A Dynamic Job Grouping-Based Scheduling for Deploying Applications with Fine-Grained Tasks on Global Grids

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Abstract

Although Grids have been used extensively for executing applications with compute-intensive jobs, there exist several applications with a large number of lightweight jobs. The overall processing undertaking of these applications involves high overhead time and cost in terms of *(i)* job transmission to and from Grid resources and, *(ii)* job processing at the Grid resources. Therefore, there is a need for an efficient job grouping-based scheduling system to dynamically assemble the individual fine-grained jobs of an application into a group of jobs, and send these coarse-grained jobs to the Grid resources. This dynamic grouping should be done based on the processing requirements of each application, Grid resources' availability and their processing capability.

In this paper, we present a scheduling strategy that performs dynamic job grouping activity at runtime and convey the detailed analysis by running simulations. In addition, job processing granularity size is introduced to facilitate the job grouping activity in determining the total amount of jobs that can be processed in a resource within a specified time.

Keywords[€]: job grouping, grid computing, and scheduling.

1 Introduction

The emerging computational Grids, as mentioned by Foster and Kesselman (1999), provide a new platform for executing large-scale resource intensive applications on a number of heterogeneous computing resources across political and administrative domains. Typically, an application requires an execution set that consists of several jobs, where each job is considered as the atomic unit of computation. In a Grid computing environment, Berman, Fox and Hey (2002) describe that a scheduler is responsible for selecting the best suitable machines or computing resources in the Grid for processing jobs to achieve high system throughput.

Grids consist of resources connected over high latency networks. Thus, they implicitly favour coarse-grained jobs with a heavy computational component, so that the computation-communication ratio (CCR) encourages distributing them for processing on remote resources as referred to in Gray (2003). In the case of an application with a large number of jobs with small scale processing requirements, the total communication time between each job and the resource seems to be more than the total computation time of each job at the resource. However, coarse-grained jobs (meta-jobs) can be created by aggregating a suitable number of jobs at the user-level, and submitted the aggregated jobs to the scheduler for deployment as stated in Buyya, Date, et. al. (2004). This, however, creates a programming burden on the application developer as he/she will have to be aware of the complexities of Grid environment. Alternatively, the small scaled jobs can be submitted individually. This option leads to high communication time and cost, since each small job is associated with transmitting and processing overhead time and cost. Consequently, the CCR for such an execution tends to be unfavourable. Moreover, this also leads to poor utilization of the resources. Therefore, there is a need for a scheduling strategy to group the jobs at the scheduling level according to the processing capabilities of the available resources, and proceed with the job scheduling and deployment activities.

This paper presents and evaluates a dynamic scheduling strategy that maximizes the utilization of Grid resource processing capabilities, and reduces the overhead time and cost taken to execute the jobs on the Grid. The proposed job scheduling strategy takes into account: *(i)* the processing requirements for each job, *(ii)* the grouping mechanism of these jobs, known as a job grouping, according to the processing capabilities of available resources, and *(iii)* the transmitting of the job grouping to the appropriate resource.

The job grouping is done based on a particular granularity size. ***Granularity size*** is the time within which a job is processed at the resources. It is used to measure the total amount of jobs that can be completed within a specified time in a particular resource. Relationship between the total number of jobs, processing requirements of those jobs, total number of available Grid resources, processing capabilities of those resources and the granularity size should be determined in order to achieve the minimum

MI	: Million instructions or processing requirements of a user job
MIPS	: Million instructions per second or processing capabilities of a resource
Processing Time	: Total time taken for executing the user jobs on the Grid
Computation Time	: Time taken for computing a job on a Grid resource
JobList	: List of user jobs submitted to the broker
RList	: List of available Grid resources
JList_Size	: Total number of user jobs
RList_Size	: Total number of available Grid resources
Job_List$_i$_MI	: MI of ith user job
RList$_j$_MIPS	: MIPS of jth Grid resource
Granularity_Size	: Granularity size (time in seconds) for the job grouping activity
Total_JMI	: Total processing requirements (MI) of a job group (in MI)
Total_RMI$_j$	: Total processing capabilities (MI) of jth resource
	Total_RMI$_j$ = RList$_j$_MIPS *Granularity_Size
GJobList	: List of job groups after job grouping activity
TargetRList	: List of target resources of each job group

Figure 1: List of terms and their definitions

job execution time and cost, and maximum utilization of the Grid resources. In order to evaluate the proposed job scheduler, GridSim toolkit, as discussed in Buyya and Murshed (2002), is used to model and simulate Grid resources and application scheduling.

The rest of this paper is organized as follows: Section 2 briefly discusses related work, whereas Section 3 presents the proposed job grouping algorithm and its strategy. Some simulations and experiments were conducted on the proposed scheduler algorithm using GridSim toolkit and the results are presented in Section 4. Finally, Section 5 concludes the paper and mentions some future work.

2 Related Work

In cellular manufacturing systems, job grouping has been used to enhance efficiency of machinery utilization as mentioned by Logendran, Carson and Hanson (2002).

Similarly, Gerasoulis and Yang (1992), in the context of Directed Acyclic Graph (DAG) scheduling in parallel computing environments, named grouping of jobs to reduce communication dependencies among them as clustering. However, the aim of clustering is to reduce the inter-job communication and thus, decreasing the time required for parallel execution. For example, Edge-Zeroing, as discussed in Sarkar (1989), tries to reduce the critical path of the job graph. Another example is Dominant Sequence Clustering (DSC), as explained by Yang and Gerasoulis (1994), that trying to reduce the longest path in a scheduled DAG. Once the clustering is complete, mapping of clusters to processors becomes another hard problem. Some heuristics for cluster mapping are discussed and compared in Radulescu and van Gemund (1998). These heuristics aim to maximize the number of jobs that can be executed in parallel on different processors.

In this work, we focus on scheduling jobs which do not require communication with each other. Also, the overall aim of this work is to create coarse-grained jobs by grouping fine-grained jobs together in order to reduce the job assignment overhead, that is, the overhead of starting a new job on a remote node.

A study of scheduling heuristics for such jobs and similar problem was conducted in James, Hawick and Coddington (1999). Among others, two clustering algorithms - round-robin with clustering and continual adaptive scheduling - were discussed and compared for various job distributions. Within the former algorithm, jobs were grouped in equal numbers, while in the latter algorithm, the nodes are made to synchronize after each round of execution. In our case, as we will describe later on, the jobs are grouped according the ability of the remote node. Also, the job groups are dispatched as and when the nodes become available thus eliminating the overhead of a synchronisation step.

3 Algorithm Listing

Figure 1 shows the terms that are used throughout this paper and their definitions. The job grouping and scheduling algorithm is presented in Figure 2. Figure 3 depicts an example of job grouping and scheduling scenario where 100 user jobs with small processing requirements (MI) are grouped into six job groups according to the processing capabilities (MIPS) of the available resources and the granularity size.

The overall explanation of Figure 2 is as follows: once the user jobs are submitted to the broker or scheduler, the scheduler gathers the characteristics of the available Grid resources. Then, it selects a particular resource and multiplies the resource MIPS with the granularity size where the resulting value indicates the total MI the resource can process within a specified granularity size. The scheduler groups the user jobs by accumulating the MI of each user job while comparing the resulting job total MI with the resource total MI. If the total MI of user jobs is more than the resource MI, the very last MI added to the job total MI will be removed from the job total MI. Eventually, a new job (job group) of accumulated total MI will be created with a unique ID and scheduled to be executed in the selected resource. This process continues until all the user jobs are grouped into few groups and assigned to the Grid resources. The scheduler then sends the job groups to their corresponding resources for further computation. The Grid resources process the received job

```
-----------------------------------------------------------------------
Algorithm 1.0 Job Grouping and Scheduling Algorithm
-----------------------------------------------------------------------
m := 0;
for i:= 0 to JobList_Size-1 do
    for j:=0 to RList_Size-1 do
        Total_JMI := 0;
        $Total\_RMI_j$ := $RList_j$_MIPS*Granularity_Size;
        while Total_JMI ≤ $Total\_RMI_j$ and i ≤ JobList_Size-1 do
            Total_JMI := Total_JMI + $JobList_i$_MI;
            i++;
        endwhile
        i--;
        if Total_JMI > $Total\_RMI_j$ then
            Total_JMI := Total_JMI – $JobList_i$_MI;
            i--;
        endif
        Create a new job with total MI equals to Total_JMI;
        Assign a unique ID for the newly created job;
        Place the job in $GJobList_m$;
        Place $RList_j$ in $TargetRList_m$;
        m++;
    endfor
endfor
for i:= 0 to GJobList-1 do
    Send $GJobList_i$ to $TargetRList_i$ for job computation;
endfor
//Job computation at the Grid resources
for i:= 0 to GJobList-1 do
    Receive computed $GJobList_i$ from $TargetRList_i$;
endfor
```

Figure 2: Listing of the Job Grouping and Scheduling Algorithm

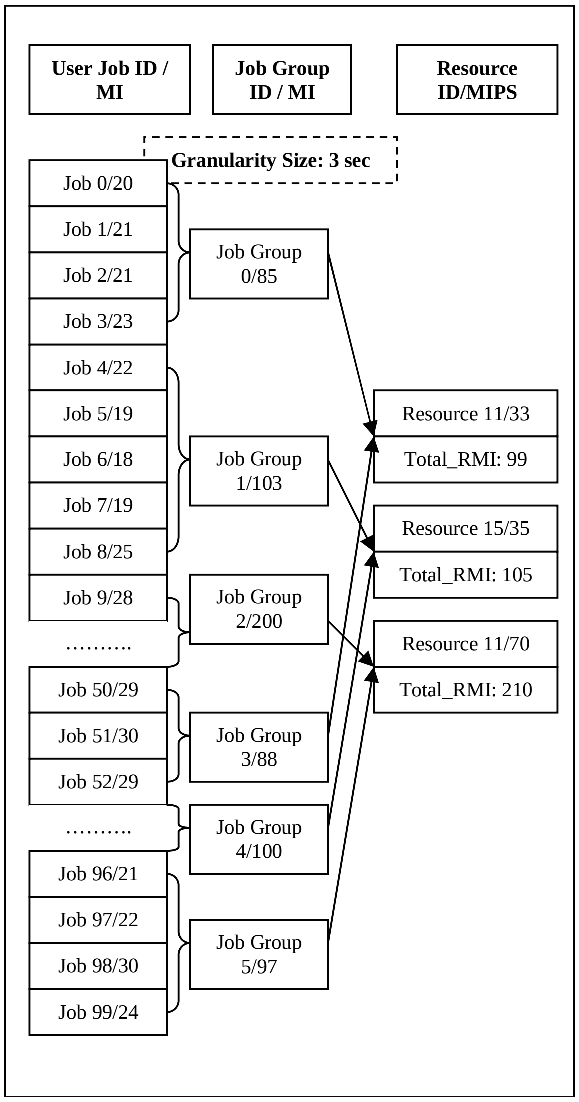


Figure 3: An Example of a Job Grouping Strategy

groups and send back the computed job groups to the Grid user. The scheduler then gathers the computed job groups from the network through its I/O port or queue.

In Figure 3, the granularity size is set to 3 seconds for example. The scheduler selects a resource of 33 MIPS and multiply the MIPS with the given granularity size. In total, that particular resource can process 99 MI of user jobs within 3 seconds. The scheduler then gathers the user jobs by accumulating their MI up to 99 MI. In this case, the first 4 jobs are grouped together resulting in 85 MI. The fifth job has MI of 22 and grouping of 5 jobs will results in 107 MI, which is more than the total processing capability of the selected resource. Once a group of first four jobs is created, the scheduler assigns a unique ID to that group. It then selects another resource and performs the same grouping operations. This process continues until all the jobs are grouped into a number of groups. Finally, the scheduler sends the groups to the resource for job computation.

4 Evaluation

4.1 Implementation with GridSim

GridSim toolkit is used to conduct the simulations based on the developed scheduling algorithm. Figure 4 depicts the simulation strategy of the proposed dynamic job grouping-based scheduler which is implemented using the GridSim toolkit. The system accepts total number of user jobs, processing requirements or average MI of those jobs, allowed deviation percentage of the MI, processing overhead time of each user job on the Grid, granularity size of the job grouping activity and the available Grid resources in the Grid environment (step 1-3). Details of the available Grid resources are obtained from Grid Information Service entity that keeps track of the resources available in the Grid environment. Each Grid resource is described in terms of their various characteristics, such as resource ID, name, total number machines in each resource, total processing elements (PE) in each machine, MIPS of each PE, and bandwidth speed. In this simulation, the details of the Grid resources are

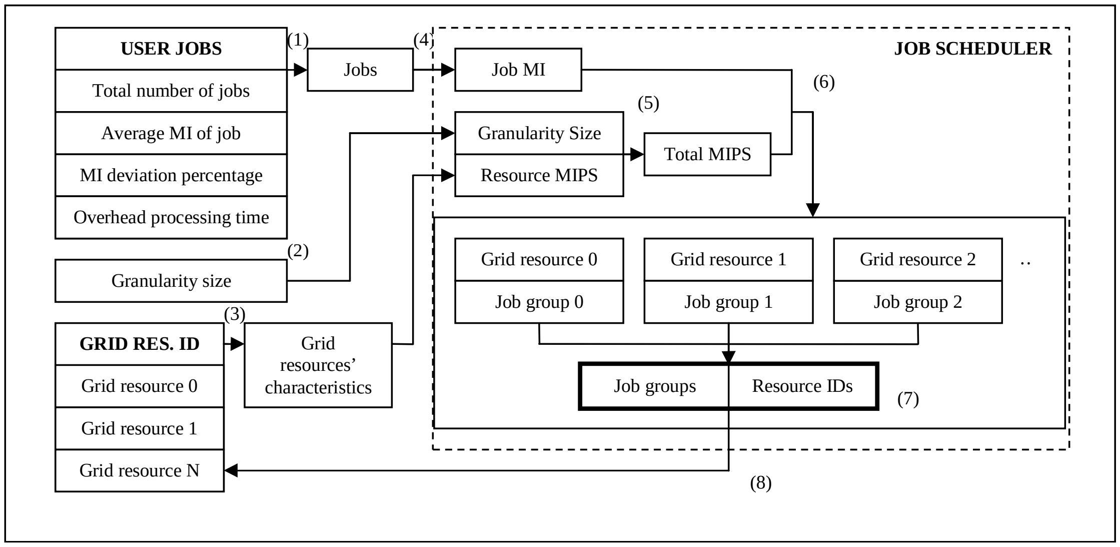


Figure 4: The simulation strategy for dynamic job grouping-based scheduler

Gridlet	: User job
Group	: Total number of Gridlet groups created from Gridlet grouping process
R	: Resource
A_MI	: Average MI rating of Gridlet or Gridlet length in MI
G_Size	: Granularity size in seconds
R_MIPS	: Resource processing capabilities in MIPS
D_%	: MI deviation percentage
OH_Time	: Processing overhead time of each Gridlet in seconds
Process_Time	: Gridlet processing time in seconds
Process_Cost	: Processing cost of the Gridlets
PE	: Processing elements in each resource

Figure 5: List of terms used within the evaluation and their definition.

Resource	MIPS	Cost per second
R1	200	100
R2	160	200
R3	210	300
R4	480	210
R5	270	200
R6	390	210
R7	540	320

Table 1: Grid resources setup for the simulation.

store in a file which will be retrieved during the simulations.

After gathering the details of user jobs and the available resources, the system randomly creates jobs according to the given average MI and MI deviation percentage (step 4). The scheduler will then select a resource and multiply the resource MIPS with the given granularity size (step 5). The jobs will be gathered or grouped according to the resulting total MI of the resource (step 6), and each created group will be stored in a list with its associated resource ID (step 7). Eventually, after grouping all jobs, the scheduler will submit the job groups to their corresponding resources for job computation (step 8).

4.2 Experimental Setup

Figure 5 lists the terms used within this section and their definitions. The inputs to the simulations are total number of Gridlets, average MI of Gridlets, MI deviation percentage, granularity size, resource MIPS and Gridlet processing overhead time.

The tests are conducted using seven resources of different MIPS, as showed in Table 1.The MIPS of each resource is computed as follows:

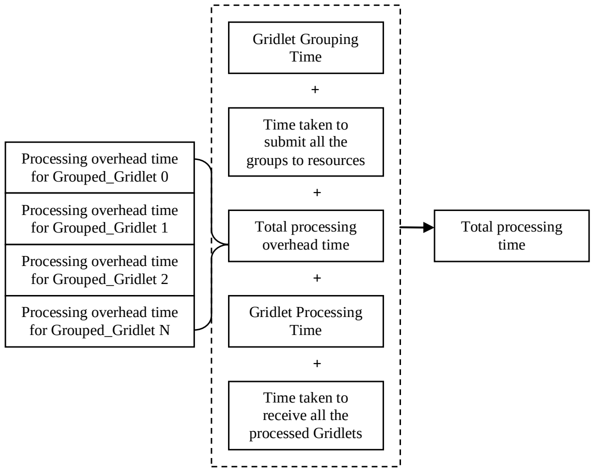
*Resource MIPS = Total_PE * PE_MIPS*, where

Total_PE = Total number of PEs at the resource,

PE_MIPS = MIPS of PE

Each resource has its own predefined cost rate for counting the charges imposed on a Grid user for executing the user jobs at that resource. The MIPS and cost per second are selected randomly for the simulation purpose.

In the simulation, the total processing time is calculated in seconds based on the overhead time for processing



Gridlet Grouping Time
+
Time taken to submit all the groups to resources
+
Total processing overhead time
+
Gridlet Processing Time
+
Time taken to receive all the processed Gridlets
Processing overhead time for Grouped_Gridlet 0
Processing overhead time for Grouped_Gridlet 1
Processing overhead time for Grouped_Gridlet 2
Processing overhead time for Grouped_Gridlet N
Total processing time

Figure 6: Processing time

each Gridlets, and the time taken for performing Gridlet (job) grouping process, sending Gridlets to the resources, processing the Gridlets at the resources and receiving back the processed Gridlets. This time computation is depicted in Figure 6. In real world, the overhead time for each job depends on the current network load and speed. In the simulations, the processing overhead time (OH_Time) of each Gridlet is set to 10 seconds.

The total processing cost is computed based on the actual CPU time taken for computing the Gridlets at the Grid resource and at the cost rate specified at the Grid resource, as summarized below:

Process_Cost = *T* * *C*, where

T = Total CPU Time for Gridlet execution, and

C = Cost per second of the resources.

4.3 Experiments, Results and Discussions

4.3.1 Experiment 1: Simulation with and without Job Grouping

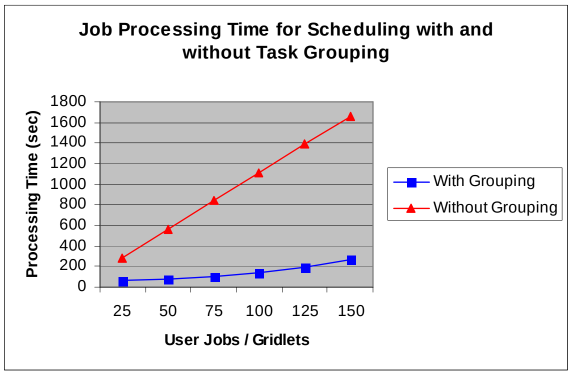
Simulations are conducted to analyse and compare the differences between two scheduling algorithms: first come first serve and job grouping-based algorithm described in section 3 in terms of processing time and cost. Resources R1 through R4 are used for these simulations.

Table 2 shows the results of the simulations with and without job grouping method conducted with granularity size of 30 seconds and Gridlet average MI of 200. The simulations managed to execute maximum of 150 Gridlets within 30 seconds. As depicted in Figure 7, the total processing time and cost are increasing gradually for simulations without job grouping method compared to simulations with job grouping method.

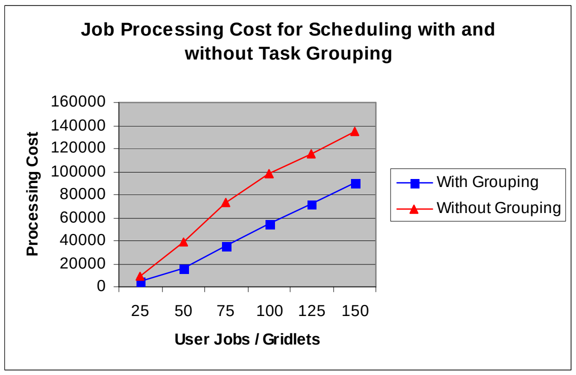
When scheduling 25 Gridlets, simulation with job grouping method groups the Gridlets into one group according to resource R1's MI of 6000 (200*30). Therefore, the total OH_Time is only 10 seconds and the resulting total Process_Time is 64 seconds. The job grouping, scheduling and deploying activities take up to 54 seconds. On the other hand, simulation without job grouping sends all the Gridlets individually to resource R1 and the total OH_Time is 250 seconds (25*10) leads to total Process_Time of 280 seconds. In this case, the total Gridlet computation time (30 seconds) is much less than the total communication time (250 seconds).Without grouping, a simulation from 25 to 100 Gridlets yields a massive increase of 297% in total Process_Time, whereas simulation with grouping yields only 112.5% rise in terms of in total Process_Time. As the number of Gridlets grows, the total Process_Time increases linearly for simulation without job grouping since total communication time increased with number of Gridlets. In simulation with grouping, the communication time remains constant and major contribution to the total Process_Time comes from Gridlet computation time at the resources. With 150 Gridlets, four Gridlet groups are created, and each resource received one Gridlet group. Here, 1.48% of the total Process_Time is spent for communication purpose, whereas in simulation without grouping, 90.3% of total Process_Time is spent for the same communication purpose.

Number of Gridlets	**With Grouping**			**Without Grouping**	
	Number of Groups	**Process_Time (sec)**	**Process_Cost**	**Process_Time (sec)**	**Process _Cost**
25	1	64	4979	280	9333
50	2	82	15992	561	38946
75	3	99	35904	838	73485
100	4	136	55332	1112	97741
125	4	186	72332	1388	115673
150	4	270	90124	1662	134843
A_MI:200 D_%:20% G_Size:30 sec R_MIPS: 200,160,210,480 OH_Time:10 sec					

Table 2: Simulation with and without job grouping for average MI of 200 and granularity size of 30 seconds



(a)

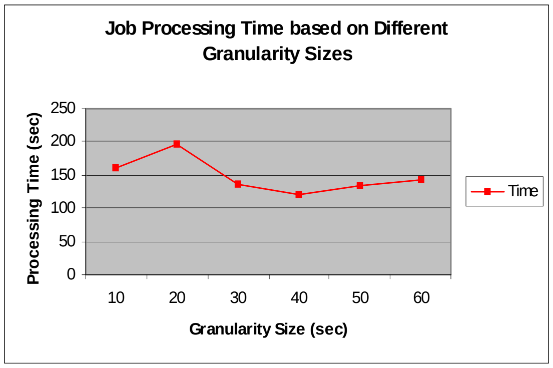


(b)

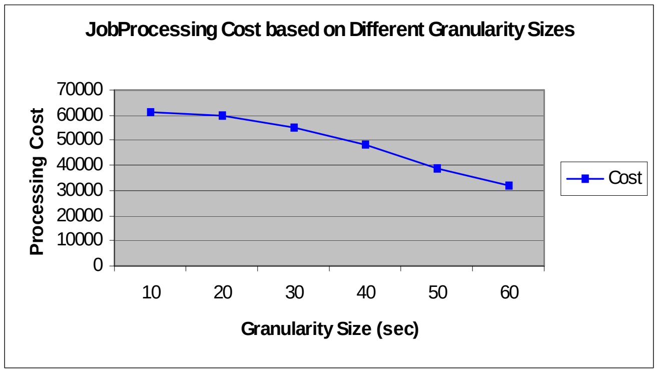
Figure 7: Processing time (a) and cost (b) for executing 150 Gridlets of 200 average MI within the granularity size of 30 seconds

Granularity Size (sec)	10	20	30	40	50	60
Process_Time (sec)	160	196	136	120	135	143
Process_Cost	61231	60073	55333	48179	38878	31890
Number of Groups	7	4	4	3	3	2
Gridlets: 100; A_MI:200; D_%:20%; OH_Time:10 sec; Resource: R1-R7						

Table 3: Simulation with job grouping for different granularity sizes



(a)



(b)

Figure 8: (a) Processing time and (b) cost for executing 100 Gridlets of 200 average MI using different granularity sizes

In terms of Process_Cost, the time each Gridlet spends at the Grid resource is taken into consideration for computing the total Process_Cost. In simulation with job grouping, only a small number of Gridlets (Gridlet groups) are sent to each resource and therefore, the amount of total overhead time is reduced. In simulation without job grouping, each small scaled Gridlet sustains a small amount of overhead time at the Grid resources. Therefore, the total overhead time incurred by all the Gridlets at the Grid resource leads to higher processing cost. For example, when processing 25 Gridlets individually at the Grid resource, the total Process_Cost comes up to 9333 units, whereas simulation with job grouping reduces this cost to 4979 units.

4.3.2 Experiment 2: Simulation of Different Granularity Sizes with Job Scheduling

Simulations are conducted using different granularity sizes to examine the total time and cost taken to execute 100 Gridlets on the Grid. Resources R1 through R7 are used for these simulations.

Table 3 and Figure 8 depict the results gained from simulations carried out on 100 Gridlets of 200 average MI using different granularity sizes. Table 4 and Figure 9 show the processing load at each Grid resources when different granularity sizes are used. The term 'Gridlet Computation Time' in Table 4 refers to the total time taken for each resource to compute the assigned Gridlet groups. The communication time is not included in this computation time.

Granularity	Resource/MIPS							Gridlet Computation
Size (sec)	R1/200	R2/160	R3/210	R4/480	R5/270	R6/390	R7/540	Time (sec)
10	1995	1549	2094	4771	2509	3761	3217	86
20	3904	3126	4108	8756				152
30	5809	4775	6094	3217				91
40	7843	6337	5715					86
50	9802	7940	2153					97
60	11898	7997						117

Table 4: Processing load at the grid resources for different granularity sizes

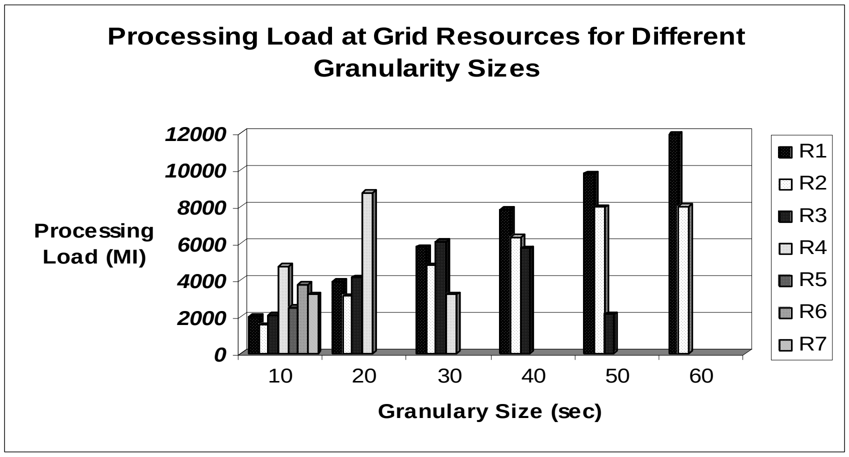


Figure 9: Processing load at the grid resources for different granularity sizes

From the simulation, it is observed that the total Process_Time for granularity size of 10 seconds is less than the one observed for granularity size of 20 seconds. When granularity size is 10 seconds, 7 job groups are created (from 100 user jobs) and each resource computes one job group of almost balanced MI. Since the Gridlet computations at the Grid resources are done in parallel and each resource has less processing load (balanced Gridlet MI), all the Gridlet groups can be computed rapidly, in 86 minutes.

In the case of granularity size of 20 seconds, four Gridlet groups are created and 44% of the total Gridlet MI is scheduled to be computed at resource R4 since it can support up to 9600 MI. Average Gridlet MI percentage at the other resources is about 18.7%. Therefore, R4 spent more time in computing the Gridlet group which leads to higher total Process_Time.

For granularity size 30 seconds, four Gridlet groups are produced and resource R3 receives the most MI, about 30.6% of the total MI. The total MI scheduled to all the resources does not defer much as in the previous case. Therefore, all the resources can complete the Gridlet computation in 91 minutes.

The minimum Process_Time is achieved when the granularity time is 40 seconds. The Gridlet computation time is same as for the granularity size of 10 seconds, but less communication time is taken (30 seconds) for dealing with three Gridlet groups.

In terms of Process_Cost, the resulting cost highly depends on the cost per second located at each resource and total Gridlet MI assigned to each resource. In the simulations, cost per second of using resource R3 (300 units) and R7 (320 units) are more than the other resources. Therefore, involving these resources in Gridlet computation will increase the total Process_Cost, e.g. all the resources are used for Gridlet computation when granularity size is 10 seconds, which costs 61231 units. When the granularity size is 20 seconds, R7 is not engaged in the computation. However, assigning a large number Gridlet MI (8756 MI) to R4 results in high total Process_Cost of 60073 units. When the granularity time is 30 seconds, balanced distribution of the MI among four resources reduces the total Process_Cost. Another point is that the total MI assigned to resource R1 is increased as the granularity size increases. Since R1's cost per second is very low (100 units), the total Process_Cost decreases gradually for granularity sizes 40, 50 and 60 seconds.

From the experiments, it is clear that job grouping method decreases the total processing time and cost. However, assigning a large number of Gridlet MI to one particular resource will increase the total processing time and cost. Therefore, during the job grouping activity, a balanced relationship should be determined between total number of groups to be created from job grouping method, resources' cost per second, and MI distribution among the selected resources.

5 Conclusion and Future Work

The job grouping strategy results in increased performance in terms of low processing time and cost if it is applied to a Grid application with a large number of jobs where each user job holds small processing requirements. Sending/receiving each small job individually to/from the resources will increase the total communication time and cost. In addition, the total processing capabilities of each resource may not be fully utilized each time the resource receives a small scaled job. Job grouping strategy aims to reduce the impact of these drawbacks on the total processing time and cost. The strategy groups the small scaled user jobs into few job groups according to the processing capabilities of available Grid resources. This reduces the communication overhead time and processing overhead time of each user job.

Future work would involve developing a more comprehensive job grouping-based scheduling system that takes into account QoS (Quality of Service) requirements as mentioned by Abramson, Buyya, and Giddy (2002) of each user job before performing the grouping method. In addition, each resource should be examined for their current processing load, and jobs should be grouped according to the available processing capabilities. Finally, need to consider grouping jobs that using common data for execution.

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