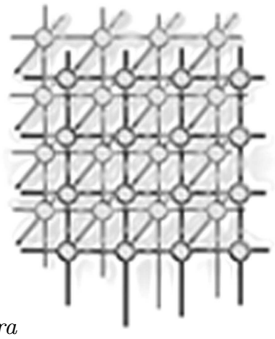
CONCURRENCY AND COMPUTATION: PRACTICE AND EXPERIENCE
Concurrency Computat.: Pract. Exper. 2003; **1**:1–2 *Prepared using* cpeauth.cls *[Version: 2002/09/19 v2.02]*

Advanced eager scheduling for Java-based adaptive parallel computing



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SUMMARY

Javelin 3 is a software system for developing large-scale, fault tolerant, adaptively parallel applications. When all or part of their application can be cast as a master-worker or branch-and-bound computation, Javelin 3 frees application developers from concerns about inter-processor communication and fault tolerance among networked hosts, allowing them to focus on the underlying application. The paper describes a fault tolerant task scheduler and its performance analysis. The task scheduler integrates work stealing with an advanced form of eager scheduling. It enables dynamic task decomposition, which improves host load-balancing in the presence of tasks whose non-uniform computational load is evident only at execution time. Speedup measurements are presented of actual performance on up to 1,000 hosts. We analyze the expected performance degradation due to unresponsive hosts, and measure actual performance degradation due to unresponsive hosts.

KEY WORDS: concurrent programming, branch-and-bound, eager scheduling, fault tolerance, Grid computing, parallel computing

INTRODUCTION

Most distributed computing systems that harvest idle cycles do so for problems that admit a master-worker algorithm that is simple in at least two respects:

- Each task's computational load is known at compile time, possibly as a function of data parameters (e.g., the number of pixels to be rendered in a raytracing task);

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Contract/grant sponsor: National Partnership for Advanced Computational Infrastructure (NPACI).

Received ¡Date¿
Revised ¡Date¿
Accepted ¡Date¿

- Worker tasks do not communicate among themselves. They merely report their result to the master process.

Developing efficient distributed computations for such problems is desirable for at least two reasons: First, such algorithms can be found for many important problems (e.g., protein folding, genetic sequencing, parameter sweep optimization problems). Second, such algorithms have a natural *distributed* implementation. The number of such distributed systems is growing rapidly. For example, there is SETI@home [4] from UC Berkeley, the *fight against cancer* [3] from Parabon Computation, *folding@home* [1] from Stanford for studying protein folding, *screensaver lifesaver* [5] from Oxford in collaboration with United Devices that searches for anti-cancer drugs, and *fight AIDS at home* [17] from Entropia.

It is nonetheless important to discover more complex algorithm classes that can be efficiently implemented as adaptively parallel computations. Branch-and-bound is a class that encompasses a large set of algorithms. The simple Master-Worker algorithms, described above, form a degenerate case. Branch-and-bound's implementation is more complex for several reasons:

- The fixed-depth task decomposition tree associated with Master-Worker generalizes to a dynamic-depth task decomposition tree.
- The task decomposition tree is not balanced. It can be quite irregular, due to the bounding process (also known as pruning), in a way that depends on the problem instance, and thus is known only at execution time.
- Tree pruning, to proceed efficiently, requires communication among the compute hosts, as they discover new bounds.

Although Branch-and-bound generalizes the simple Master-Worker class of algorithms and is challenging to implement efficiently in an adaptively parallel setting, it is a challenge worth accepting. A wealth of important combinatorial optimization problems are routinely solved via branch-and-bound (e.g., computationally complex problems such as Integer Linear Programming and combinatorial auction winner selection [37]). Thus, if we can efficiently speed up branch-and-bound in an adaptively parallel setting, then the usefulness of, and demand for, adaptively parallel computing will increase dramatically.

It is difficult to implement adaptively parallel branch-and-bound so that speedup scales to large processor sets. Our previous work scales *only* to around 100 hosts with nearly perfect speedup [33]. The speedup scalability problem concerns the decision as to which tasks should be further decomposed, and which should not (and thus be completely solved within a single compute host). To understand this scalability problem, we must understand the branch-and-bound process. A branch-and-bound algorithm seeks an optimum solution from among a set of feasible solutions. The size of this set is typically exponential in the size of the original problem. For example, the set of feasible tours in an asymmetric Traveling Salesman Problem (TSP) of a complete graph with 23 nodes is 22! or around 1.6×10^{15} tours. The space of feasible solutions is progressively partitioned (branching), forming a *problem tree*. Each node contains a *partial* feasible solution. The node *represents* the set of feasible solutions that are extensions of its partial solution. As branching continues (progresses down the problem tree), the nodes contain more complete partial solutions, and thus represent smaller sets of feasible

solutions. For example, when casting the TSP as a branch-and-bound problem, a node in the problem tree contains a partial tour, and *represents* the set of all tours containing that partial tour. As one progresses *down* the nodes of the problem tree, the nodes represent larger partial tours. As the size of a partial tour increases, the number of full tours containing the partial tour clearly decreases.

Tasks correspond to nodes in the problem tree: Each gives rise to a set of smaller tasks until the task represents a node in the tree that is small enough to be explored by a single host. Such tasks are called *atomic*. One can programmatically define atomic tasks as those whose corresponding problem sub-trees are of a *fixed height*, k, possibly a function of the problem tree's height (see Figure 3). In the TSP case, such an atomic task represents no more than $k!$ feasible tours. For example, in an 18-node input graph, if $k = 11$, there is $17!/11!$ or about 9 million atomic tasks, each of which represents 11! or about 40 million tours! Although an atomic task is computed on a single host, the number of tours that actually need to be explored depends on how much of the task's corresponding sub-tree can be *pruned*, which *depends on the problem instance*. Consequently, the number of tours to be examined, in this example, can vary from 0 to about 40 million! Having atomic tasks whose computational load is so variable makes high speedups problematic, when deploying on a large number of processors.

We cannot have k be a function of the number of processors; in adaptively parallel computing, this number *varies at execution time*. Work-stealing is distributed among the compute hosts: Its parameters cannot include *time-varying global properties* of the distributed system. Neither can we reduce the maximum variation in the atomic task's computation load by simply reducing k; this substantially increases the number of tasks. The overhead of managing a large number of tasks becomes prohibitive. For example, reducing k to 5 in an 18-node graph increases the number of tasks from 40 million to almost 14 *billion*! We thus are motivated to *vary the atomic threshold at execution time*.

This paper presents a novel integrated work-stealing, eager scheduler that efficiently schedules and reschedules tasks, dynamically varying the atomic threshold according to the *perceived* load characteristics of the adaptively parallel computation (failed compute hosts are indistinguishable from hosts that respond slowly either because they *are* slow, or because they are working on a large atomic task, or some combination thereof). Experimental results show good speedup in our benchmark branch-and-bound problem, TSP, using as many as 1,000 compute hosts. We expect comparable speedups on larger numbers of hosts for larger problem instances. Since the scheduler balances the load among compute hosts and *reschedules tasks that are assigned to failed hosts*, we demonstrate an implementation of adaptively parallel branch-and-bound that both scales to a large number of compute hosts and tolerates faults (both node and link).

The system is implemented with pure Java for reasons that include supporting heterogeneous resources. *Measuring* speedup is a focus of this paper, however. This requires a *controlled* experimental environment of dedicated processors. For our large speedup experiments, we used the San Diego Supercomputing Center's IBM Blue Horizon, which happens to be a homogeneous multiprocessor. Our earlier experience with heterogeneous environments, albeit smaller ones, has been reported elsewhere [32].

The principle contributions of this paper to the study of adaptively parallel computing are:

- the novel dynamic depth eager scheduling method, and
- an analysis, and experimental validation, of the quantity of degradation due to unresponsive hosts.

These contributions enable the Javelin distributed computing system (i.e., it tolerates host failure) to perform branch and bound on over 1000 processors with good speedup.

Background

A few years ago a pair of developments ushered in a new era. One was the announcement of the SETI@home [4] project. Since then, similar projects have arisen (see above). While such applications are of the simple Master-Worker variety, they promote a vision of a world-wide virtual supercomputer [25, 6] or globally distributed computations.

The related development was an emerging vision of a computational *Grid*, an "integrated, collaborative use of high-end computers, networks, databases, and scientific instruments owned and managed by multiple organizations." [24]. The Globus project [24] is the best known manifestation of that vision. In contrast to Globus, which is open source, Avaki is a proprietary version of that vision, rooted in Legion research [28], as is Sun's GridEngine [2]. Such systems are not Java-centric, and indeed *must be* language-neutral. The Millennium Project [20] is a "system of systems" project where a key element of the research is how constituent systems interact. The Ninja project [43] is developing an infrastructure for Internet-based *services* that are scalable, fault tolerant, and highly available.

Some application development or deployment systems are *explicitly* based on the grid, such as AppLeS for parameter sweep computation by Casanova et al. [16], and Condor-G by Frey et al. [26] (where Condor [21] makes use of several grid services, such as GSIFTP). EveryWare [45] pushed this envelope by presenting an application development toolkit that was demonstrated to "leverage Globus, Legion, Condor, NetSolve Grid computing infrastructures, the Java language and execution environment, native Windows NT, and native Unix systems in a single, globally distributed application"[45]. In such an environment, the experiment ran on compute resources that were shared by other applications. Thus, measuring speedup is problematic, and was not done. This is unfortunate for us, since the application, a Ramsey number search, was implemented as a branch-and-bound problem. Using the toolkit to develop an application that interfaces with this disparate set of components is reputed to require extremely broad expertise. The explicit goal of the GrADS project is to *simplify* the development and performance tuning of such distributed heterogeneous applications destined for the Grid [30].

There is a growing niche of coarse-grain, parallel applications for which the Java programming system is a suitable environment. Java's attraction includes its solution to the portability/interoperability problem associated with heterogeneous machines and OSs. Please see [42] for an enumeration of other advantages. The use of a virtual machine is a significant difference between Java-based systems and previous systems. Typically, the Java niche includes new applications, which thus do not need to interface with legacy code. These Java-based efforts are orthogonal to the Grid work: In principle, they can be loosely coupled to the Grid via Grid protocols: *Advances in one can be leveraged by the other*. The Java CoG Kit[42] facilitates such leveraging activity. The Java-based research can be partitioned into:

1. systems that run on a processor network whose extent and communication topology are known *a priori* (although which particular resources are used to realize the processor network may be set at *deployment time*, perhaps via Grid resource reservation mechanisms);
2. systems that make no assumption about the number of processors or their communication topology.

Category 1 includes, for example, Java MPI systems and applications. JavaSymphony [22], also in this category, is an extensive pure Java class library constituting a high-level API that enables the application programmer to direct the exploitation of the application's parallelism, the physical system's locality (represented as a virtual hierarchy of physical compute nodes), and load-balancing based on both static and dynamic properties (e.g., storage capacity and available memory). *Manta* [39], another example, elegantly shows that wide-area networks, modelled as two-level networks, can efficiently support large, coarse-grain parallel computation. Ibis [41] is, in a sense, an outgrowth of the Manta research. It is a programming environment that is portable (it is pure Java), robust in the face of dynamically available networks and processors, and has efficient, object-based communication. Its flexibility and efficiency derive from its implementation on top of a carefully designed Ibis Portability Layer, a set of interfaces whose implementation can be plugged in at runtime. Ibis's authors intend to investigate the incorporation of adaptive parallelism by exposing the application to dynamic information about available compute and network resources. Such an Ibis would be in category 2.

Systems of category 2 can be further subdivided:

- those that support adaptive parallelism (originally defined in [27]);
- those that do not.

The second of these categories includes, for example, the system by Casanova et al. for *statically* scheduling parameter sweep computations on a set of resources determined a priori via the Grid). The first category includes Popcorn [15], Charlotte [10], Atlas [9], Javelin, and Bayanihan [38], among others. Popcorn [15] was the first Internet-based Java-centric project, as far as we know, that explicitly used market mechanisms (e.g., Vickrey auctions) to motivate "sellers" of computational capacity. Charlotte used eager scheduling, introduced by the Charlotte team, and implemented a fully distributed shared memory. It was designed for a local area network (LAN). ParaWeb [14] emulates a fully functional shared memory parallel computer, and hence also is best suited to a LAN. Atlas is a version of Cilk-NOW intended for the Internet setting.As a master's project, it terminated abruptly, and, in our opinion, without reaching its full potential: testing never exceeded eight processors. Bayanihan also uses eager scheduling. Its initial implementation however does not scale to large numbers of processors. Nibhanupudi et al. [36, 35] present work on adaptive BSP, an efficient, programmer-friendly model of parallel computation suitable for the harvesting of idle cycles in a LAN.

Several systems have emerged for *distributed* computations on the Internet. Wendelborn et al. [44] describe an ongoing project to develop a geographical information system (PAGIS) for defining and implementing processing networks on diverse computational and data resources. Hawick et al. [29] describe an environment for service-based meta-computing. Fink et al. [23] describe Amica, a meta-computing system to support the development of coarse grained

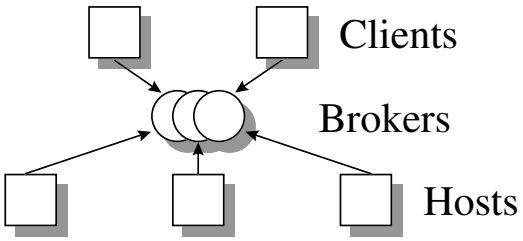


Figure 1. The Javelin 3 architecture.

location-transparent applications for distributed systems on the Internet, and includes a memory subsystem. In the Globe project, Bakker et al. [7] take the view of distributed objects as their unifying paradigm for building large-scale wide area distributed systems. They appear to intend to do for objects what the world wide web did for documents. Support for objects can differ in partitioning, replication, consistency, and fault tolerance, in a way that is opaque to clients.

Within this informal taxonomy, Javelin is Java-based, and supports coarse-grained, adaptively parallel computation. It is compatible with large-scale cluster settings, LAN/WAN, and even corporate intranets.

ARCHITECTURE

This section briefly introduces the basic architectural concepts of Javelin 3. It is intended for readers who are not familiar with Javelin; for more details, see [18, 32, 34].

The Javelin 3 architecture retains the basic structure of its predecessors, Javelin and Javelin++. There are three system entities — clients, brokers, and hosts. A *client* is a process seeking computing resources; a *host* is a process offering computing resources; a *broker* is a process that coordinates the allocation of computing resources. Each process maps to a single Java Virtual Machine. Figure 1 illustrates the architecture. Clients register their tasks to be run with a broker; hosts register their intention to run tasks with a broker. The broker assigns tasks to hosts that, then, run the tasks and send results back to the clients. The role of a host or a client is not fixed. A machine may serve as a Javelin host when it is idle (e.g., during night hours), while being a client when its owner wants additional computing resources.

All communication in Javelin 3 is handled by Java RMI. The system is *multi-threaded* to reduce the delay associated with blocking RMI calls.

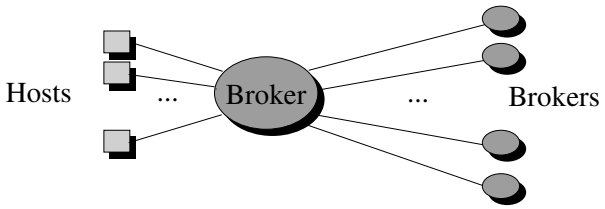


Figure 2. Broker connections.

Broker network & host tree

The topology of the broker network is an *unrestricted graph of bounded degree*. Thus, at any time a broker can only communicate with a constant number of other brokers. This constant may vary among brokers.Similarly, a broker can only handle a constant number of hosts. If that limit is exceeded, hosts must be redirected to other brokers. The bounds on both types of connection give the broker *network* the potential to scale to arbitrary numbers of participants. Figure 2 shows the connection setup of a broker.
When a host connects to a broker, the broker enters the host in a logical tree structure. The top-level host in the tree does not receive a parent; instead it later becomes a child of the client. This way, the broker maintains a *pre-organized tree of hosts* which are set on standby until a client becomes active. When a client connects, or client information is remotely received from a neighboring broker, the whole tree is activated in a single operation and the client information is passed to the hosts.

Brokers can individually set the branching factors of their trees, and decide how many hosts they can administer. In case of a host failure, the failed node is detected by its children and the broker restructures the tree with a heap-like operation.

SCALABLE COMPUTATION

The work stealing scheduler

Task scheduling in Javelin 3 is done via *work stealing*, a distributed scheduling scheme made popular by the Cilk project [12]. Work stealing is entirely demand driven — when a host runs out of work it requests work from some host that it knows. Work stealing balances the computational load, as long as the number of tasks per host is high — a property well suited for adaptively parallel systems. Please see [40] for a discussion of several approaches to work stealing. In work stealing, victim selection can be either deterministic or randomized. In Cilk [11], randomized work stealing was proven asymptotically optimal. However, that

proof does not apply to a heterogeneous Internet setting. Indeed, from experiments comparing randomized and deterministic work stealing, conducted in a heterogeneous processor setting by Neary et al. [32], they conclude "Thus, our comparison has no clear winner".

In Javelin 3, tasks get split in a double-ended task queue until a certain minimum granularity — determined by the application — is reached. Then, they are processed. When a host runs out of local tasks, it selects a neighboring host and requests work from that host. Since the hosts are organized as a tree, the selection of the host to steal work from follows a deterministic algorithm based on the tree structure. Initially, each host retrieves work from its parent, and computes one task at a time. When a host finishes all the work in its deque, it attempts to steal work, first from its children, if any, and, if that fails, from its parent. This strategy ensures that all the work assigned to the subtree rooted at a host gets done before that host requests new work from its parent. Work stealing helps each host get a quantity of work that is commensurate with its capabilities. The client is the root of its tree of hosts. When the client machine's work stealer detects that no work is available to steal, it initiates *eager scheduling*, which is discussed below: Deterministic work stealing precisely defines the trigger for eager scheduling to start.

Shared memory for bound propagation

In the master-worker model of computation, shared memory is not needed. It might appear that we cannot implement shared memory efficiently among networked processors in a manner that *scales*; the communication latency is too large. However, for branch-and-bound computation:

- Only a *small amount* of shared memory is needed, because only one `int` or `double` is needed to represent a solution's cost.
- A *weak shared memory model* suffices; if a host's copy of best cost is stale, correctness is unaffected. Only performance may suffer — we might search a subspace that could be pruned.

It thus suffices to implement the shared memory using a pipelined RAM (aka PRAM) model of cache consistency [31]. This weak cache consistency model can be implemented with scalable performance, even in a geographically distributed setting.

In Javelin 3, when a host discovers a solution with a better cost than its cached best cost, it sends this solution to the client. If the client agrees that this indeed is a new best cost solution (it may not be, due to certain race conditions), it updates its cached best cost solution, and "broadcasts" the new best cost to its entire tree of hosts. That is, it propagates the new best cost to its children, who propagate it to their children, and so on, down the host tree. Bound propagation is handled *asynchronously* by a separate bound propagator thread.

ADVANCED EAGER SCHEDULING

This section first explains our fault tolerance strategy based on *distributed eager scheduling*. In the next section, we describe an additional fault tolerance feature of Javelin 3: Detecting and

correcting failures in the host tree. Finally, we analyze the performance of eager scheduling under certain assumptions and in the presence of a constant host failure rate.

Eager scheduling

*Eager scheduling re*schedules a task to an idle processor, in case its result has not been reported. It was introduced and made popular by the Charlotte project [10].It efficiently and relentlessly progresses towards the overall solution in the presence of host and link failures, and varying host processing speeds. In addition, it also balances the computational load. The Javelin 3 eager scheduler is located in the client process, which is at the root of the host tree. Although this may seem like a bottleneck with respect to scalability, it is not, as we shall explain below. (The master-worker eager scheduler is unchanged from earlier versions of the system, Javelin++ [32] and Javelin 2 [34]. It uses a fixed-depth, tree-based scheme with a circularly linked list of undone tasks.)

The branch-and-bound eager scheduler

Eager scheduling is challenging for branch and bound computation. To begin with, the computation produces two types of result, which must be handled differently:

1. A *positive result* is a new best cost solution. It is propagated to all hosts as soon as possible, and leads to more efficient pruning of the search tree.
2. A *negative result* is a solution subspace that has either been fully examined, or pruned from the search tree.

In comparison, a master-worker computation only produces "negative" results under this terminology. The eager scheduler does not handle positive results in Javelin 3; they are handled by the bound propagation mechanism. Negative results are handled by the eager scheduler.

In a branch-and-bound computation, the size of the feasible solution space is typically *exponential* in the size of the input. The algorithm may need to examine all feasible solutions to find the minimum cost solution. A partial solution, p, is "pruned" when the *lower bound* on the cost of any feasible solution that is an extension of p is more costly than the currently known minimum cost solution. To detect problem termination, the eager scheduler eventually must know that a node is pruned or represents only sub-optimal solutions. If a separate communication is required to inform the eager scheduler of each such node, the quantity of communication would nullify the benefits of parallelism. Three mechanisms are used to avoid communication overload. First, whole subtrees of the search space are packaged as a single, atomic task. Second, information about pruned nodes is computed by the eager scheduler *lazily*: The scheduler *must* know what nodes can be pruned when no work is left to steal. However, at that time, it may have a smaller upper bound, enabling it to prune *more* of the problem tree. Thirdly, hosts aggregate negative results over a time interval, sending them to their parent only periodically. (Based on a small set of TSP experiments, we have set this time interval to 5 sec. It currently is a compile-time parameter.) To reduce runtime, we adjust the computation/communication ratio by adjusting the initial *size* of atomic tasks.

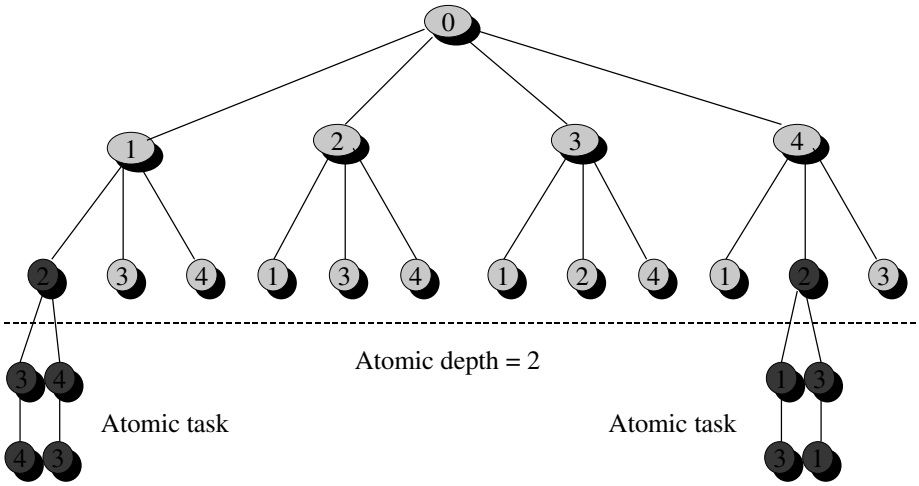


Figure 3. Atomic tasks and atomic depth.

Figure 3 shows an example of the search tree division into atomic and non-atomic tasks. Here, the *atomic depth* parameter is set to 2, which means all tasks that are 2 nodes below the root node are considered atomic and are processed by hosts with no further subdivision. Many of these tasks may in fact be pruned away, due to an existing better minimum cost bound. We have highlighted two portions of the tree that show the extent of local computation of an atomic task. The eager scheduler itself never processes any portion of the search tree below the atomic depth level, although it will analyze the top portion of the tree based on negative results and its own min cost bound. (The numbers that label nodes in the tree correspond to node numbers in the graph comprising the TSP instance: a root to leaf path in the search tree corresponds to a partial tour in the TSP instance.)

For performance reasons, we want to balance the computational *size* of the hosts' atomic tasks with the client's computation of result handling and eager scheduling, so that neither the client nor the hosts have to wait for one another. Additionally, we want the number of atomic tasks to be much larger than the number of hosts, to keep them all well utilized, even when some are *much* faster than others. This lower bound on the size of the atomic task (to prevent the client process from becoming a bottleneck) implies an upper bound on the number of atomic tasks we can create from any particular branch-and-bound computation. This upper bound, in turn, bounds the *number* of hosts that can be used effectively to solve the branch-and-bound computation. Thus, *decreasing* eager scheduling time *decreases* the minimum size of atomic tasks, which *increases* the number of atomic tasks, which *increases* the number of hosts that can be used effectively, which *decreases* the execution time.

A factor that pulls in the other direction of the preceding analysis concerns the relationship between eager scheduling and atomic task size: The *smaller* the atomic task size, the *more* atomic tasks there are, the *more* work must be done by the eager scheduler.

Deferred Detection of Pruned Nodes

The branch-and-bound eager scheduler employs *lazy* or *deferred* detection of pruned nodes, which takes place only after the initial round of work stealing has ended, and the first host finds itself out of work and sends a work request to the eager scheduler. At this point the eager scheduler infers what nodes representing partial solutions have been pruned, and which atomic tasks need to be rescheduled.

Method

The basic data structure required is a *problem tree*, which the eager scheduler, located in the client process, maintains to keep track of the computation status. Each atomic task is a leaf in this problem tree. The root of the problem tree represents the complete branch-and-bound computation. Its children are the subproblems resulting from branching — a single split of the root problem. This branching (splitting) continues, as we proceed down the problem tree: We subdivide it into smaller and smaller search spaces. A parameter, the *atomic depth*, determines at what level splitting stops. At that point, a host will search the space for a solution that is less than the current minimum cost solution.

As with the master-worker model of computation, each node (task) in the problem tree can be in one of 3 states: *done*, meaning the results for the subproblem have been received by the eager scheduler; *partially done*, meaning that results have been received by the eager scheduler for some but not all descendants of this subproblem (i.e., some but not all subproblems of this subproblem); and *undone*, meaning that no results have been received by the eager scheduler for this subproblem. In addition to the tree structure, undone tasks are put in a circular linked list. Tasks are eagerly scheduled from this circular list until it becomes empty: there are no undone tasks. This indicates completion of the computation; the eager scheduler then propagates a termination signal down the host tree. The processing itself consists of two distinct routines: *result processing* and *task selection*, given in Figure 4.

Figure 5 illustrates Javelin 3 eager scheduling. One significant difference to master-worker eager scheduling is that here, the tree is *not* pre-generated — doing so would be prohibitive for memory reasons (branch-and-bound search tree can be huge, and we only need to process a small portion at a time). In Figure 5(a), we see how the results of the atomic tasks with IDs 4 and 6 have arrived at the eager scheduler. The eager scheduler subsequently marks these tasks as *done*, and all their ancestors including the root as *partly done*. Figure 5(b) shows how, assuming no further results arrive at the eager scheduler and work stealing has failed, the eager scheduler analyzes the current situation: Based on its current min cost bound, it infers that the task with ID 3 was pruned from the tree, and subsequently marks task 1 as *done*. Finally, in Figure 5(c), we show how the eager scheduler selects task 5 as the next *undone* piece of work. This task will now be reissued for host computation.

```
public void processResult(Task t)
{
  insert t into ProblemTree;
  mark t done;
  mark its ancestors in ProblemTree as either
       partially done or done, as appropriate;
  maintain undone task list;
}

public Task selectTask()
{
  // esTask refers to last eagerly scheduled node
  while ( (esTask = esTask.next() ) != null )
  {
    while ( esTask != null && !esTask.isAtomic() )
    {
      generate esTask's children & their costs;
      insert children into ProblemTree;
      maintain undone task list;
      esTask = selectTask( 1 of these children );
    }
    if ( esTask.isAtomic() )
    {
      if ( esTask.hasBeenRescheduled() )
      {
        // dynamic depth increment
        esTask.incrementAtomicDepth();
        continue;
      }
      return esTask; // have atomic node to process
    }
    // else no feasible atomic node on this path of ProblemTree
  }
  done = true;  // set terminate signal
  return null;
}
```

Figure 4. Eager scheduling: processing a result, and selecting a task.

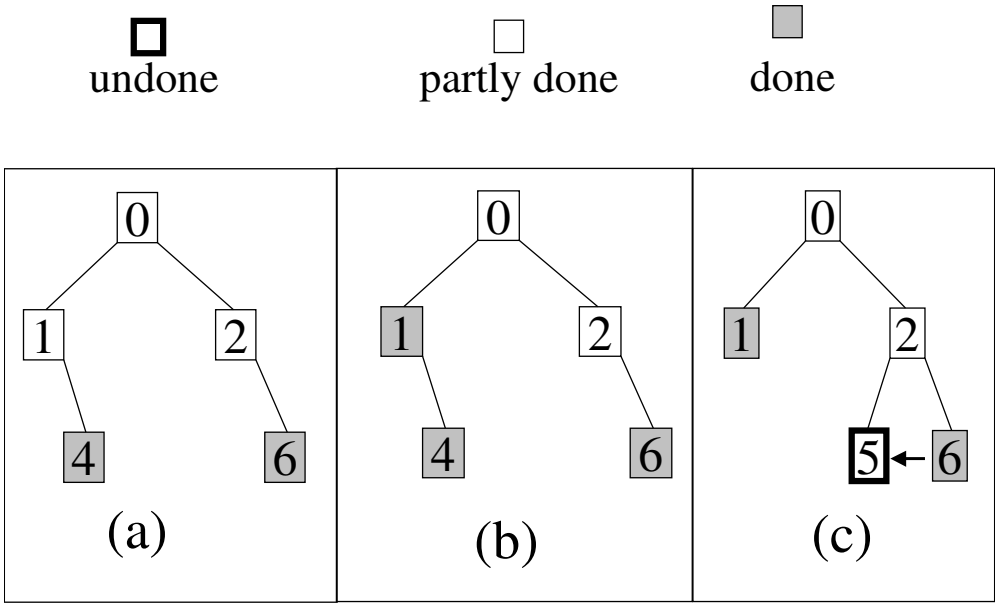


Figure 5. (a) Results 4 & 6 arrive. (b) Deferred detection of pruned task 3. (c) Task 5 selected.

Dynamic Depth Expansion

Our experience has shown that, due to the inherent irregularity of many branch-and-bound problems (e.g., the TSP), computation times for tasks with a fixed atomic depth parameter vary greatly; in fact, some pieces compute in milliseconds, as they are quickly pruned; others may take more than half the time of the *complete computation*. Figure 6(a) shows a situation in which a single large atomic task forms the bulk of the computation.

We therefore improved the fixed-depth eager scheduling scheme described in [34] by adding a *dynamic depth* component, which increases the atomic depth of eagerly scheduled pieces on each new round. Thus, larger tasks can be sub-divided into tasks representing smaller subproblems and distributed to several hosts. This dynamic depth expansion has greatly improved the performance and scalability of our system. Figure 6(b) shows an example of this mechanism: a large atomic task is sub-divided by incrementing the atomic depth. If the resulting sub-divided tasks are still too big, the process can be repeated, as shown in Fig. 6(c).

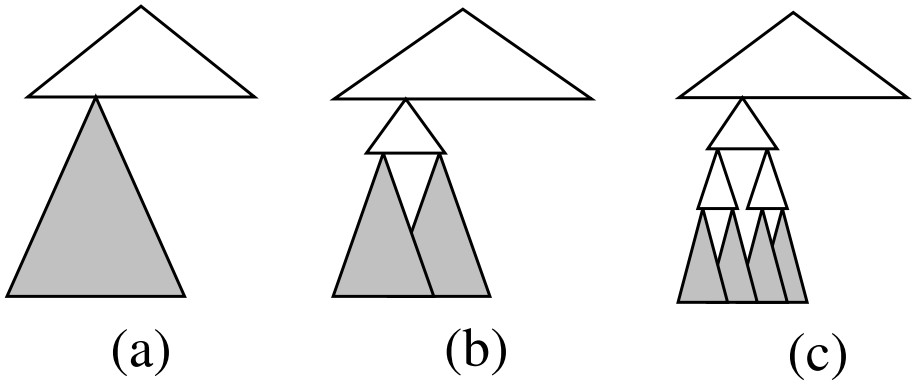


Figure 6. (a) Large atomic task. (b) Single-depth split increment. (c) Double-depth split increment.

Repairing the host tree

If a host located at a leaf position in the tree fails (or retreats from the system), it does not affect other hosts very much, since the failed host, when detected, is just taken off the detecting host's address list. When a non-leaf host fails, remedial action is more complex. A failed host blocks communication among its children. Eager scheduling guarantees that the work that was assigned to the failed host is re-assigned eventually to hosts that remain accessible to the client. But, it clearly is desirable to fix a broken tree as fast as possible, especially if the failed host is the root of a large subtree of hosts. Javelin 3 automatically fixes a tree as soon as a host failure is detected. As a precondition, we assume that *the broker is a stable participant*, since it runs the tree manager.

The tree repair scheme works as follows: When a host is assigned a position in the tree, it is given information on how to contact its parent. If a host later detects that its parent is dead, it immediately notifies the broker of this condition. If the empty position has already been reported and filled, the tree manager traverses the tree representation, and returns the new parent to the host. However, if the host is the first to report the failure, the tree manager re-heaps the tree. Figure 7 illustrates the situation where node 1 has failed and is replaced by node 6, which is moved to its new position.

At present, the tree repair scheme only can cope with host failures, i.e., all hosts that detect a failure must agree on that observation. Currently, a single host is unable to distinguish between host failure and link (communication) failures. In the case of a link failure between a host and only one of its children, the present scheme reports a failure to the broker even when sibling hosts can still communicate with the "failed" parent host. Clearly, what is needed is a form of *quorum consensus* algorithm. Therefore, our basic scheme needs to respond in a more sophisticated way to link failures. This is a topic of future research in Javelin 3.

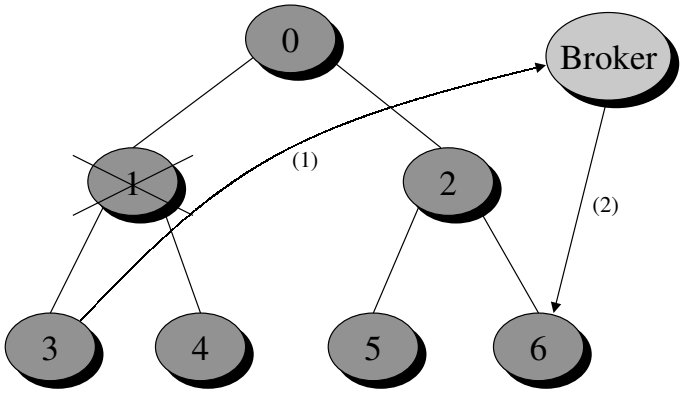


Figure 7. Host 1 fails; host 3 detects failure; broker preempts host 6.

Eager scheduling analysis

Leaf Node Failures

Let T_n denote the running time of an experiment with n hosts with identical compute power. If a leaf node fails in the host tree, eager scheduling guarantees that all lost work, i.e., all the pieces that the failed host was currently working on or that had not been reported back to the eager scheduler yet, eventually is rescheduled. (However, if a host successfully reported a completed task to the eager scheduler before the host failed, the eager scheduler will know that that particular task does not need to be rescheduled.) Thus, a trivial upper bound on the running time with a single failure is T_{n-1}. By the same reasoning, if there are k leaf node failures, the expected running time is at least as fast as T_{n-k}. We assume *the client is a stable participant*; thus, in the worst case (all other hosts fail), the expected running time degenerates to T_1. If we make a few more assumptions, we obtain a much tighter bound on the expected running time:

1. The time to calculate an individual, atomic piece of work Δt is negligible in comparison to the total compute time of the problem T, and
2. The average communication latency l between hosts is negligible in comparison to Δt.

$$l \ll \Delta t \ll T$$

3. The total number of failures k is small compared to the number of initial hosts, n:

$$k \ll n.$$

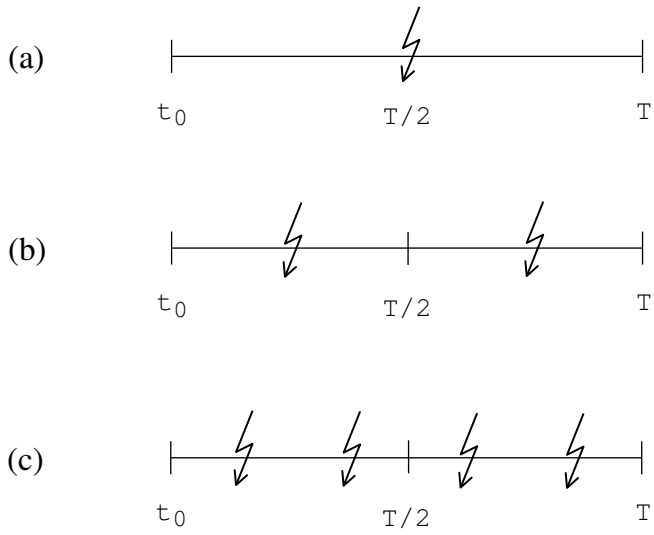


Figure 8. Different failure scenarios.

In the absence of failures, with n identical hosts participating in the computation, each host contributes approximately $1/n$ to the computation. Under the above assumptions, if a failure occurs at time t somewhere between the beginning of the computation, t_0, and the end, t_1 (with $T = t_1 - t_0$), then the contribution of the failed host is approximated by $\frac{t-t_0}{T}/n$. When the failure occurs exactly halfway through the computation, as shown in Figure 8(a), the contribution of the failed host is $1/2n$. If 2 hosts fail half-way through the computation, the effect thus is as if we had one fewer hosts throughout the whole computation. Let $E_T(i)$ denote the expected running time for i failures. Hence, $E_T(2) = T_{n-1}$. For any k halfway failures, the expected running time

$$E_T(k) = T_{n-k/2}.$$

The above result holds even under failures that don't occur exactly halfway through the computation: For instance, if two failures occur at times that are symmetric to the halfway point, the effect is as if both failures had occurred mid-way. Figure 8(b) illustrates this. Thus, assuming a *constant failure rate*, as depicted in Figure 8(c), the effects of failures combine pairwise, and the above formula holds. Obviously, if the failure rate is too high, the

assumptions are violated, and performance degenerates. However, our experiments indicate that the degradation is graceful.

Non-Leaf Node Failures & Tree Repair

Under the tree repair scheme described above, the consequences of a host failure higher up the tree are reduced to that of a leaf node failure, and the above formula holds.

EXPERIMENTAL RESULTS

We begin with a series of experiments designed to demonstrate the scalability of our system, followed by experiments to validate the preceding fault tolerance performance analysis. For these tests, we had access to three dedicated parallel machines:

1. A 96-processor Beowulf cluster at our Computer Science Department at UC Santa Barbara. This machine has six 500 MHz Pentium III quad-processor nodes, and 36 400 MHz Pentium II dual processors, each with 512 MB or 1 GB of memory, running Red Hat Linux 6.2.
2. A 192-processor Beowulf cluster at University of Paderborn, Germany. This machine has 96 850 MHz Pentium III dual-processor nodes, each with 512 MB memory, running Red Hat Linux 7.1.
3. An 1152-processor IBM Blue Horizon at NPACI, San Diego[†]. The machine has 144 SP Power3 8-processor nodes, clocked at 375 MHz, with 4 GB of memory per node. The OS is AIX.

We tested our system on these dedicated architectures in order to obtain clean speedup curves in the classical sense, and to work in a controlled test environment. Previously, we published results obtained on a LAN [32].

Scalability experiments

For the scalability experiments, we chose to run a classical branch-and-bound application, the *Traveling Salesman Problem* (TSP). In brief, the TSP can be stated as follows:

> Given a weighted, directed graph $G = (V, E)$, find a *minimum weight tour*: a closed path that visits each $v \in V$ exactly once.

Figure 9 shows a simple instance of the TSP. Here, the graph is undirected, which can be viewed as a special case of a directed graph with both corresponding directed edges having identical weight. The edges of the minimum-weight tour for this instance are in bold in the figure.

[†]According to the latest Top 500 list, this is currently the 18th most powerful machine in the world.

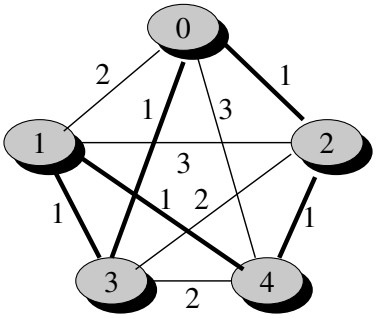


Figure 9. An instance of the TSP.

Figure 10 shows the corresponding complete search tree for this simple instance. From this, it is clear that even for very small instances of the problem, search trees can be huge. In fact, it is well known that the TSP falls into the category of NP-complete problems, for which all currently known algorithms leading to a general solution have at least exponential worst-case complexity.

Our TSP application is a simple, depth-first algorithm for local computation. A breadth-first component is introduced by running the problem in parallel. In the current version, a node in the search tree corresponds to a partial path. A lower bound on all tours containing that partial path is obtained from the following relaxation of the TSP (a variation of the 1-tree relaxation [8]): The weight of the partial path plus the weight of a minimum weight spanning tree (MST) that connects all nodes *not* on the path as well as the partial path's two endpoints. When the edges are pre-sorted by weight and the parent node's minimum weight spanning tree is given, it is easier to compute the child node's minimum weight spanning tree via Kruskal's algorithm.

The Effect of Dynamic Depth Expansion

To demonstrate the effect of our dynamic depth expansion, we varied the depth increment parameter from 0 through 5 for a given test graph. Figure 11 shows a set of speedup curves for a smaller, 32-node graph, run on the Paderborn Linux cluster. Although these are speedup curves in the classical sense, the base case is not measured on a single processor. Instead, we show speedup over T_4, the time it took 4 processors to compute the test graph. The reasons for this are twofold:

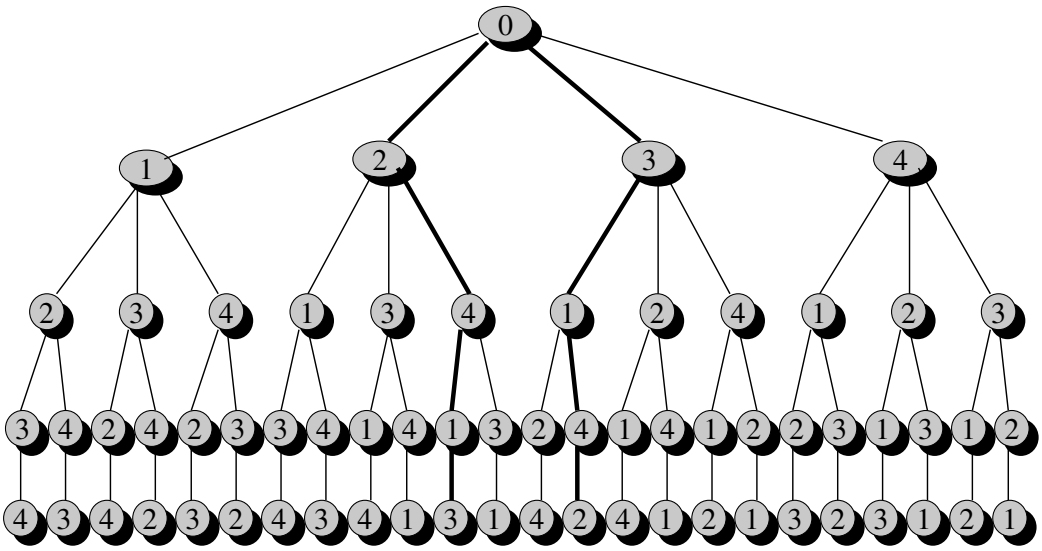


Figure 10. A TSP search tree.

1. The time to complete a run with 4 processors is approximately 3 hours. The time to run on a single processor is therefore prohibitively long, and since speedup in that region of the curve is close to optimal [33], it does not add anything qualitatively.
2. In taking a 4-processor experiment as our base case, we eliminate some of the potential for observing superlinear speedup by adding a breadth-first component to our local depth-first algorithm.

The results show that speedup was mediocre with 0 increment (*dinc0* in the diagram), i.e., with a *static* atomic task size. This is due to a single large piece in this graph that imbalances the load and lengthens the critical path. With an increment of 1 per round, the result improves.

For the 32-node graph, when atomic tasks contain subtrees of height 29, a dynamic depth increment of 1 splits an "atomic" task into 29 subtasks minus the pruned subtasks; a dynamic depth increment of 2 splits such an "atomic" task into $29*28 = 812$ subtasks minus the pruned subtasks; a dynamic depth increment of 5 splits such an "atomic" task into $29*28*27*26*25$ subtasks minus the pruned subtasks. In general, for an n-node graph whose initial atomic tasks are at depth d, using a dynamic depth increment of i yields $(n-1-d)!/(n-1-d-i)!$ subtasks minus the pruned subtasks. *Lazy* eager scheduling is crucial, since it enables aggressive pruning.

In our experiments, increments of 2 and 3 yield more speedup than an increment of 1, although the improvement is not so dramatic. The best results were obtained with an increment of 4 for this graph, at least until the saturation point was reached at 64 processors and the

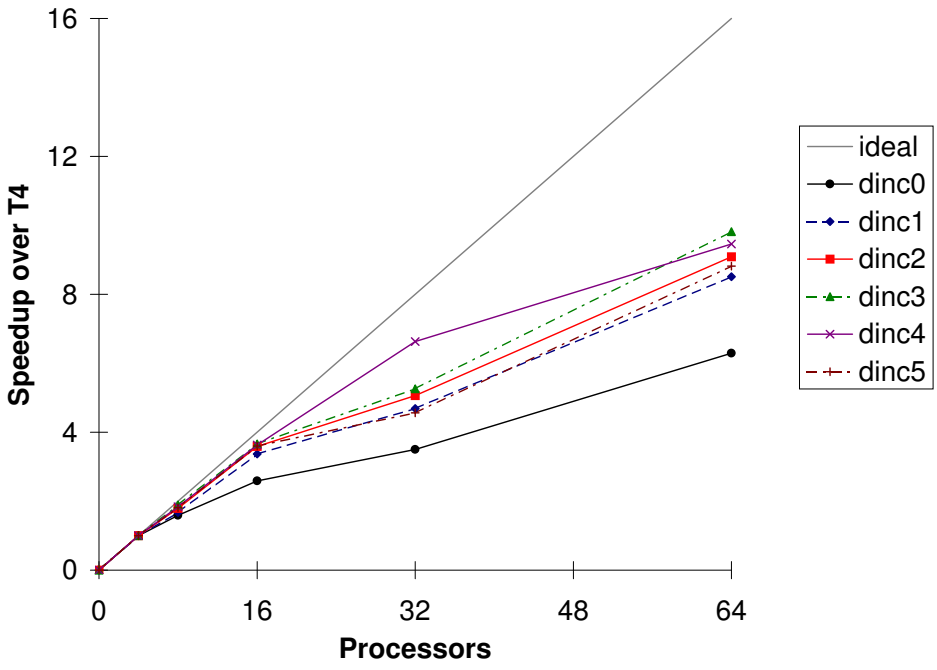


Figure 11. Speedup over T_4 for varying depth increments.

overall running time became too short. An increment of 5 performed much worse, about the same as 1. This is due to the large number of tasks per round generated by such high increments, placing an additional burden on the client process and the communication system. Other experiments with different graphs generally confirmed the following observations:

- For each graph, there is an individual optimum depth increment, usually around 2 or 3.
- The more imbalance a graph shows with a 0 increment, the more likely it is that a higher increment yields a better result.
- Dynamic depth expansion is most useful in the center of the curve, when overall running times are still long enough to split up large pieces. For the smaller host configurations, it is often not needed to achieve good results; in the very largest configurations, the short total running time means that some remaining large pieces will still prolong the critical path.

In summary, this feature has greatly improved the system's performance, and enables good speedups for graphs that were previously deemed unsuitable.

Table I. Input graph parameters for TSP.

Graph	Depth increment	Completion time (T_{64})	Average time/task	Maximum time/task
35k	1	13.31 h	222 s	8.27 h
36c	2	21.87 h	177 s	9.18 h
37e	1	13.88 h	430 s	6.93 h
37e	2	12.39 h	200 s	6.57 h

Finding Suitable Input Graphs

For our largest experiments, the test graphs were complete, undirected, weighted graphs of 35–37 nodes, with randomly generated integer edge weights w, $0 \leq w < 1000$. These graphs were complex enough to justify parallel computing, but small enough to enable us to run tests in a reasonable amount of time. By using complete graphs as input, we ensure that the graphs were dense, making this type of graph the hardest to process for a given size. Also, we are not exploiting any special case, such as the Euclidian TSP, where the edge set satisfied the triangle inequality. For such graphs, an upper bound for the TSP that is less than or equal to 3/2 the optimum can be obtained via Christofides's algorithm [19, 13].

The procedure of finding input graphs itself is tedious: we generated some 45 candidate graphs over time, and tested them on a small set of hosts — initially 20, later 64 — to get an idea of the problem size. Many of the candidate graphs proved either too simple (running time too short) or too hard (running time too long). We considered graphs that ran in approximately 10–20 hours on 64 processors of the Paderborn Linux cluster. Our aim was to find graphs that would run for 2-4 hours on 1000 processors on NPACI's IBM Blue Horizon. Table I shows some characteristic data for the graphs that we used in our large scale experiments, measured on IBM Blue Horizon. In addition to the 64-processor running times, the table shows the average time per atomic task and the maximum time per atomic task. Minimum times are on the order of several milliseconds; thus, the variance in atomic task sizes is huge. For graph 37e, the average time per task decreases by over 50% when the dynamic depth increment is changed from 1 to 2 — this is indeed the desired effect of splitting large "atomic" tasks. In Figure 12, the curve for 1 input graph consists of 5 measurements (64 processors, 256 processors, 512 processors, and 1024 processors) and burned approximately 5,000 to 10,000 units of our Blue Horizon allocation. Our total allocation was only 25,000 units. We thus were motivated to be extremely frugal with those units.

Large Scale Experiments

The next set of results, shown in Figure 12, were run on the IBM Blue Horizon. Here, we chose a base case of 64 processors, for the same reasons stated above. The results show good speedup up

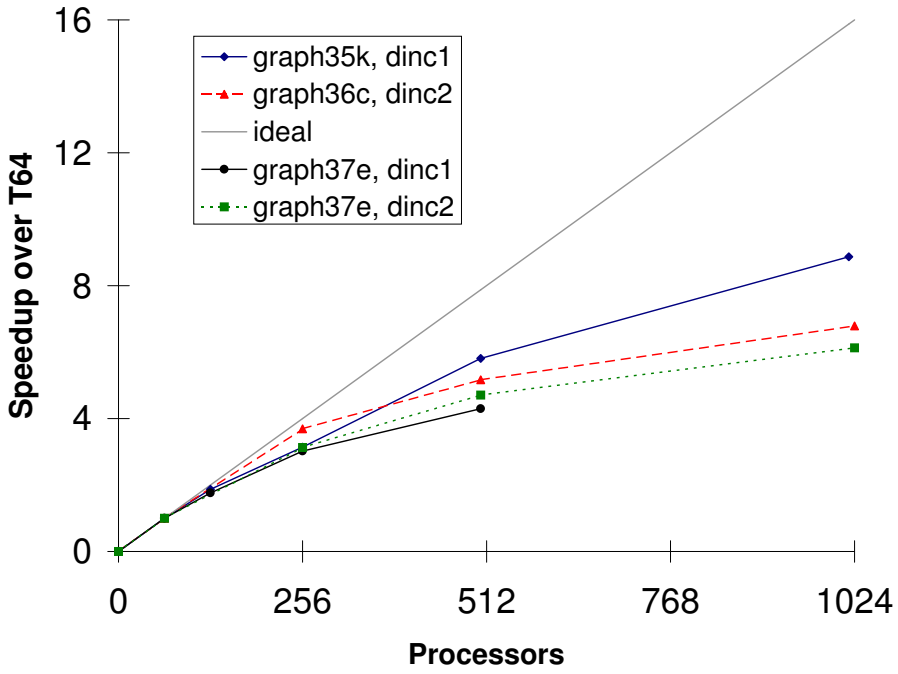


Figure 12. Speedup over T_{64} on IBM Blue Horizon.

to around 500 processors. Again, we can show the benefit of dynamic depth expansion: for graph 37e, with an increment of 1, speedup dropped off strongly at 500 processors (so much so that we omitted the 1024-processor test; it clearly was not going to beat graph 35k, dinc 1). With an increment of 2, the result was better in every configuration. Interestingly, our best result, for graph 35k, was achieved with depth increment 1 — the graph showed no further improvement for higher increments, which means that it was evenly balanced to begin with. The largest measurements, on up to 1024 processors, show some decrease in speedup and efficiency. We attribute this to the overall increase in communication-to-computation ratio: the total time to compute the problem with 1024 hosts was between 40 minutes and 2 hours, depending on the graph. Our experience shows that communication overhead becomes significant when overall running time drops below one hour. Also, any large pieces not yet split up by dynamic depth expansion lengthen the critical path. At this point, we are convinced that the system is not at fault — if we increase the size of the test graph, we should see better speedup. This, however, was not possible with the current allocation of 20,000 units on Blue Horizon. Instead, we would require around 80,000 units for such large tests.

Overall, these results are much improved, compared to earlier versions of Javelin: Due to algorithmic improvements, faster processors, and the advent of a faster JVM in the JDK 1.3 release, we are able to test graphs whose search trees are several orders of magnitude larger, even though communication latency remains the same. Scalability is significantly higher, too: we were able to fully utilize up to 1024 processors on the IBM Blue Horizon machine, without reaching an obvious scalability limit of our software.

Fault tolerance experiments

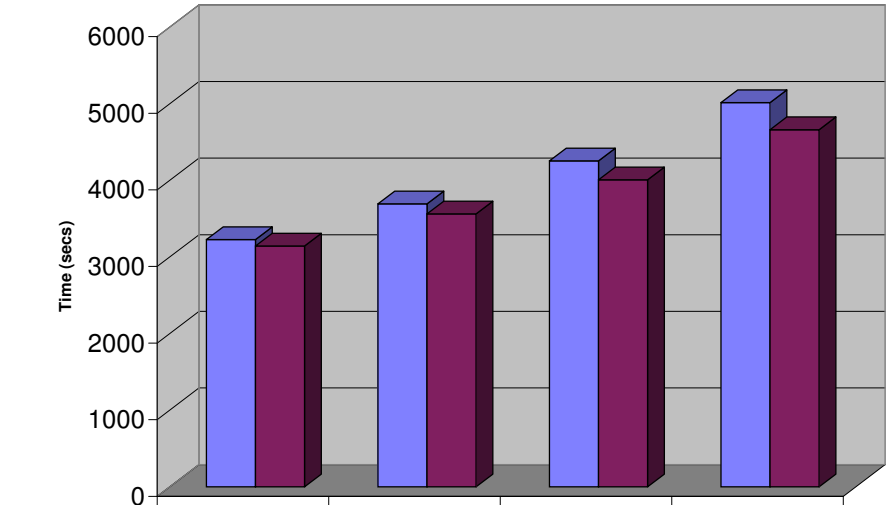
We present some experiments designed to validate our eager scheduling analysis. In these tests, we run a raytracing application: a classical example of a master-worker computation, its atomic task running time variance is relatively low; in a branch-and-bound example like the TSP, running times vary significantly. High variance in the running time of atomic tasks violates the first of assumption: the running time of atomic tasks Δt is *not* negligible in comparison to the total compute time of the problem T.

In all these tests, we render a scene of 5,223 objects on up to 10 hosts under a *single* broker, using the 400 MHz dual processor nodes of our local Linux cluster. Figure 13 compares running times with and without induced failures. The right columns show failure-free runs of 9, 8, 7, and 6 hosts. The left columns show results of tests in which we killed a number of hosts at times symmetric to the computation's halfway point. In the leftmost experiment, we started 10 hosts, and killed 2 during the computation. According to our analysis, $T_{10}(2)$ should equal T_9; the measured result was within 3% of this prediction. The next result, $T_{10}(4)$, was within 4% of the predicted value, T_8. $T_{10}(6)$ was approximately 6% slower than its predicted value, T_7. Finally, $T_{10}(8)$, a test in which we killed 8 out of 10 hosts during the computation, was within 7.5% of the target, T_6.

The increasing gap between the times with and without failures can be explained by the non-negligible loss of work in this scenario: The average running times of the atomic tasks were about 27 secs, and maximum times were as large as 57 secs. The more hosts are killed, the more work needs to be rescheduled and redistributed; a small overhead is to be expected. That is, our third assumption—the number of failures is small compared with the original number of processors—is violated, since 80% of the starting hosts were killed. Overall, we consider these results a confirmation of our analysis.

CONCLUSION

Javelin 3 harvests unused machine cycles of networked computers for ultra-large, coarse-grained *adaptively parallel* applications. It runs well on large cluster machines and networked workstations, as long as the ubiquitous Java platform is installed. We use work stealing, integrated with an advanced form of eager scheduling, to balance the computational load and achieve fault tolerance and scalability. The TSP branch-and-bound application is a stress test of our system, because the computational load of tasks at the same depth in the search tree can vary from being less than 1 millisecond to more than half the time to complete the entire computation. To cope with this computational load variance, the eager scheduler dynamically



	T10(2) = T9	T10(4) = T8	T10(6) = T7	T10(8) = T6
failures	3226	3693	4253	5015
no failures	3144	3562	4007	4661

Figure 13. Fault tolerance on PII 400 processors.

decreases the size parameter of an atomic task. This new form of eager scheduling substantially improves the system's performance: We can now solve much larger problems than before, and also obtain better speedups for problems that previously did not scale well.

Performance for our test graphs show nearly ideal speedups through 256 hosts. When 512 are used, speedup tapers off. Only when 1,024 hosts are used do speedups reduce substantially. With larger problem instances (e.g., those that take 256 processors 20 or more hours to complete) we expect higher speedups even using 1,024 or more processors. We believe that the principle impediment to better speedups is the short running time using 1,024 hosts: Large tasks not broken up by the eager scheduler prolong the critical path.

The quantification of performance degradation due to host failures that our model predicts is confirmed by the measurements taken of the raytracing application. The model thus enables users to predict their application's performance as a function of host failure rates, as long as the model's assumptions remain valid.

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