rest of this paper we denote by `static1` the static heuristic presented above. Its complexity is

$$O \left( n|\mathcal{E}| + s^3 + n \log n + n(\Delta T \cdot \Delta \mathcal{P} + \Delta T \log(\Delta T)) + ms^2 + n \max_{1 \leq i \leq s} c_i \right)$$

which is an order of magnitude less than the complexity of the min-min scheme: we no longer have a  $n^2$  term. Here the *closest* policy only induces a complexity increase of  $O(ms^2)$  as, in the worst case, each file is needed on all servers, and to find the closest server, one must search them all.

## 5.2 Variants of the static heuristics

### Critical path scheduling of communications: variant `critic`

Instead of scheduling the communications task by task, we schedule at once all the necessary communications. This way, we hope to be able to give a higher priority to the most important communications.

Consider the transfer of a file  $F$  from a server  $S_i$  to a server  $S_k$ , through a single other server  $S_j$ . The transfer is thus composed of two local communications, the second ( $S_j \xrightarrow{F} S_k$ ) depending upon the first ( $S_i \xrightarrow{F} S_j$ ). To schedule the whole set of communications, we build the dependence graph of the local communications where each vertex represents a local communication, and where there is an edge from a first vertex to a second if and only if the first one represents a local communication that must have been realized before the second can occur. In our example, there would be an edge from the vertex representing  $S_i \xrightarrow{F} S_j$  to the vertex representing  $S_j \xrightarrow{F} S_k$ . Our dependence graph is obviously a directed acyclic graph (DAG). It contains at most  $O(ms)$  vertices (at the end, at worst each file is on each server).

We associate to each vertex  $S_i \xrightarrow{F} S_j$  of the dependence graph a *weight* equal to the computation time of the tasks mapped to the cluster  $C_j$  and depending on the file  $F$ , plus the time of the communication itself. We define the *cost* of a vertex as the sum of its weight and of the weights of all the vertices reachable from it. Finally, in a critical path approach, we schedule the communications in decreasing order of their associated vertices *costs*.

The complexity of this whole communication scheduling is  $O(ms \log(ms))$  (note that the costs are computed in  $O(ms)$  through a simple graph traversal). Of course, to reach such a low complexity, we assume, as we did for the `min-min` heuristic, that new communications are always scheduled after previously scheduled communications which use the same physical links.

### Highest priority to *ready* tasks: variant `readiness`

In the basic version of the heuristic, tasks are selected by following strictly the increasing order on the task costs (Step 5 of Algorithm 3). In the `readiness` variant, each time we try to schedule a new task, we consider the next task in this order, *unless* there is a task  $T_i$  which is *ready* for a server  $S_j$ , in which case we immediately schedule  $T_i$  on  $S_j$ . A task is called *ready* for a server, if the server repository holds all the files that the task depends upon. So, a ready task can be scheduled at no communication cost.

Maintaining lists of ready tasks costs  $O(s|E|)$ . Indeed, on each server, we maintain for each task the number of its missing files. Each time a new file arrives on a server, we decrease the number of missing files for all tasks that depend upon it.

---

**Postponing the mapping of tasks to servers: the static2 heuristic**

In the `static1` heuristic, a task is mapped on a server on which its *cost* is minimal. Following ideas in [9], we only use the *cost* to determine in which order the tasks are considered. Thus, we sort, for each server, the tasks by increasing cost. Once the sorted lists are computed, we still have to map the tasks to the servers and to schedule them. The tasks are scheduled one-at-a-time. When we want to schedule a new task, on each server  $S_i$  we evaluate the completion time of the first task (according to the sorted list) which has not yet been scheduled. The completion time evaluation is identical to the equivalent evaluation performed by the `min-min` heuristic. Then we pick the pair task/server with the lowest completion time. This way, we obtain our second static heuristic (see Algorithm 4), which includes by default the *readiness* variant. We denote this heuristic `static2` in the rest of this paper. As `static1`, `static2` follows the *closest* policy of Section 4.6.

The overall complexity of the `static2` heuristic is:

$$O\left(n|\mathcal{E}| + s^3 + sn \log n + s|\mathcal{E}| + ns\Delta T(\Delta\mathcal{P} + s + \log(\Delta T)) + n \max_{1 \leq i \leq s} c_i\right)$$

---

**Algorithm 4** Structure of the `static2` heuristic
 

---

- 1: **for** each server  $S_j$  **do**
  - 2:   **for** each task  $T_i$  **do**
  - 3:     compute the cost  $a(T_i, S_j)$
  - 4:   build the list  $L(S_j)$  of the tasks sorted in increasing value of  $a(T_i, S_j)$
  - 5: **while** there remains tasks to schedule **do**
  - 6:   **for** each server  $S_j$  **do**
  - 7:     **if** there are tasks ready for  $S_j$  **then**
  - 8:       let  $T_i$  be any task ready for  $S_j$
  - 9:     **else**
  - 10:       let  $T_i$  be the first unscheduled task in  $L(S_j)$
  - 11:       use Algorithm 1 to compute the date  $t$  at which all the files required for the execution of  $T_i$  will be available on  $S_j$
  - 12:       evaluate the minimum completion time of  $T_i$  on  $S_j$  knowing  $t$  (as computed above) and considering the cluster  $C_j$  as a single processor
  - 13:       pick a couple  $(S_j, T_i)$  whose minimum completion time is minimal
  - 14:       map  $T_i$  on the cluster  $C_j$
  - 15:       use Algorithm 1 to schedule the communications needed by the execution of  $T_i$  on  $S_j$
  - 16:     **for** each server  $S_j$  **do**
  - 17:       greedily schedule the tasks mapped on  $S_j$
-

### 5.3 Dynamic heuristics

In our static heuristics, we first define the order in which the tasks are considered, and all the other scheduling decisions (communication definition and scheduling) are implied by this original order. However, this order is based on a cost which is truly relevant when there is a single task in the system. Indeed, the cost formula does not take into account the fact that some other tasks may need the same files, and thus misses the possibility of new sources (created as the execution proceeds) for these files. To remedy this flaw, we introduce a more dynamic scheme, while trying to conserve a low complexity heuristic. The structure of our dynamic heuristics is described by Algorithm 5.

---

#### Algorithm 5 Structure of the dynamic heuristics

---

```

1: for each task  $T_i$  do
2:   for each server  $S_j$  do
3:     compute the cost  $a(T_i, S_j)$ 
4:   while there are tasks to be scheduled do
5:     for each server  $S_i$  do
6:       pick the task(s) of lowest dynamic cost(s) on  $S_i$ 
7:       among the tasks picked at Step 5, select the couple(s)  $(S_i, T_j)$  of lowest dynamic cost(s),
         taking into account the amount of work already assigned to cluster  $C_i$ 
8:       for each selected couple  $(S_i, T_j)$  in any order do
9:         map  $T_j$  on the cluster  $C_j$ 
10:        use Algorithm 1 to schedule the communications needed by the execution of  $T_i$  on
           $S_j$ 
11:        Re-evaluate the costs whose value may have changed
12:   for each server  $S_j$  do
13:     greedily schedule the tasks mapped on  $S_j$ 

```

---

#### A dynamic cost

Our dynamic cost function is built along the line of the cost defined by Equation 1 using the simple communication estimation of Equation 2 and replacing the constant “source” function by a dynamic “closest” function:

$$a(T_i, S_j) = Op_{e_{k,i} \in \mathcal{E}} \text{comm}(\text{closest}(F_k, S_j)) + \frac{t_i}{\sum_{1 \leq l \leq p(j)} s_{j,l}} \quad (3)$$

The “closest” function, when invoked on a file  $F$  and a server  $S$ , returns the identity of the server which is closest to  $S$  and which holds the file  $F$  *at the time the function* was invoked. In other words, the “closest” function takes into account the mapping decisions taken before its invocation.

A new problem arises: the ability to compute the “closest” function at the lowest possible cost. To reach this goal, each server holds a table of the other servers sorted in increasing

distance (in communication time). Building such a list costs the computation of all the pairwise distances plus the sorting of the  $s$  tables, that is  $O(s^3 + s^2 \log s) = O(s^3)$ . Each time a new communication is decided involving a file  $F$ , the value of  $closest(F, S_i)$  is recomputed for any server  $S_i$ . This is done in constant time by checking whether the new server holding  $F$  has a lower rank, in the table defined above, than the previous *closest* server for this file. As, in the worst case, each file is only sent once to each of the servers, there are at most  $O(sm)$  of these constant-time updates.

Each time the value of a function  $closest(F_k, S_j)$  changes, we recompute the value of  $a(T_i, S_j)$  if and only if task  $T_i$  depends upon file  $F_k$ , i.e.  $e_{k,i} \in \mathcal{E}$ . Any of these updates is in constant time if the operator “Op” is the sum operator, and cost  $O(\Delta T)$  if “Op” stands for “max”. Therefore, the overall complexity of maintaining our dynamic costs is

$$O(s^3 + sm(1 + C))$$

where  $C = 1$  if “Op” is the sum operator and  $C = \Delta T$  if “Op” is the max operator.

### Picking the next task(s) to be scheduled

Once we have defined our dynamic cost, we have to decide how to use it to select the new task(s) to be scheduled. We have the choice either to pick a single new task at a time or to pick a set of  $k$  tasks. The former scheme is in spirit closer to the min-min heuristic. The latter scheme may be less expensive. In both versions, we once again target a low complexity.

#### Heuristic dynamic1

A simple way of picking a single new task would be to search, on each server, which task has the lowest complexity, and then search for the minimum over the servers. This is exactly what the min-min heuristic does. Such a selection scheme costs  $O(n^2s)$  which may be prohibitive. In order to speed-up the search of the task of lowest cost, we maintain on each server a heap of the task costs. Then, on each server, the selection of the task of lowest cost is done in constant time. However, each time we update a cost, we have to pay an additional cost of  $O(\log n)$  for the removal of an element from the heap and the addition of a new one<sup>1</sup>. Therefore, the overall complexity of this heuristic is:

$$O\left(n|\mathcal{E}| + s^3 + sm(1 + C) + s(m + n) \log n + n\Delta T(\Delta\mathcal{P} + s + \log(\Delta T)) + n \max_{1 \leq i \leq s} c_i\right).$$

#### Heuristic dynamic2

Another way of decreasing the complexity of the selection of the “closest” task candidate is to select, on each server,  $k$  tasks of lowest costs, instead of only 1 task. Such a selection

<sup>1</sup>The removal of any element in a heap cost  $O(\log n)$  if we maintain a table associating any element stored in the heap to its position in the heap. Maintaining such a table does not increase the theoretical complexity of the heap operations.

can be realized in linear time in the worst case [2, 6]. Therefore, we select the  $k$  tasks of lowest cost on each server. As a task may appear in the “closest” set of different servers, we sort the  $k.s$  couples (task, server) that we obtain according to their costs, and we pick the  $k$  distinct tasks of lowest costs. Therefore, the overall complexity of this heuristic is:

$$O\left(n|\mathcal{E}| + s^3 + sm(1 + C) + \frac{n}{k}(ns + ks \log(ks)) + n\Delta T(\Delta\mathcal{P} + s + \log(\Delta T)) + n \max_{1 \leq i \leq s} c_i\right).$$

## 6 Simulation results

In order to compare our heuristics, we have simulated their executions on randomly built platforms and graphs. We have conducted a large number of experiments, which we summarize in this section.

### 6.1 Simulation platforms

**Platform graphs:** they are composed of 7 servers. The graph of the servers is either a clique, a random tree, or a ring.

**Clusters:** we have recorded the computational power of different computers used in our laboratories (in Lyon and Strasbourg). From this set of values, we randomly pick values whose difference with the mean value was less than the standard deviation. This way we define realistic and heterogeneous clusters randomly containing 8, 16, or 32 processors.

**Communication links:** the communication links between the servers are randomly built along the same principles as the set of processors.

**Communication to computation cost ratio:** The absolute values of the communication link bandwidths or of the processors speeds have no meaning (in real life they must be pondered by application characteristics). We are only interested by the relative values of the processors speeds, and of the communication links bandwidths. Therefore, we normalize processor and communication characteristics. Also, we arbitrarily impose the communication-to-computation cost ratio, so as to model three main types of problems: computation intensive (ratio=0.1), communication intensive (ratio=10), and intermediate (ratio=1).

### 6.2 Task graphs

We run the heuristics on the following four types of tasks graphs. In each case, the size of the files and tasks are randomly and uniformly taken between 0.5 and 5.

**Two-one:** each task depends on exactly two files: one file which is shared with some other tasks, and one un-shared file.

**Random:** each task randomly depends on 1 up to 50 files.

**Partitioned:** this is a type of graph intermediate between the two previous ones; the graph is divided into 20 chunks of 75 tasks, and in each chunk each task randomly depends on 1 up to 10 files. The whole graph contains at least 20 different connected components.

**Forks:** each graph contains 100 fork graphs, where each fork graph is made up of 20 tasks depending on a single and same file.

Each of our graphs contains 1500 tasks and 1750 files, except for the fork graphs which also contain 1500 tasks but only 70 files. In order to avoid any interference between the graph characteristics and the communication-to-computation cost ratio, we normalize the sets of tasks and files so that the sum of the file sizes equals the sum of the task sizes times the communication-to-computation cost ratio.

The initial distribution of files to server is built randomly.

### 6.3 Results

Heuristic	Relative performance	Standard deviation	Relative cost	Standard deviation
min-min+closest	1.01	0.04 (3.7%)	4200	790 (19%)
min-min	1.17	0.16 (14%)	3600	820 (23%)
static2	1.28	0.23 (18%)	5.2	1.5 (28%)
static2+max	1.29	0.23 (18%)	5.6	1.3 (23%)
static1+readiness	1.84	0.54 (29%)	1.9	0.6 (30%)
static2+max+critic	1.91	0.64 (33%)	6.4	1.1 (17%)
static2+critic	1.92	0.66 (34%)	5.9	1.2 (20%)
static1	1.93	0.60 (31%)	1.7	0.5 (31%)
static1+readiness+max	2.06	0.83 (40%)	2.0	0.5 (28%)
static1+max	2.08	0.85 (41%)	1.8	0.5 (30%)
random	118	380 (320%)	1.5	0.3 (19%)

Table 1: Relative performance and cost of the best ten heuristics and of the naive *random*.

Table 1 summarizes all the experiments. In this table, we report the performance of the best ten heuristics, and of the naive *random*, together with their cost (i.e. their CPU time). This is a summary of 36,000 random tests (1,000 tests over all four task graph types, three platform graph types, and three communication-to-computation cost ratios). Each test involves 27 heuristics:

- min-min and its variant min-min+closest.

- The three static heuristics: `static1`, `static1+readiness`, and `static2`. These heuristics are declined with the variants `max` (“Op” is the max operator instead of the sum, cf. Section 5.1) and `critic`.
- The dynamic heuristics `dynamic1` and `dynamic2`, the latter using sets of either  $k = 10$  or  $k = 100$  tasks. These heuristics are also declined with the variants `max` and `critic`.
- The naive `random` heuristic, which randomly picks the next task to be scheduled and the server on which to execute it. Once these decisions are randomly taken, the communication and tasks are scheduled as in the `static1` heuristic. We include this naive heuristic as a lower bound on performance.

For each of the 36,000 tests, we compute the ratio of the performance of all heuristics over the best heuristic for the test, which gives us a *relative performance*. The best heuristic differs from test to test, which explains why no heuristic in Table 1 can achieve an average relative performance exactly equal to 1. In other words, the best heuristic is not always the best of each test, but it is closest to the best of each test in the average. The optimal relative performance of 1 would be achieved by picking, for any of the 36,000 tests, the best heuristic for this particular case. (For each test, the relative cost is computed along the same guidelines, using the fastest heuristic.)

Figures 8 through 13 present detailed comparisons of all the heuristics, by types of task graphs, by communication to computation ratio, or by types of platform graphs.

From all these results, we can see that the two versions of `min-min` are the best heuristics, and that `min-min+closest` is almost always the best heuristic. We see that the *closest* variant has a great beneficial impact of about 15% in performance for a reasonable overhead cost of 16%. This is the reason why we use by default the *closest* variant in the `static1` and `static2` heuristics.

As observed in [9], the *readiness* variant has a significant impact on performance. For the `static1` heuristic, it induces a performance gain of about 5% for an overhead cost of 10%. So, we use it by default in the `static2` heuristic.

The four versions of the `static2` heuristics are in the top ten. Furthermore, the two basic versions are within 28% of the best heuristic for... 0.1% of its cost! Surprisingly, the way in which sets of communications are approximated in the cost function has almost no influence on the quality of the output. Indeed, there is no significative performance difference between the version `static2`, which over-pessimistically approximates the sets of communications, and the version `static2+max`, which over-optimistically approximates them. This certainly emphasizes the impact of the precise evaluation of the minimum completion time which is used to decide which task is scheduled next. This precise evaluation induces a 30% improvement in performance (when comparing to `static1+readiness`) but at the price of an overhead cost of about 220%.

None of our dynamic heuristics made the top ten. The first one is ranked 14: this is the `dynamic1+max` heuristic. Its relative performance equals 2.43, which is almost twice as worse as `static2`, and its relative cost is 14. The `dynamic2` heuristic using sets of 10 tasks ranks 15 with a relative performance of 2.51 and a relative cost of 26 (increasing the size of sets



to 100 tasks, the relative performance slightly increases to 2.54 while the relative cost drops to 5.2). These results are rather disappointing. We were able to design dynamic heuristics of reasonable complexities, but their performances are quite low. As our decision process does not take into account the amount of communications already scheduled, and their destinations, our dynamic heuristics may tend to map all the tasks on the same processor. This would obviously lead to network congestion.

Looking at Figures 10 and 11, we see that our heuristics have the same behavior whatever the communication to computation ratio is. Furthermore, our best heuristic, `static2`, has almost exactly the same relative performance whatever this ratio is. This shows the robustness of these heuristics.

Finally, we introduced the naive `random` heuristic as a lower bound on the quality of the task mapping and scheduling. Figures 8 and 9 show that the `random` heuristic is extremely bad on the *fork* graphs. It appears that when the task graph contains evident sharing properties, as in the *fork* graphs, our heuristics are able to take advantage of them. On the contrary, on the *fork* graphs, `random` is as bad as usual and the gap widens. On the other types of graphs, the performance of `random` is not as bad as one could have expected. This may be due to our choice to have a random initial distribution of files to servers. Our simulation systems may be too general, and thus too difficult, for any heuristics to have tremendous performance. Also, our simulation platforms may be small enough to limit the impact of the randomness of `random`. Nevertheless, our best heuristics still show significant improvements in comparison to `random`, while this is not always the case for the dynamic heuristics (not a good mark for them!). We ran the `static2` and `random` heuristics on a larger system of 20 servers, 50000 tasks, and 62500 files. Table 2 shows the relative performance (the lower the numbers in the table, the better the `static2` heuristic) of `static2` when compared to `random` on the original and on the larger system. We clearly see that in comparison the relative performance of `static2` improves when the system become larger.

Task graph	Original system	Larger system
Two-one	0.36	0.17
Random	0.31	0.29
Partitioned	0.57	0.37
Forks	0.002	0.00005

Table 2: Relative performance of `static2` in comparison to `random`.

## 7 Conclusion

In this paper, we have dealt with the problem of scheduling a large collection of independent tasks, that may share input files, onto collections of distributed servers. On the theoretical side, we have shown a new complexity result, that shows the intrinsic difficulty of the combinatorial problem of deciding where to move files.

On the practical side, our contribution is twofold:

- We have shown how to extend the well-known `min-min` heuristic to the new framework; this turned out to be more difficult than expected, and we had to introduce (and justify) several restrictive assumptions upon the routing and communication scheduling.
- We have succeeded in designing a collection of new heuristics which have reasonably good performance but whose computational costs are an order of magnitude lower than `min-min`. Specifically, the best heuristic `static2` produces schedules whose makespan is 30% higher than `min-min`, but whose cost (in CPU time) is 800 times smaller.

We plan to deploy the heuristics presented in this paper for a large medical application, with servers in different hospitals in the Lyon-Grenoble area, and we hope that the ideas introduced when designing our heuristics will prove useful in this real-life scheduling problem.

## References

- [1] F. Berman. High-performance schedulers. In I. Foster and C. Kesselman, editors, *The Grid: Blueprint for a New Computing Infrastructure*, pages 279–309. Morgan-Kaufmann, 1999.
- [2] M. Blum, R. W. Floyd, V. Pratt, R. R. Rivest, and R. E. Tarjan. Time bounds for selection. *Journal of Computer and System Sciences*, 7(4):448–461, 1973.
- [3] H. Casanova, A. Legrand, D. Zagorodnov, and F. Berman. Using Simulation to Evaluate Scheduling Heuristics for a Class of Applications in Grid Environments. Technical Report 99-46, Laboratoire de l’Informatique du Parallélisme, ENS Lyon, Sept. 1999.
- [4] H. Casanova, A. Legrand, D. Zagorodnov, and F. Berman. Heuristics for Scheduling Parameter Sweep Applications in Grid Environments. In *Ninth Heterogeneous Computing Workshop*, pages 349–363. IEEE Computer Society Press, 2000.
- [5] P. Chrétienne, E. G. Coffman Jr., J. K. Lenstra, and Z. Liu, editors. *Scheduling Theory and its Applications*. John Wiley and Sons, 1995.
- [6] T. H. Cormen, C. E. Leiserson, and R. L. Rivest. *Introduction to Algorithms*. The MIT Press, 1990.
- [7] M. R. Garey and D. S. Johnson. *Computers and Intractability, a Guide to the Theory of NP-Completeness*. W. H. Freeman and Company, 1991.
- [8] A. Giersch, Y. Robert, and F. Vivien. Scheduling tasks sharing files on heterogeneous clusters. Research Report RR-2003-28, LIP, ENS Lyon, France, May 2003.
- [9] A. Giersch, Y. Robert, and F. Vivien. Scheduling tasks sharing files on heterogeneous master-slave platforms. In *PDP’2004, 12th Euromicro Workshop on Parallel, Distributed and Network-based Processing*. IEEE Computer Society Press, 2004.

- [10] M. Maheswaran, S. Ali, H. Siegel, D. Hensgen, and R. Freund. Dynamic matching and scheduling of a class of independent tasks onto heterogeneous computing systems. In *Eight Heterogeneous Computing Workshop*, pages 30–44. IEEE Computer Society Press, 1999.
- [11] A. Schrijver. *Combinatorial Optimization: Polyhedra and Efficiency*, volume 24 of *Algorithms and Combinatorics*. Springer-Verlag, 2003.
- [12] B. A. Shirazi, A. R. Hurson, and K. M. Kavi. *Scheduling and load balancing in parallel and distributed systems*. IEEE Computer Science Press, 1995.

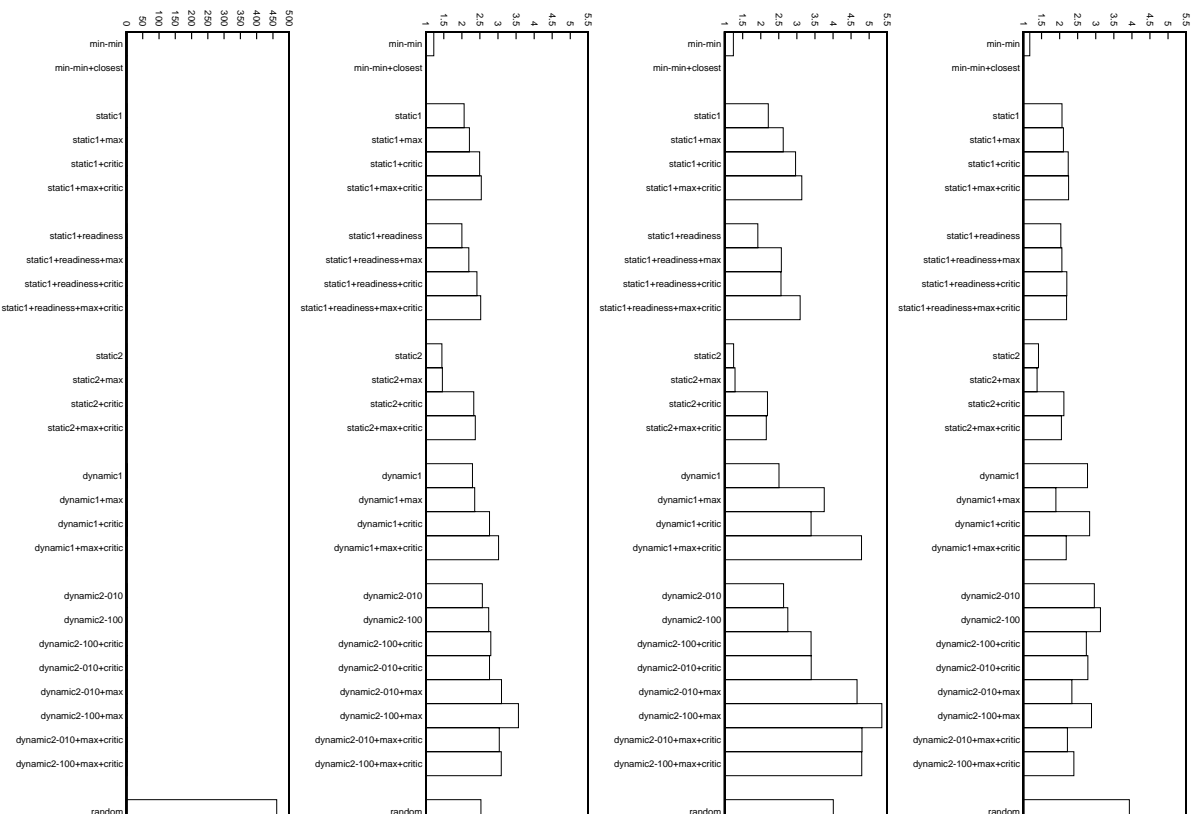


Figure 8: Relative performances of the schedules produced by the different heuristics average on three communication to computation ratios and three types of platform graphs, for the four types of graphs (from top to bottom: *Two-one*, *Random*, *Partitioned*, and *Forks*).

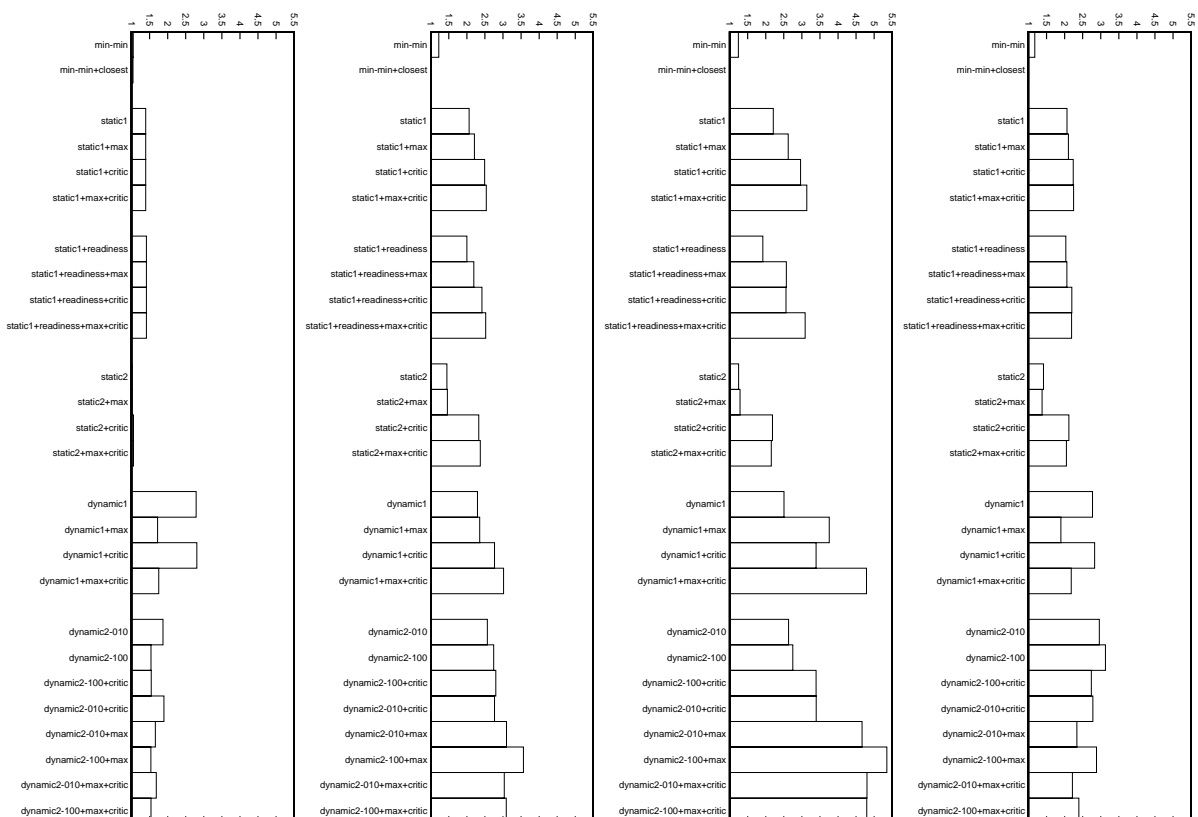


Figure 9: Relative performances of the schedules produced by the different heuristics (*except random*) average on three communication to computation ratios and three types of platform graphs, for the four types of graphs (from top to bottom: *Two-one*, *Random*, *Partitioned*, and *Forks*).

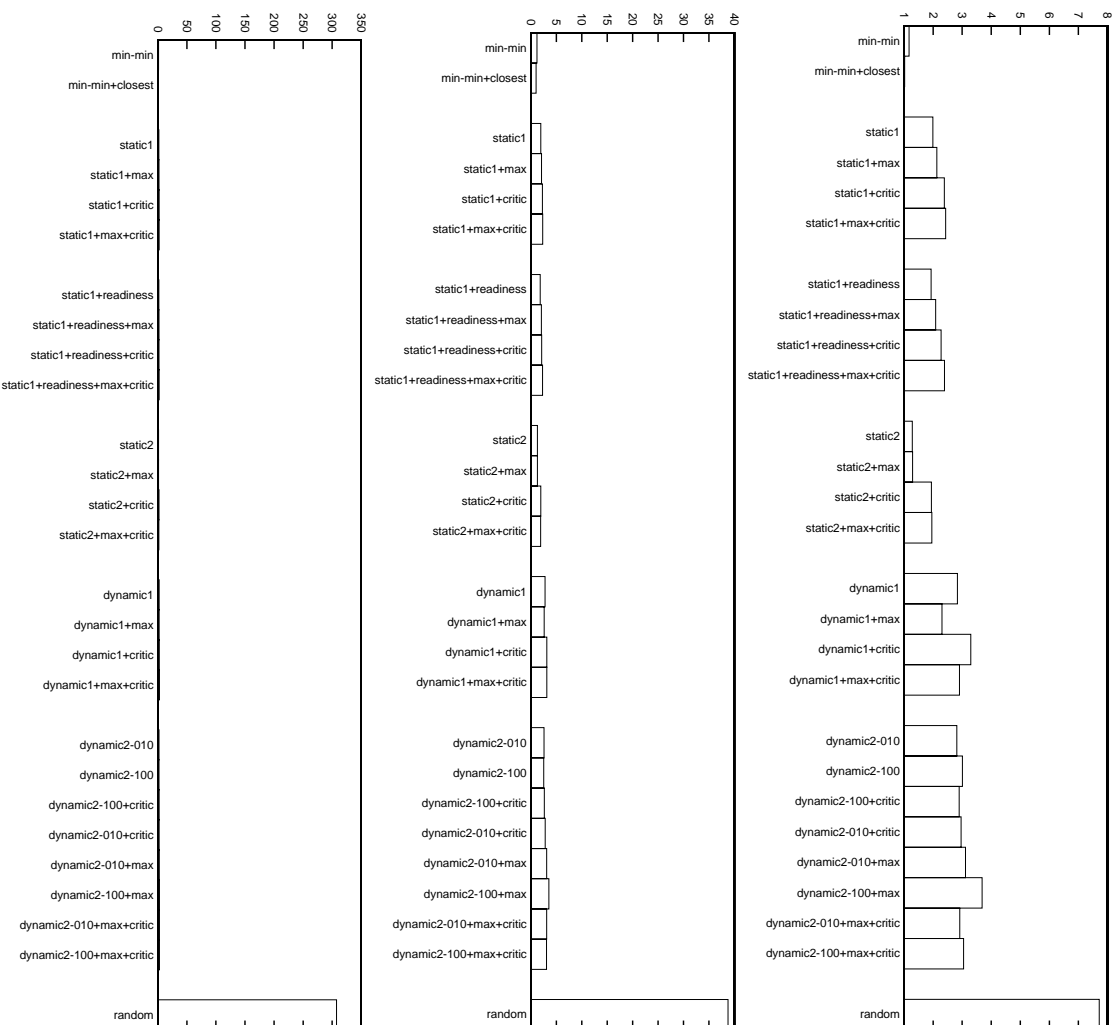


Figure 10: Relative performances of the schedules produced by the different heuristics average on the four types of graphs and three types of platform graphs, with a communication to computation ratio equal, from top to bottom, to: 0.1, 1.0, and 10.

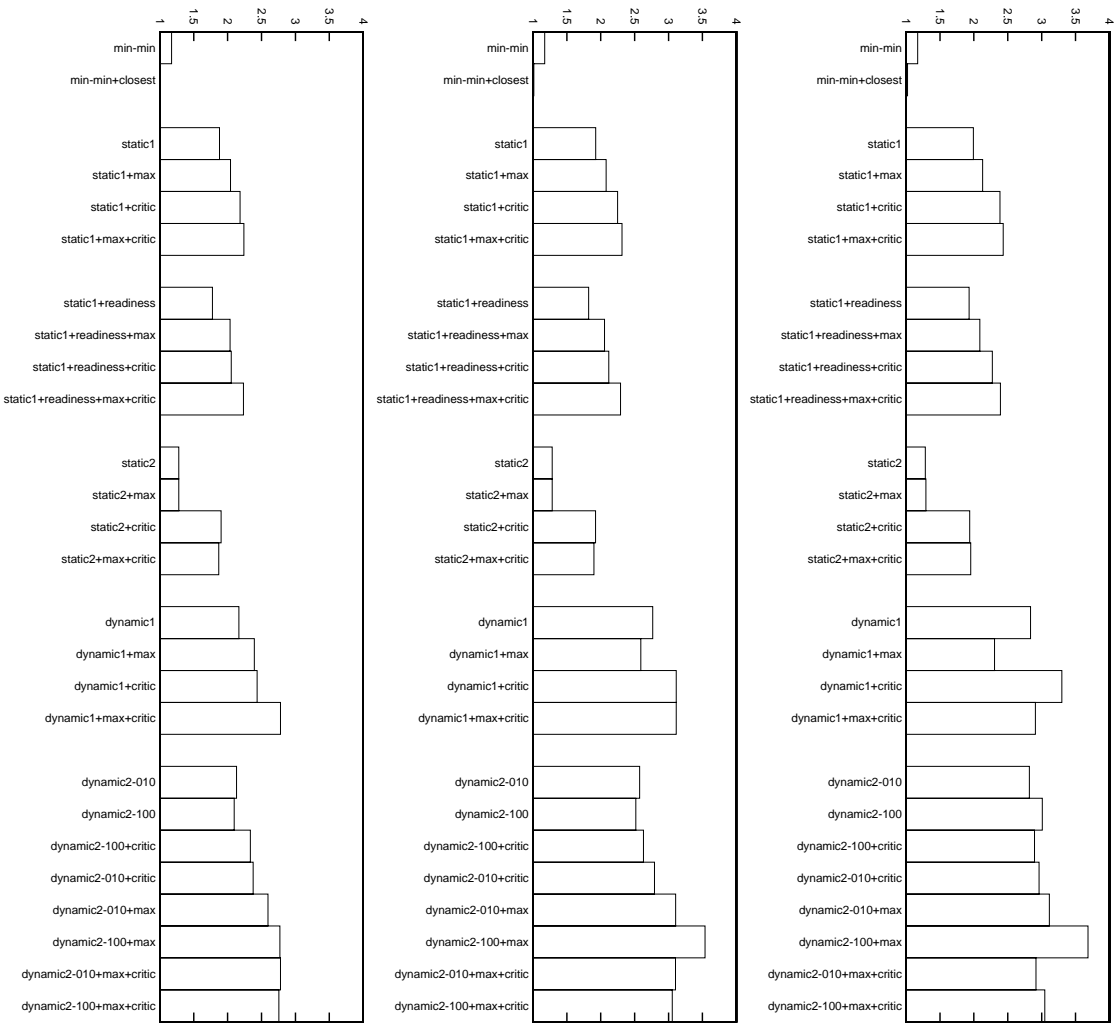


Figure 11: Relative performances of the schedules produced by the different heuristics (*except random*) average on the four types of graphs and three types of platform graphs, with a communication to computation ratio equal, from top to bottom, to: 0.1, 1.0, and 10.

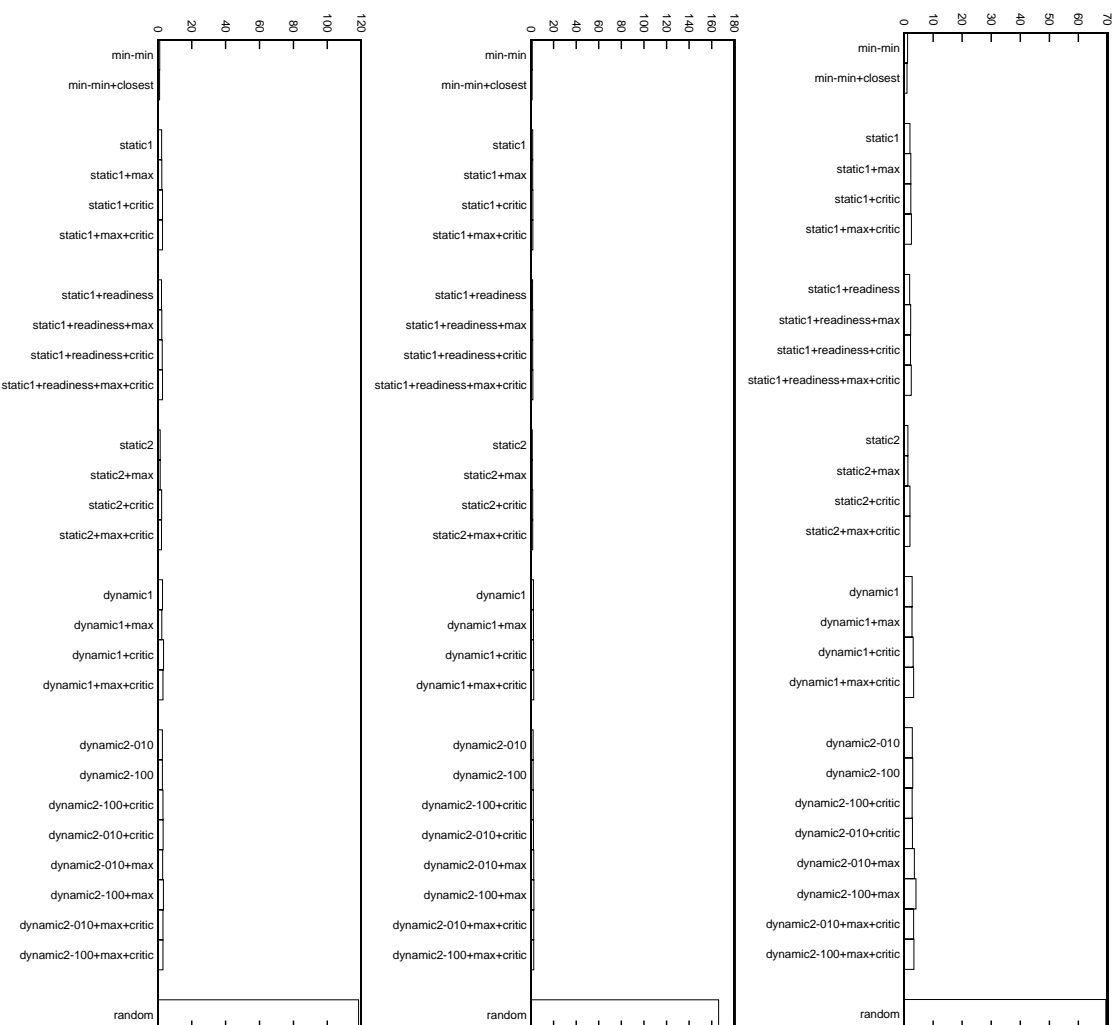


Figure 12: Relative performances of the schedules produced by the different heuristics average on the four types of graphs and three communication to computation ratios, for the three types of platform graphs, from top to bottom: clique, random tree, and ring.



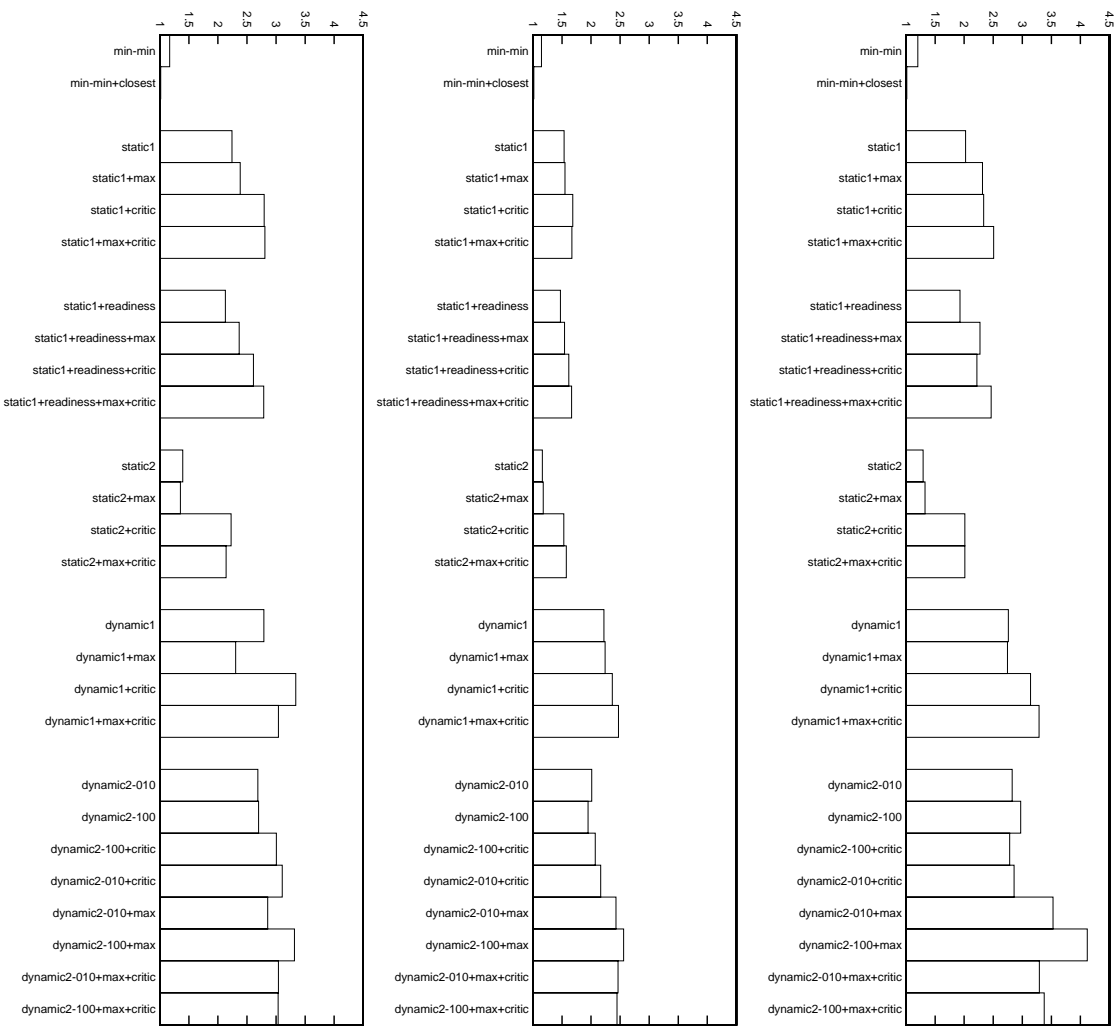


Figure 13: Relative performances of the schedules produced by the different heuristics (*except random*) average on the four types of graphs and three communication to computation ratios, for the three types of platform graphs, from top to bottom: clique, random tree, and ring.



---

Unit é de recherche INRIA Lorraine, Technopôle de Nancy-Brabois, Campus scientifique,  
615 rue du Jardin Botanique, BP 101, 54600 VILLERS LÈS NANCY  
Unit é de recherche INRIA Rennes, Irisa, Campus universitaire de Beaulieu, 35042 RENNES Cedex  
Unit é de recherche INRIA Rhône-Alpes, 655, avenue de l'Europe, 38330 MONTBONNOT ST MARTIN  
Unit é de recherche INRIA Rocquencourt, Domaine de Voluceau, Rocquencourt, BP 105, 78153 LE CHESNAY Cedex  
Unit é de recherche INRIA Sophia-Antipolis, 2004 route des Lucioles, BP 93, 06902 SOPHIA-ANTIPOLIS Cedex

---

Éditeur  
INRIA, Domaine de Voluceau, Rocquencourt, BP 105, 78153 LE CHESNAY Cedex (France)  
<http://www.inria.fr>  
ISSN 0249-6399