Cooperating Coscheduling in a Non-dedicated Cluster^{*}

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Abstract. Our research is focussed on keeping both local and parallel jobs together in a time-sharing NOW. In such systems, new scheduling approaches are needed to allocate the underloaded resources among parallel jobs. In this paper, a distributed system, named Cooperating CoScheduling, is presented to assign CPU and memory resources efficiently by applying resource balancing and dynamic coscheduling between parallel jobs. This is shown experimentally in a PVM-Linux NOW.

1 Introduction

Time-slicing scheduling techniques [1,4] exploit the unused resources of a Network Of Workstations (NOW), by running both parallel and local jobs together. In this framework, the coscheduling of parallel jobs becomes a critical issue. Some studies [6,5] have shown the good performance of dynamic coscheduling techniques when many local users compete with a single parallel job. Dynamic coscheduling deals with minimizing the communication waiting time of parallel processes. With this aim, when parallel tasks are dynamically coscheduled, the arrival of a message will cause the dispatch of the target task. Unfortunately, dynamic coscheduling performance can slow down drastically when the number of parallel jobs competing against each other (MultiProgramming Level (MPL)) is increased. This is due to the fact that if the resources are not well-balanced between the competing parallel tasks, the completion of each process of a parallel job will require a different amount of time, and the entire job must wait for the slowest process before it can synchronize.

A new technique, called Cooperating CoScheduling (CCS), is presented in this paper. CCS improves dynamic coscheduling techniques by balancing the CPU and memory resources between parallel jobs throughout the NOW. Each node manages its resources efficiently by combining local – basically communication events, local user logging and computational capabilities–, and foreign runtime information (i.e. the local user logging onto a remote node) provided by their cooperating nodes. CCS is implemented in a PVM-Linux NOW.

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2 CCS: Cooperating CoScheduling

Our framework is a non-dedicated NOW, where all nodes are under the control of the CCS scheme. In each node, a time-sharing scheduler is assumed with task preemption based on the ranking of tasks according to their priority. The scheduler works by dividing the CPU time into *epochs*. In every epoch, each task is assigned a specific time slice and priority. In order to give preference to I/O-bound processes, the priority of each task is inversely proportional to the CPU used during the last epoch. A Memory Management Unit is assumed with demand-paging virtual memory. A SPMD model is assumed for parallel jobs. We assume that each node applies a *dynamic coscheduling* technique [5]. This means that every local scheduler increases the receiving task priority according to the number of packets in its reception queue, even causing CPU preemption of the task being executed inside.

The need to preserve local job performance limits the resources assigned to parallel tasks. This may lead to non-desirable situations (see fig. 1(a)). A parallel job (J_1) is executed on $node_1$ and $node_2$ with 25% of resources (CPU and Memory), while the local user has the remaining 75% available. Simultaneously, another parallel job (J_2) is executed with full resources on $node_4$ and $node_5$. Meanwhile, $node_3$ assigns half of the resources to each parallel job following a fairness policy. This uneven taxing of resources creates a situation where some processes of the parallel program run slower than others. However, if $node_3$ had knowledge about the status of J_1 and J_2 jobs in the remaining nodes (cooperating nodes), it could take better decisions by giving J_2 more resources than J_1 . Thus, the situation shown in fig. 1(b) would be achieved. In this case, J_1 has the same amount of resources in each node, while J_2 has more resources available than in the previous case. This way, the NOW resources are better balanced.

This example illustrates the three main aims of the CCS algorithm, namely: a) the *performance of local jobs*; b) the *uniform allocation of the CPU and memory resources* assigned to each parallel job throughout the cluster; and c) the *coscheduling* of communicating parallel jobs.

2.1 Cooperating CoScheduling Mechanism

This section explains how CCS achieves the objectives set out above.

Job interaction. We use priority as a mechanism to limit the interference of parallel jobs in the resources (CPU and memory) needed by local tasks. In the CPU, when $node_i$ detects the presence of a local user, it will assign a time slice to parallel and locals tasks equal to $DEF_QUANTUM_i * L$ and $DEF_QUANTUM_i * (1 - L)$, respectively. $DEF_QUANTUM_i$ is the base time slice of $node_i$ and L is the minimum percentage of resources assigned to parallel jobs. The minimum term is related to the fact that if parallel tasks require a bigger percentatge of CPU than L , then they will be able to use the portion allocated to local tasks, whenever local tasks are not using this. It is assumed that L has the same value across the cluster. In order to quantify the heterogeneous nature of a NOW, we have used the Power Weight [1] ($W_i = BOGO_i / BOGO_{max}$),

Fig. 1. (a and b) Example of applying CCS. (c) Workload 3.

where $1 \leq i \leq n$ (number of nodes) and $BOGO_{i/\max}$ is a measurement of the computational capabilities of the i th and fastest node, respectively. Note that this measurement is provided by some o.s (p.e. Linux) in the boot period. Thus, the base time slice of each node is set relative to its Power Weight ($DEF_QUANTUM_i = DEF_QUANTUM/W_i$), where $DEF_QUANTUM$ is the base time slice of the local o.s. (p.e. Linux=210ms).

The memory (M_i) is divided into two pools: one for the local tasks (M_i^L) and the other for parallel jobs ($M^D = \min_{i=1}^n(M_i) * L$). Note that the same minimum memory size (M^D), will be guaranteed to parallel tasks in each node. As in the CPU case, if parallel tasks require a bigger memory size than M^D then they will be able to use the portion allocated to local tasks, whenever local tasks are not using this. However, in the nodes where swapping is activated and the memory requirements of the parallel tasks exceed their assigned part (M^D), the parallel task with most pages mapped in memory (*swapping_task*) will be stopped. Consequently, the resident size of the remaining tasks will be increased and the swapping activity will also be reduced [2].

Cooperating Scheme. In order to balance resources throughout the cluster, the cooperating nodes should interchange status information. The key question is which information should be interchanged. An excess of information could slow down the performance of the system, increasing its complexity and limiting its scalability. For this reason, only the following four events are notified:

1. *LOCAL*: when there is local user activity in a *node*, it sends the identifier of the parallel jobs executing in such node to all its cooperating nodes.
2. *NO_LOCAL*: if the local activity finishes, the node sends a notification message to its cooperating nodes.
3. *STOP*: when *swapping_task* is stopped, the node sends the identifier of the penalized job to its cooperating nodes.
4. *RESUME*: when the *swapping_task* restarts, the node informs its cooperating nodes of this event.

When a cooperating node receives one of the above events, it will reassign the resources according to the following rules. (1) The scheduler with more than one parallel tasks under its management will assign a quantum equal to $(DEF_QUANTUM_i * L)$ or zero to those tasks notified by *LOCAL* or *STOP* events, respectively. (2) In order to ensure that a parallel job is not slowed down by any local user across the cluster, a node will only reassign more resources to a task notified by a *NO-LOCAL* event when the number of *LOCAL* received events coincides with the *NO-LOCAL* received events. (3) If a node receives a *STOP* notification for a parallel task, this task will be chosen as *swapping-task*, whenever the memory is exhausted. (4) If a node with overloaded memory receives the *STOP* event for a task different than *the swapping-task*, the kernel will stop the notified task and the *swapping-task* will be resumed. (5) If a node with overloaded memory receives a *RESUME* event associated with the *swapping-task*, the kernel will restart the notified task and a new *swapping-task* will be chosen. Applying these rules, we show experimentally (see extended version [3]) that the cluster reaches a stable state.

3 Experimentation

CCS was implemented and tested in a PVM (v.3.4) - Linux (v.2.2.15) cluster. A complete description of the CCS implementation can be found in [3]. Our cluster was composed of eight Pentium II and eight Pentium III with 128 and 256 MB of memory and a Power Weight (W_i) of 0.43 and 1, respectively. All of them were connected through a Fast Ethernet network.

The performance of the parallel jobs was evaluated by running four PVM benchmarks from the NAS suite with class A and B: *IS* and *FT*, *MG* and *EP*. Three workloads (*Wrk1*, *Wrk2* and *Wrk3*) with different job sizes and *Multi-Programming Level* (MPL) were defined. *Wrk1* is characterized by a MPL equal to 1, while *Wrk2* and *Wrk3* are 2. *Wrk1* continuously executes a benchmark of size 16 chosen randomly according to a discrete uniform distribution. *Wrk2* continuously executes two size 16 jobs with the constraint that parallel tasks fit in their assigned memory portion (M^D). *Wrk3* executes one size 16 job together with two size 8 jobs (see fig. 1(c)) without any memory constraint. Additionally, fig. 1(c) shows the execution time and memory requirements of every benchmark on a dedicated system. Each workload was executed for 4 hours.

The local workload was carried out by running one synthetic benchmark, called *local*. This allowed the CPU load, memory requirements and network traffic used by the local user to be fixed. According to the monitoring of real local users [3], we defined two different local user profiles: a user with high CPU requirements, denoted as *CPU*, and a user with a high requirements for interactivity, denoted as *Xwin*. These parameters were set at (0.65, 35MB¹ and 0KB/s) and (0.20, 84MB¹ and 3KB/s) for *CPU* and *Xwin* users, respectively. In order to simulate the high variability of local user behavior, the local execution time was modeled by a two stage hyper-exponential distribution with means,

¹ Memory requirements do not include kernel memory.

Fig. 2. (left) Slowdown of local and (center) parallel tasks with four local users. (right) Slowdown of parallel tasks varying the number of local CPU users.

by default, of 10min and 60min and a weight of 0.6 and 0.4 for each stage. At the end of its execution, the *local* benchmark returns the system call latency, memory and network bandwidth and wall-clock execution time.

Three environments were evaluated: the plain LINUX, the DYNAMIC and the CCS schedulers. Note that the DYNAMIC scheduler applies exclusively a dynamic coscheduling technique without any restrictions of the resources used by parallel jobs and any exchanging of information between cooperating nodes.

The performance of the parallel and local jobs was validated by means of the *Slowdown* metric (which is the average of 5 different executions). The next section shows a summary of the extended version of the experimentation [3].

3.1 Experimental Results

Fig. 2 (left) shows the slowdown of *local* according to the percentage of resources assigned to parallel tasks (L). L was varied between 20% to 50%. This trial was repeated twice: once with only CPU users and again with *Xwin* users. We can see that *LINUX* and *PREDICTIVE* gave the worst performance for local tasks. The peak obtained with the *Wrk3* is because the *Wrk3* memory requirements exceed the main memory size of some nodes with local activity and as a consequence, swapping is performed without guaranteeing any minimal memory size to local tasks. With the exception of the *Wrk3* case, it is worth pointing out the low intrusion for the *Xwin* users. This is due to the priority given by Linux to I/O processes. The impact of CCS rises slightly when the MPL is increased to 2 (*Wrk2* and *Wrk3*), although this is always limited to below values of 1.25 and 1.6 for *Xwin* and CPU users respectively, even in the worst case for local tasks ($L = 50\%$). For the rest of the trials, the local workload is exclusively made up of CPU local users (the most unfavorable case for parallel performance).

Fig. 2 (center) shows the slowdown in the performance of parallel jobs under the same conditions explained above. In general, *LINUX* obtains the worst results due mainly to the absence of coscheduling between communicating tasks. *DYNAMIC* obtains the best results for *Wrk1* while *CCS* obtains the best results for *Wrk3*. This degradation for *DYNAMIC* in the *Wrk3* case is due to the fact

that high or moderate page fault frequency in one node can drop parallel job performance drastically, vastly exceeding in this way the coscheduling benefits. In the case of *Wrk2*, *CCS* obtains better results than *DYNAMIC* for $L \geq 30$. This is due to the fact that the resources are better balanced under *CCS* and thus, all PVM jobs can progress across the NOW in a coordinated way. Fig. 2 (right) shows the slowdown on *Wrk2* and *Wrk3* when the number of local users was varied between 0 and 8. For the *Wrk2* case, *CCS* maintains a nearly constant slowdown in a non-dedicated environment, while *DYNAMIC* performance is slightly degraded when local users are increased. This is due to the absence of a mechanism for balancing resources across the NOW. Regarding the *Wrk3* case, *CCS* obtains the best results with this workload because *CCS* can distribute NOW resources better between parallel jobs of different sizes.

4 Conclusions and Future Work

In this paper, a new technique, named Cooperating CoScheduling (*CCS*), is presented. The main aim of *CCS* is to exploit the unused computing capacity of a non-dedicated cluster without disturbing local jobs excessively. This is achieved by means of combining balancing of resources and coscheduling between parallel jobs. In doing so, each *CCS* node assigns its resources dynamically, based on a combination of local and foreign runtime information provided by its own o.s. and its cooperating nodes, respectively. Thus, local decisions are taken in a coordinated way across the NOW. The performance of *CCS* has been tested in a PVM-Linux cluster and compared with other coscheduling policies. The results obtained demonstrated its good behavior, substantially reducing the response time of local tasks and improving, in some cases, the slowdown of parallel tasks with respect to other coscheduling policies.

Our next work is directed towards extending *CCS* to be applied together with a space-slicing technique. Our aim is to execute multiple parallel programs in every cluster partition by means of applying the *CCS* technique in each one.

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