Resource Information Aggregation in Hierarchical Grid Networks

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Abstract

We propose information aggregation as a method for summarizing the resource-related information, used by the task scheduler. Through this method the information of a set of resources can be uniformly represented, reducing at the same time the amount of information transferred in a Grid network. A number of techniques are described for aggregating the information of the resources belonging to a hierarchical Grid domain. This information includes the cpu and storage capacities at a site, the number of tasks queued, and other resource-related parameters. The quality of the aggregation scheme affects the efficiency of the scheduler's decisions. We use as a metric of aggregation efficiency the Stretch Factor (SF), defined as the ratio of the task delay when the task is scheduled using complete resource information over the task delay when an aggregation scheme is used. The simulation experiments performed show that the proposed aggregation schemes achieve large information reduction, while enabling good task scheduling decisions as indicated by the SF achieved.

1 Introduction

In Grid Networks, a scheduler receives requests for the use of resources and assigns the tasks so as to optimize some objective function. The scheduler makes its decisions based on information about the resources, such as their computational or storage capacity, their availability, etc, which are usually collected by information services called monitoring systems [1],[3].

In this work we propose a number of information aggregation techniques for summarizing the resource-related information, used by the task scheduler. With the emergence of a number of Grid services (e.g., Amazon EC2 and S3, Microsoft Azure) it will soon become necessary of summarizing their resource related information with a unified manner. This way it will be possible for a task scheduler to use efficiently the resources of the one or the other service, without at the same time being necessary for the corresponding service to publish in detail its resources characteristics. Moreover the proposed techniques can reduce the amount of resource-related information that is transferred, stored and processed. We expect that in the near future, as more resources of various types (clusters, PCs, mobile phones, etc) participate in Grids, the amount of information that will have to be transferred and processed will be quite large. This can lead to network congestion and overuse of the resources.

We assume that resources/sites are grouped into hierarchical domains and the information related to the sites in each domain, is aggregated before being sent to a higher level. Each site is assigned a vector of cost parameters that records its computation or storage capacity, its availability, and other parameters. Next, the cost vectors of the sites belonging to a given domain are aggregated into a single cost vector for the entire domain, by performing appropriate associative operations to the cost parameters. We also introduce so-called domination relations that reduce the number of vectors aggregated and stored. When a task request arrives, the scheduler selects the domain where the task will be executed, by applying an optimization function to the collected and aggregated cost vectors.

A drawback of information aggregation is that the efficiency of a scheduler using such information may be negatively affected. This introduces a trade-off between the amount of information exchanged (and used by the scheduler) and the efficiency of the scheduling decisions. We propose information aggregation schemes that produce aggregated information of different quality, improving or deteriorating the scheduling decisions. These techniques are presented in a general way, permitting their combination and the creation of new ones. We perform a large number of experiments to evaluate the proposed aggregation techniques. We use as a metric the Stretch Factor (*SF*), defined as the ratio of the task delay when the task is scheduled using complete resource information over the task delay when an aggregation scheme is used. Our simulation results show that the proposed schemes achieve large information reduction, while maintaining good scheduling quality, in comparison to the case where no aggregation is performed. The amount of information is measured with the number of cost vectors used by the task scheduler in order to make its decisions.

The remainder of the paper is organized as follows. In Section 2 we report on previous work. In Section 3 we formulate the problem. In Section 4 we introduce the proposed aggregation techniques. In Section 5 we experimentally evaluate the proposed techniques. Finally, in Section 6 we conclude the paper.

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2 Previous Work

In Grid Networks, information collection is performed by the monitoring systems. In [1] a number of monitoring systems are presented and categorized. These systems are often organized in a hierarchical structure, which is consistent with the structure of the Grids and the Data Networks. In these networks, sites are organized in domains that build up to hierarchical structures. Hierarchical routing plays a major role in Data Networks, as a way to minimize the routing tables required for the very large topologies encountered in Internet's infrastructure. [4] is one of the first works investigating hierarchical routing.

A central issue in hierarchical routing is topology information aggregation [5],[6], which tries to summarize and compress the topology information advertised at higher levels. In order to perform routing efficiently, the aggregated information should adequately represent the topology and the other characteristics of the network, such as the delay and bandwidth. In [7] a topology aggregation scheme subject to multi-criteria (delay and bandwidth) constraints is presented.

Generally, most scheduling algorithms presented to date [8],[9],[10],[11],[12] make their decisions using exact resource information, which may, however, be outdated by the time it is used due network delays. In contrast, in this work the scheduler makes its decisions using the aggregated resource information and we examine the trade-off between the amount of information exchanged (and used by the scheduler) and the quality of these decisions.

Most previous works [5],[6],[7] consider the aggregation of network-related information and the effects of this aggregation on the routing process. Also, the idea of information aggregation has appeared in P2P [17] and in sensor networks [18]. In the current work, we consider the aggregation of Grid resource-related information and investigate the effects of this aggregation on the scheduling process. To the best of our knowledge this is the first time grid information aggregation techniques are investigated and evaluated based on such a criterion. Scheduling using incomplete information has also been considered in [15], where, a technique is presented for monitoring large Grid Networks that selects a statistically valid sample and measures the behavior of the sample members, instead of monitoring each individual system.

3 Problem Formulation

We consider a Grid consisting of N sites, partitioned according to a hierarchical structure in a total of L domains D_j, $j=1,2,\dots,L$. Each site i, $i=1,2,\dots,N$, has computational and storage capacity C_i and S_i, respectively, and belongs to one of the L domains. Site i publishes its resource information as a vector V_i, that may contain various parameters:

$$V_i = (C_i, S_i, \dots).$$

These vectors are collected per domain D_j and are published to a higher level of the hierarchy, in the form of a matrix of vectors:

$$M_j = \begin{bmatrix} V_1 \\ V_2 \\ \vdots \\ V_{|D_j|} \end{bmatrix} = \begin{bmatrix} (C_1, S_1, \dots) \\ (C_2, S_2, \dots) \\ \vdots \\ (C_{|D_j|}, S_{|D_j|}, \dots) \end{bmatrix},$$

where $|\cdot|$ denotes the cardinality of a set and $1,2,\dots,|D_j|$ are the sites contained in domain D_j. By performing appropriate operations on the parameters of the information vectors contained in the information matrix M_j, M_j is transformed into the *aggregated information matrix* $\hat{M}_j$.

The Grid scheduling problem is usually viewed as a hierarchical problem that has two levels. At the higher level a central scheduler decides the domain D_j a task will be assigned to, and at the lower level a domain scheduler DS_j, decides the exact site in the domain where the task will be executed (Figure 1). The information collection and aggregation is performed, similarly, by a two level monitoring system, consisting of a central monitor CM and the domain monitors DM_j, $j=1,2,\dots,L$. Our work can also apply in the case of a multi-level Grid system with distributed scheduling and monitoring entities. A user located at some site generates tasks T_m, $m=1,2,\dots$, with computational workload W_m.

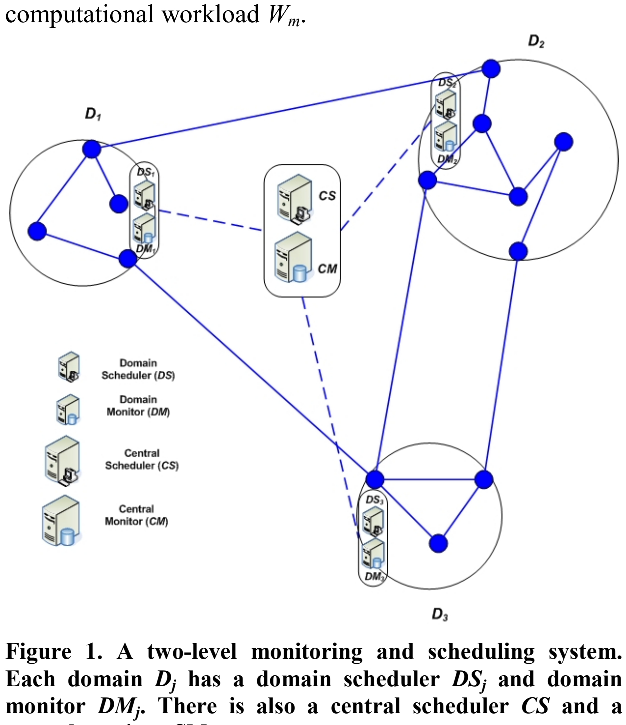


Figure 1. A two-level monitoring and scheduling system. Each domain D_j has a domain scheduler DS_j and domain monitor DM_j. There is also a central scheduler CS and a central monitor CM.

4 Information Aggregation

4.1 The Proposed Scheme

The proposed scheme consists of an information aggregation algorithm together with a task scheduling algorithm that uses this information. In Algorithm 1 we present the pseudocode for the information collection and aggregation scheme.

Algorithm 1 Resource Information Collection and Aggregation

1. Each site i, i=1,2,…,N, belonging to some domain D_j periodically or reactively (when information changes) publishes its information vector V_i to the domain monitor DM_j.
2. Each domain monitor DM_j, j=1,2,…,L, puts together these vectors to form the information matrix M_j.
3. Domain monitor DM_j, j=1,2,…,L, periodically or reactively (when information changes) computes its aggregated information matrix $\hat{M}_j$ and publishes it to the central monitor *CM*.
4. The *CM* collects the aggregated information matrices.

In Algorithm 2 we present the scheduling scheme that uses the aggregated information.

Algorithm 2 Task Scheduling

1. Upon the arrival of a task T_m, the central scheduler *CS* looks at the domain matrices provided by the central monitor *CM*.
2. The central scheduler *CS* applies an optimization function to the vectors contained in the domain matrices and selects the information vector V that produces the largest value.
3. The *CS* assigns the task T_m to the domain D_j, where the vector V originated from, and forwards the task to the domain scheduler DS_j.
4. The domain scheduler DS_j receives the task and selects the exact site the task will be scheduled on, using exact resource information.

4.2 Information Parameters and Aggregation Operators

We present the resource information parameters of interest in this work, and the operators used for their aggregation. For every parameter, different operators can also be used (e.g. min, max, sum, average), depending on the needs of the applications and the scheduling algorithms used. Next, we list some of these parameters and operators, giving a brief explanation of their usage:

- The computational capacities C_i of the sites, measured in Millions Instructions per Second (MIPS), in a domain D_j can be aggregated by performing a minimum representative operation or an additive operation:

$$\hat{C}_j = \min_{i \in D_j} C_i \quad \text{or} \quad \hat{C}_j = \sum_{i \in D_j} C_i \, .$$

  Using the minimum representative operator we obtain the minimum capacity of any site in the domain D_j, which would be useful for conservative task scheduling. Using the additive operator we obtain the total computational capacity in the domain, which would be useful for scheduling when a task's workload is divisible, and can be assigned to different resources simultaneously.
- The storage capacities S_i of the sites, measured in MB, in a domain D_j can be aggregated as following:

$$\hat{S}_j = \sum_{i \in D_j} S_i \quad \text{or} \quad \hat{S}_j = \max_{i \in D_j} S_i \, .$$

  The first definition is useful when the data of a task can be stored in a distributed way across the domain, while the second when the data have to be stored at a single site.
- The number of tasks N_i assigned to the sites can be aggregated over a domain D_j as following:

$$\hat{N}_j = \sum_{i \in D_j} N_i \, .$$

- The estimated time FT_i in the future at which a computational resource belonging to site i will be freed can be aggregated over all sites of domain D_j by using a minimum representative operator:

$$\hat{FT}_j = \min_{i \in D_j} FT_i \, .$$

  Using this aggregated value the scheduler will know the earliest time at which some site in domain D_j will be free to execute a new task.
- The *Start times* (*ST*) and *End times* (*ET*) of the tasks assigned to sites of a domain can be aggregated by finding the time periods where all sites in the domain are executing a task. This means that during the remaining time periods, there is at least one resource that is idle and available for scheduling new tasks. This information may be useful for schedulers performing timed and advance resource reservations [13],[14].

4.3 Aggregation Schemes

4.3.1 Single Point Aggregation Scheme

In the *single point* aggregation scheme the information vectors of the sites in each domain are aggregated into a single information vector by applying various associative operators. We show an example of the application of the *single point* aggregation technique, where the size of the information matrix M_j is reduced from $|D_j|$ to 1:

$$M_j = \begin{bmatrix} V_1 \\ V_2 \\ \vdots \\ V_8 \end{bmatrix} = \begin{bmatrix} (C_1, S_1, \ldots) \\ (C_2, S_2, \ldots) \\ \vdots \\ (C_8, S_8, \ldots) \end{bmatrix} \Rightarrow \hat{M}_j = \begin{bmatrix} \hat{V} \end{bmatrix} = \begin{bmatrix} (\hat{C}, \hat{S}, \ldots) \end{bmatrix}$$

The information transferred to the higher levels is greatly reduced using this aggregation technique, at the cost, however, of degraded quality of the aggregated information.

4.3.2 Intra-Domain Clustering Aggregation Scheme

In the *intra-domain clustering* aggregation technique, the sites of each domain D_j j=1,2,…,L, are partitioned into $h_j \le |D_j|$ *intra-domain clusters*. For the sites belonging to each cluster l, l=1,2,…,h_j, the aggregated vector $\hat{V}_l$ is calculated and sent to domain monitor DM_j. The aggregated information matrix $\hat{M}_j$ that contains the aggregated information vectors of the clusters $\hat{V}_l$, l=1,2,…,h_j, is sent to the higher levels.

Various approaches can be used for clustering the sites of a domain:

- Sites can be clustered randomly.
- A clustering function can be applied to each site's information vector and the sites that yield closer values are grouped together. This way the intra-domain clusters obtained consist of sites with similar characteristics and the aggregated information vector better represents the sites in the intra-domain cluster.
- The clustering can be performed so as to maximize the time periods during which the sites belonging to a given cluster are unavailable (as indicated by their ST and FT's). This way the start ($\hat{ST}$) and finish times ($\hat{FT}$) of an aggregated vector will better describe the availability of the sites in a cluster. In [16] a resource selection method is presented that increases the time overlapping of the tasks assigned to different sites and decreases it for tasks belonging to the same site. We can use a similar method for performing the clustering of the sites.

We show an example of the application of the intra-domain clustering aggregation technique, where the size of the information matrix M_j is reduced from $|D_j|$=8 vectors to h_j=3 vectors.

$$M_j = \begin{bmatrix} V_1 \\ V_2 \\ \vdots \\ V_7 \\ V_8 \end{bmatrix} = \begin{bmatrix} (C_1, S_1, \ldots) \\ (C_2, S_2, \ldots) \\ \vdots \\ (C_7, S_7, \ldots) \\ (C_8, S_8, \ldots) \end{bmatrix} \Rightarrow \hat{M}_j = \begin{bmatrix} \hat{V}_1 \\ \hat{V}_2 \\ \hat{V}_3 \end{bmatrix} = \begin{bmatrix} (\hat{C}_1, \hat{S}_1, \ldots) \\ (\hat{C}_2, \hat{S}_2, \ldots) \\ (\hat{C}_3, \hat{S}_3, \ldots) \end{bmatrix}$$

The number of intra-domain clusters per domain influences the amount of information passed to higher levels and the efficiency of the scheduler's decision.

4.3.3 Reducing Aggregated Information using Domination Relations

Using the concept of *dominated resources,* we can further prune the number of information vectors processed by the domain monitors or the number of aggregated information vectors processed by the central monitor. Specifically, we will say that information vector V_1 *dominates* information vector V_2, if V_1 is better than V_2 with respect to all the cost parameters.

For example, consider the information vectors $V_1 = (C_1, S_1, FT_1)$ and $V_2 = (C_2, S_2, FT_2)$. We say that V_1 dominated V_2 if the following conditions hold:

$$C_1 > C_2,\ S_1 > S_2 \text{ and } FT_1 < FT_2$$

The V_2 information vector can then be discarded from further consideration, since the site (or domain) characterized by V_2 is inferior to the site (or domain) characterized by V_1 with respect to all parameters of interest.

4.4 Domain Selection Cost Functions

When a new task arrives the CS performs the following operations in order to select the appropriate domain for the task's execution:

- It discards all the aggregated information vectors that do not satisfy the task requirements (e.g. storage requirements).
- An optimization function is applied to the remaining vectors and the domain giving the largest value is selected.

5 Performance Evaluation

5.1 Simulation Environment

We consider a number of sites that are randomly grouped into domains, each of an approximately equal number of sites. Site i is characterized by its computational capacity C_i, measured in MIPS and number of tasks N_i under execution or in its queues. Unless stated otherwise, the capacities of the sites are chosen from a uniform distribution between 1000 and 10000 MIPS. The number of tasks at each site is also chosen from a uniform distribution between 5 and 200 tasks. One could argue that the assumption of a uniform distribution of tasks per site is not so realistic, since a good scheduling algorithm would result in a more balanced and correlated distribution. However, we are not interested in a specific scheduling algorithm, but in examining the quality of the information provided by the aggregation schemes for performing scheduling decisions. In our simulations we also examine other distributions of tasks to the sites. Each new task has workload uniformly distributed between 1000 and 10000 MI and no data dependencies, so no data transfers occur. Moreover, network related issues are not considered in this work.

5.2 Aggregation Schemes Evaluated

We implemented and evaluated the following schemes:

- *FlatCpuFreeStart*: This scheme assumes a-priori knowledge of the task workloads. Site i calculates and publishes an information vector $V_i = \{C_i, FT_i\}$ containing its computational capacity C_i and the estimated future time FT_i when all the queued tasks will have completed their execution. The scheduler has complete knowledge of the information vectors of all the sites based on which it assigns a new task T_m to the site i that will execute the task sooner:
$$\min_i \{FT_i + \frac{W_m}{C_i}\}.$$
- *HierCpuFreeStart*: In this scheme the information vectors of the sites belonging to the same domain are aggregated. The aggregation of the site computational capacities and finish times is performed using the minimum representative operator: $\hat{C} = \min_i C_i$ and $\hat{FT} = \min_i FT_i$. The central scheduler *CS* assigns task T_m to the domain D_j that will complete the task sooner, using only the aggregated information vectors of the domains:
$$\min_j \{\hat{FT}_j + \frac{W_m}{\hat{C}_j}\}.$$
The selected domain's scheduler DS_j then assigns the task to a domain site, having complete knowledge of the information vectors of all the sites in the domain. The assignment again is performed based on the minimum completion time criterion:
$$\min_{i \in D_j} \{FT_i + \frac{W_m}{C_i}\}.$$
- *FlatCpuTasks*: This scheme is similar to *FlatCpuFreeStart*, except that there is no a-priori knowledge of the task workloads. The information vector $V_i = \{C_i, N_i\}$ of site i contains its computational capacity C_i and the number of tasks N_i queued at it. A new task T_m is assigned to the site i that minimizes the optimization function (Section 4.4):
$$\min_i \{\frac{C_i}{N_i}\}.$$
- *HierCpuTasks*: In this scheme the information vectors of the sites belonging to the same domain are aggregated using the minimum representative and the additive operators, respectively: $\hat{C} = \min_i C_i$ and $\hat{N} = \sum_i N_i$. The central scheduler *CS* initially assigns, using only the aggregated information vectors of the domains, a task T_m to the domain D_j that minimizes the optimization function:
$$\min_j \{\frac{\hat{C}_j}{\hat{N}_j}\}.$$
The selected domain's scheduler, DS_j, receives the task and assigns it to a domain site, having complete knowledge of the information vectors of all the sites in the domain. The assignment again is performed based on the same optimization function:
$$\min_{i \in D_j} \{\frac{C_i}{N_i}\}.$$
- *HierDominanceCpuTasks*: This scheme is similar to the *HierCpuTasks*, except that domination relations are applied to the vectors of the sites in a domain, before they are aggregated.
- *HierICCpuTasks*: This scheme is similar to the *HierCpuTasks*, except that the intra-domain clustering method is used, where sites are randomly clustered into intra-domain clusters.
- *HierDominanceICCpuTasks*: This scheme combines the *HierDominanceCpuTasks* and *HierICCpuTasks* schemes, where domination relations are applied to the vectors of the sites belonging to the same intra-domain cluster, before their aggregation.

5.3 Simulation Metrics

We are interested in the quality of the information produced by the aggregation schemes when making scheduling decisions. In our experiments we use the *Stretch Factor* (*SF*) metric, defined as the ratio of the task delay *TD* when scheduling is performed using complete resource information (*FlatCpuFreeStart, FlatCpuTasks*) over the task delay when an aggregation scheme is used (*HierCpuFreeStart, HierCpuTasks, HierICCpuTasks, HierDominanceICCpuTasks*). The task delay is the time that elapses from the task's creation until the completion of its execution. The *SF* is also encountered in the hierarchical networks related literature, where it is defined as the ratio of the average number of hops from a source to a destination when flat routing is used, over the corresponding value when hierarchical routing is used. In our work we define the following stretch factor metrics:

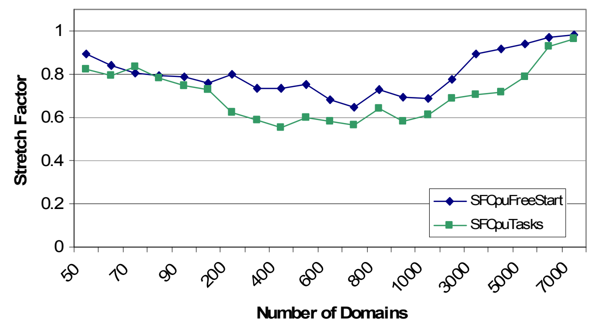
- $\text{SFCpuFreeStart} = \frac{TD_{FlatCpuFreeStart}}{TD_{HierCpuFreeStart}}$
- $\text{SFCpuTasks} = \frac{TD_{FlatCpuTaks}}{TD_{HierCpuTasks}}$
- $\text{SFCpuTasksDominance} = \frac{TD_{FlatCpuTaks}}{TD_{HierCpuTasksDominance}}$
- $\text{SFICCpuTasks} = \frac{TD_{FlatCpuTaks}}{TD_{HierICCpuTasks}}$
- $\text{SFICCpuTasksDominance} = \frac{TD_{FlatCpuTaks}}{TD_{HierICCpuTasksDominance}}$

In all cases $SF \leq 1$, since when a scheduler has complete knowledge of the resources information, it can make better decisions than when this information is aggregated. An aggregation technique is efficient when its corresponding *SF* is close to 1. An additional metric for evaluating the schemes is the amount of information (number of information vectors) produced and used by the central scheduler in making its decisions.

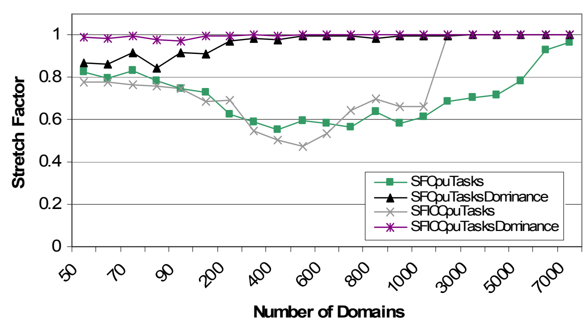
5.4 Simulation Results

In our experiments each site's characteristics are chosen among a finite set of values. For example, a site's computational capacity is an integer value between 1000 MIPS and 10000 MIPS, while the number of queued tasks is between 5 and 200 tasks. Thus, as the number of sites increases the probability that sites in different domains have similar information vectors also increases, and so does the probability that more than one "best" sites or sites similar to the "best" site exist in different domains. We represent this probability as $P_{multiple\text{-}best}$, and as our results will indicate it strongly affects the stretch factor. By "best" we mean the site that optimizes the metric of interest (task delay, or some other optimization function).

Figure 2 shows the measured stretch factors when 10000 Grid sites are clustered in a variable number of domains. The *HierICCpuTasks* and *HierDominanceICCpuTasks* aggregation schemes use h=5 intra-clusters in each domain. The stretch factor metrics behave similarly, that is, their value first decreases up to some point, after which they start increasing towards 1. This is because when the number of domains is small, then the number of sites per domain is quite high (e.g., 200) increasing the $P_{multiple\text{-}best}$ probability. As the number of domains increases, $P_{multiple\text{-}best}$ decreases and the stretch factors also decrease. After some point, as the number of domains increases and the number of sites per domain decreases, the quality of information produced by the aggregation schemes improves. This is because when there are few sites per domain, the aggregated information better represents the characteristics of its sites.



(a)



(b)

Figure 2. (a) The *SFCpuFreeStart* and the *SFCpuTasks* (b) the *SFCpuTasks*, *SFCpuTasksDominance*, *SFICCpuTasks* and the *SFICCpuTasksDominance* stretch factors, when 10000 Grid sites are clustered in a variable number of domains.

SFCpuFreeStart is generally larger than *SFCpuTasks* (Figure 2.a), indicating that different parameters in the information vectors and different operators used for their aggregation result in different quality for the information provided to the scheduler. We also observe that *SFCpuTasks* and *SFICCpuTasks* (Figure 2.b) take similar values; however, when 2000 domains are used the *SFICCpuTasks* metric reaches 1. This is because in this case each domain has 5 sites and 5 intra-domain cluster, and the aggregation scheme that produces 5 information vectors per domain, describes exactly the resources' information (in fact, no aggregation is performed in that case). We also observe that the *HierDominanceCpuTasks* and *HierDominanceICCpuTasks* aggregation schemes produce the best results. This indicates that the dominance operation, which discards dominated information vectors, improves the quality of the information provided to the scheduler. This is also confirmed when comparing the *HierDominanceICCpuTasks* and the *HierICCpuTasks* aggregation schemes. We should also note that the number of domains and sites used in our simulations, may be seem quite large in comparison to the usual values in existing Grid Networks. We took this decision in order to examine the full dynamics of the proposed aggregation techniques.

Moreover, the *HierDominanceICCpuTasks* scheme yields results that are very close to those obtained by the *FlatCpuTasks* scheme, while providing less information vectors to the central scheduler. Reducing the number of intra-domain clusters, reduces the number of information vectors produced, but also reduces the quality of the information provided, as measured by the corresponding stretch factor. Table 1 shows the number of information vectors provided by each scheme when 10000 sites are clustered in 100 domains. Also, it is not only the amount of resource information transferred that it is reduced, but also the number of control messages exchanged, the computational overhead for processing the information and the storage overhead for storing it.

Aggregation Scheme	**# of information vectors**
FlatCpuFreeStart	N = 10000
HierCpuFreeStart	$L = 100$
FlatCpuTasks	N = 10000
HierCpuTasks	$L = 100$
HierDominanceCpuTasks	$L = 100$
HierICCpuTasks (*h*=5 inter-domain clusters)	$L \cdot h = 500$
HierDominanceICCpuTasks (*h*=5)	$L \cdot h = 500$

Table 1: The number of information vectors produced by each aggregation scheme, when *N* = 10000 sites are clustered in *L* = 100 domains.

Figure 3 shows the *SFCpuTasks*, *SFCpuTasksDominance*, *SFICCpuTasksDominance,* and *SFICCpuTasks* stretch factors, when a variable number of sites are clustered in 20 domains. The *SFs* initially decrease and then, as the number of sites increases further, start increasing towards 1. This is because, initially, having more sites per domain reduces the quality of information provided by the schemes to the central scheduler. The exact amount of this reduction depends on the aggregation operators applied and the aggregation scheme used. For this reason we observe that the *HierDominanceCpuTasks* and *HierDominance-ICCpuTasks* schemes outperform the *HierCpuTasks* and *HierICCpuTasks* schemes. However, after a point, when the number of sites in each domain becomes large, the probability $P_{multiple\text{-}best}$ that there is a site in the selected domain that can execute a task as fast as the "best" site, becomes large and the *SF*s increase towards 1. This is also related to the number of different values resource characteristics can take. Figure 4 gives a better insight into this.

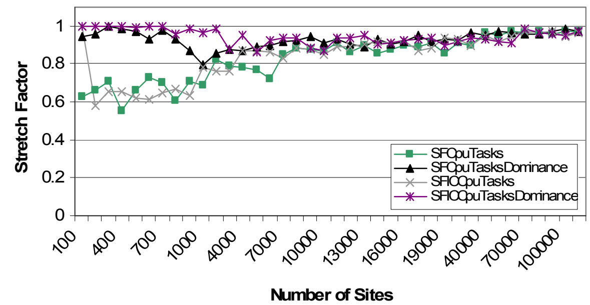


Figure 3. The *SFCpuTasks*, *SFCpuTasksDominance*, *SFICCpuTasks*, and the *SFICCpuTasksDominance SF*s, when a variable number of sites are clustered in 20 domains.

Figure 4 shows the results obtained for the *SFs* when changing the upper and lower limits of the uniform distributions assumed for the computational capacities and the number of tasks at the sites. The scenarios/probabilistic distributions used are presented in Table 2. In Figure 4 we illustrate the *SFCpuTasks* stretch factors obtained for the case where a variable number of sites are partitioned into 20 domains. Note that the number of different information vectors that the *UD03* scenario can produce is larger than the ones produced by the *UD02* scenario and even larger than those produced by the *UD01* scenario. We observe that the *SFCpuTasks* values decrease as the number of distinct values the sites' characteristics can take increase. This is because a large number of possible and different information vectors reduce the probability $P_{multiple\text{-}best}$ that more domains will have sites with information vectors similar to the "best" site. Corresponding experiments were performed for all the proposed aggregation schemes, producing similar results.

Scenario	**Computational Capacity (max/min)**	**Number of Tasks (max/min)**
UD01	10000/1000	200/5
UD02	100000/100	2000/5
UD03	1000000/10	20000/5

Table 2: Scenarios *UD01 UD02* and *UD03* correspond to different choices for the upper/ lower limits of the uniform distributions assumed for the computational capacities and the number of tasks at the sites.

Finally, we should note that the number of different information vectors produced by the aggregation schemes depends on the aggregation operators used. Specifically, as stated in [2], when two additive parameters are used, the number of possible information vectors produced is exponential, while when two restrictive operators are used (as in the information vectors we use), the number of different information vectors is polynomial. This illustrates the importance of the resource parameters and the aggregation operators on the efficiency of the aggregation schemes.

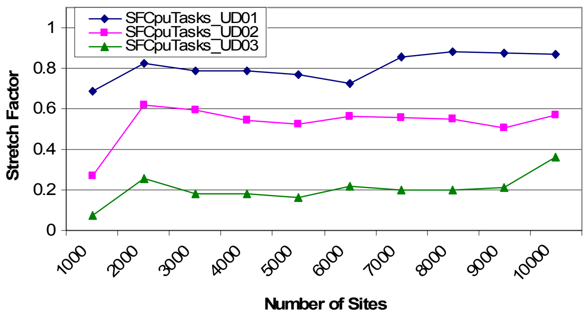


Figure 4. The *SFCpuTasks SF*s for the *UD01*, *UD02* and *UD03* scenarios (Table 2), when a variable number of sites are clustered in 20 domains.

6 Conclusions

We proposed several techniques for aggregating the resource information of the sites in hierarchical Grid domains and performing task scheduling using this information. We performed a number of simulation using the *Stretch Factor* (*SF*) as the main metric for measuring aggregation efficiency. The *SF* is defined as the ratio of the task delay when the task is scheduled using complete resource information over the task delay when an aggregation scheme is used. We observed that in many cases the proposed schemes achieve large information reduction, while enabling good task scheduling decisions as indicated by the *SF* achieved. We studied the trade-off between the amount of information exchanged (and used by the scheduler) and the scheduling efficiency. We also introduced domination relations and showed that they can increase the quality of the aggregated information. Finally, we observed that the uniformity of the sites' characteristics significantly affects the *SF*s achieved.

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