RIDGE: Combining Reliability and Performance in Open Grid Platforms*

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ABSTRACT

Large-scale donation-based distributed infrastructures need to cope with the inherent unreliability of participant nodes. A widely-used work scheduling technique in such environments is to redundantly schedule the outsourced computations to a number of nodes. We present the design and implementation of RIDGE, a reliability-aware system which uses a node's prior performance and behavior to make more effective scheduling decisions. We have implemented RIDGE on top of the BOINC distributed computing infrastructure and have evaluated its performance on a live testbed consisting of 120 PlanetLab nodes. Our experimental results show that RIDGE is able to match or surpass the throughput of the best vanilla BOINC configuration under different reliability environments, by automatically adapting to the characteristics of the underlying environment. In addition, RIDGE is able to provide much lower workunit makespans compared to BOINC, which indicates its desirability in service-oriented environments with time constraints.

Categories and Subject Descriptors:
C.2.4 [**Computer-Communication Networks**]: Distributed Systems; C.4 [**Performance of Systems**]

General Terms: Algorithms, Performance, Reliability

Keywords: Open Grids, Reputation, Scheduling, Reliability

1. INTRODUCTION

Voluntary distributed computing infrastructures have been an active area of research in the past few years. SETI@home [2] is one of the early projects that generated enthusiasm for this paradigm. Today, these infrastructures are being used in a diverse set of application domains such as bioinformatics [9], physics [15], and environment science [7]. BOINC [1] is a generalization of these projects that provides a computing infrastructure for utilizing donated resources. BOINC has a centralized server which distributes tasks to participating worker nodes and collects the results returned by these workers.

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A key problem faced by such projects is the inherent unreliability of the infrastructure. Nodes have dynamically changing workloads, may leave and join unexpectedly, or may behave maliciously. BOINC applications (like SETI) use redundant task execution coupled with voting on results to address such unreliability. A major drawback of the BOINC approach is that it relies on the application designer to set the redundancy factor for task replication. Since an application designer knows little about the actual network dynamics, determining this value is largely guesswork. However, the replication factor can have a severe impact on the performance of the application: a small value could lead to a large number of failed computations, while a large value could lead to wasted resources and reduced throughput. Moreover, the desired value of the replication factor is critically dependent on the reliability of the underlying system, and hence difficult to determine a priori.

This paper presents the design and implementation of *RIDGE (Reliable Infrastructure for Donation-based Grid Environments)*, a system designed to maximize reliability and performance of the underlying infrastructure. RIDGE achieves this by dynamically adjusting the degree of replication based on prior node behavior. In an earlier paper, we showed how intelligent replication and scheduling can improve performance through a simulation study [20]. This paper focuses on the implementation and deployment of the proposed ideas in a live environment, and explores several corresponding systems issues. We have implemented RIDGE by modifying the core BOINC infrastructure to use a different workload allocation strategy. RIDGE makes more informed decisions by observing the past behavior and estimating a reliability rating for each of the worker nodes in the system. The reliability rating of a worker node is intended to encapsulate the node's behavior in two dimensions: its correctness and timeliness in returning results. The primary motivation for exploring correctness and timeliness together is to enable RIDGE to effectively support service-oriented environments, where getting a timely result is as important as getting a correct result.

We have deployed a prototype of RIDGE and evaluated it on a live testbed consisting of 120 PlanetLab [3] nodes, using the BLAST [4] bioinformatics application. We compare the performance of RIDGE to the default BOINC infrastructure running on the same platform, using both synthetic and real reliability distributions to emulate node behaviors. Our experimental results show that RIDGE is able to match or surpass the throughput of the best vanilla BOINC configuration under different reliability environments, by automatically adapting to the characteristics of the underlying environment. In addition, RIDGE is able to provide much lower workunit makespans compared to BOINC, which indicates its desirability in service-oriented environments.

2. SYSTEM ARCHITECTURE

RIDGE is implemented on top of the core BOINC architecture, and it utilizes BOINC mechanisms for workload creation, communication with worker nodes, result gathering, etc. We first briefly describe the core BOINC architecture, followed by the RIDGE enhancements and workload allocation strategy.

2.1 BOINC Architecture

The BOINC architecture consists of a centralized server responsible for distributing work to the worker nodes. Each unit of computation (referred to as a *"workunit"*) is replicated into a fixed number of replicas (referred to as *"tasks"*). The replication factor is a static value specified by the application writer. BOINC employs a pull-based work distribution model where the worker nodes query the server for work and are assigned tasks by the server. Results are returned by workers to the server upon completion of each task execution, and are verified using a verification technique specified by the application designer. Majority voting and M-first voting are the most common verification techniques used. With Majority voting, each workunit is replicated into 2M-1 tasks and the workunit is said to have completed successfully if at least M results match. In M-first voting, each workunit is replicated into at least M tasks and a workunit is said to have completed successfully as soon as M results match. The process of verifying each result of the workunit is called *validation*. If a validation is successful, the workunit is deemed to be completed and any of its tasks that are yet to be scheduled are purged. However, if a validation fails, additional tasks are generated for the workunit in an incremental fashion until the validation is successful. A key limitation of BOINC's work assignment policy is that a static replication factor is used for all workunits, and the assignment of tasks to worker nodes is arbitrary.

2.2 RIDGE Scheduling Framework

RIDGE replaces the default BOINC workload allocation policy with a *Reputation-based scheduling* technique.The idea behind this technique is to use information about worker reliability to allocate workers to tasks in a more intelligent manner, thus increasing throughput while maintaining a target success-rate. [1] A node's reliability rating is based on the number of 'timely' and 'correct' task executions performed in the past relative to the total number of tasks allocated to it. Using these ratings, it is possible to determine effective redundancy groups, both in size and in worker composition. A more detailed description of this technique can be found in [20]. While the original algorithms were designed for Majority voting, we have extended them to work for M-first voting in this paper. The RIDGE server employs these scheduling algorithms and is driven by the following key parameters:

• *Target Success-Rate (TSRate)*: the minimal success-rate desired from the system, specified as a value in the range 0-1. The scheduling algorithms form redundancy groups such that each group is expected to return a valid result with probability at least equal to the TSRate.

• *Exec-Threshold (ExecThrld)*: the maximum time that a task execution is allowed to take for it to be considered 'timely'. The execution time is calculated as the difference between the time when the result for a task is received at the server, and the time when the task was dispatched to the worker.

• *Scheduling-Threshold (SchedThrld)*: the number of workers for which the RIDGE scheduler (described below) waits for before running the scheduling algorithm. In this paper, we use a threshold of 1 to enable a fair comparison between the RIDGE and BOINC systems.

• *MinClients*: the minimum number of workers that a workunit should be assigned to. This value could be dependent on the verification technique used or could be chosen by the application designer. For example, for M-first voting with M = 2, MinClients should be at least 2.

• *MaxClients*: the maximum number of workers that a workunit should be assigned to. This is defined to prevent RIDGE from forming arbitrarily large groups to meet the TSRate.

There is a tradeoff between success-rate and throughput. A higher replication factor will lead to a greater success rate, but may cause a drop in throughput. Thus, a designer needs to carefully set this value based on their desired success-rate and throughput. In previous work [19], we developed an adaptive algorithm that dynamically adjusts the TSRate based on the relative importance of success-rate and throughput.

A detailed discussion of this tradeoff is beyond the scope of this paper, and here, we assume an externally specified TSRate.

2.2.1 Component Architecture

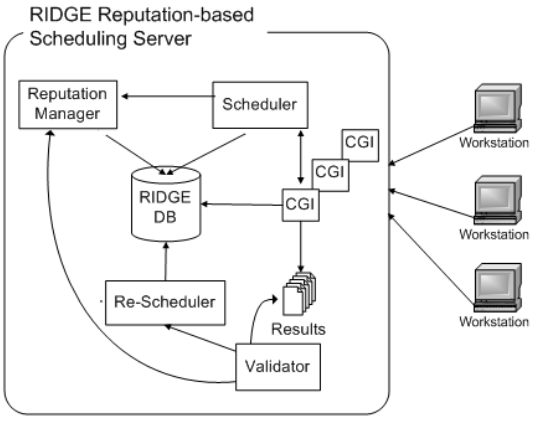


Figure 1: The RIDGE scheduling framework

We now describe the implementation of RIDGE that employs Reputation-based scheduling algorithms. Figure 1 shows the RIDGE workload distribution engine. The primary components of the RIDGE framework are:

Scheduler: The scheduler is responsible for forming redundancy groups of worker nodes based on their reliability ratings, and assigning a workunit to each group. Before each scheduling instance, the scheduler waits for the SchedThrld number of workers to arrive at the server. Effectively, this waiting transforms the work-distribution model from the BOINC work-on-demand to a batch-scheduling model. The SchedThrld is a system parameter that can be tuned based on system requirements: a larger value of the threshold results in more 'optimal' grouping, but has higher scheduling overhead and waiting time. Once it has enough workers to proceed, the scheduler obtains the reliability ratings for the available workers from the reputation manager (described below). It then runs a Reputation-based scheduling algorithm [20] to form the redundancy groups and assigns tasks to the worker nodes. The scheduler also handles partially completed workunits: ones that have not been validated successfully and thus need to be re-scheduled. As a default, these re-scheduled workunits are given priority over new

[1] Intuitively, 'Success-Rate' measures the proportion of workunits that complete successfully without the need for rescheduling.

ones, the intuition being that they can be successfully completed with much less effort. In contrast, no explicit preference is given to pending workunits in BOINC, resulting in an accumulation of pending work in the presence of large amounts of new work.

Reputation Manager: The reputation manager maintains the reliability ratings of the worker nodes. The scheduler uses these reliability ratings in making its scheduling decisions. The reputation manager is also responsible for updating the reliability ratings of worker nodes when a workunit is validated: a node's rating may be increased or decreased based on the outcome of the validation.

Validator: This is a part of the BOINC core architecture (while the others are not). The validator initiates the validation process when the required number of results for a workunit arrive at the server, and determines if an agreement is achieved. The outcome of the validation is passed on to the reputation manager, which updates the nodes' reliability ratings accordingly.

Re-Scheduler: When a validation fails, the re-scheduler decides the number of additional tasks to be created for the failed workunit, which can be based on factors such as the number of matching results obtained in the validation process, the reliability ratings of participating workers, etc. It can also discard all the tasks for the workunit and create a fresh one on its behalf, depending on the design choices made. As a default, the re-scheduler creates one additional task for the failed workunit.

2.2.2 RIDGE Workflow

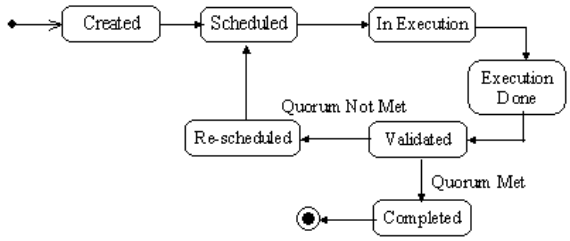


Figure 2: Workunit Life-Cycle

Figure 2 illustrates the workflow in the RIDGE framework through the life-cycle of a workunit. Workunits are *created* and put in the RIDGE database. Additional workunits are created as the work queue empties to maintain a minimum workpool size at the server. When a worker node requests work, the request handler informs the scheduler and blocks the worker node until the scheduler is ready. The worker nodes that check in with the scheduler are put in a worker queue. When the number of available workers meets the SchedThrld, the scheduler performs the allocation of workunits. In our framework, priority is given by default to partially completed workunits, whose tasks are assigned to the most reliable available workers. The remaining workers are grouped into redundancy groups, and each group is given tasks of one workunit to execute. The replication factor of each workunit varies depending on the associated group size. At this point, the workunit transitions to the *scheduled* state. Once the workunit is scheduled, the worker nodes pick up their assigned tasks and start executing them. The workunit is now in *execution*.

Each worker node returns the result of the task it executed to the server. When the minimum number of results required for validation of a given workunit have arrived, the *validation* process is triggered to verify the results. If the validation succeeds, then the workunit is considered to be complete, otherwise, the workunit is *re-scheduled*. The re-scheduler incrementally creates new tasks for this workunit, which are eventually allocated by the scheduler. Finally, depending on the outcome of the validation, the reliability ratings of the worker nodes are updated by the reputation manager.

2.2.3 Reputation-based Scheduling

Now we briefly describe the worker reliability estimation and grouping algorithms that are the key components driving the RIDGE scheduling framework.

Worker Reliability Estimation: The reliability ratings of workers are learned over time based on the results returned to the server. A worker's reliability $r_i(t)$, at time t, is given as follows:

$$r_i(t) = \frac{n_i(t)+1}{N_i(t)+2},$$

where $n_i(t)$ is the number of valid responses generated, and $N_i(t)$ is the total number of tasks attempted by a worker i at time t. A worker's rating is updated each time it is assigned a task, based on the response it returns (a missing or late response is treated as incorrect). Various heuristics have been proposed in [20] that guide how to update the ratings in the case of an unsuccessful validation. In this paper, we use the 'Neutral' heuristic, that updates a worker's rating only upon a successful validation and remains neutral otherwise.

Scheduling Algorithms: We proposed three reliability-based grouping algorithms (First Fit, Best Fit, and Random Fit) and evaluated their effectiveness through a simulation study in [20]. To facilitate effective comparison with BOINC, we use the Random Fit algorithm for workload allocation in this paper. The idea behind this algorithm is to randomly assign workers to a workunit until either the redundancy group meets the TSRate, or the group size reaches the MaxClients bound. RIDGE implements Random Fit scheduling by selecting workers in the order they arrive at the server.

The detailed algorithm is shown below:

Algorithm 1 Random-Fit (*G* worker-group, τ workunit-list, R_{max} Maximum Group-size, R_{min} Minimum Group-size, λ_{target} *Target Success-Rate*)

1: **while** $|\tau| \geq 1$ **do**
2: Select workunit τ_i from τ
3: **repeat**
4: Wait for a worker w_i to arrive
5: Add worker w_i to *G*
6: Schedule task of workunit τ_i to worker w_i
7: Calculate λ, likelihood of successful validation from group *G*
8: **until** $(|G| \geq R_{min} \wedge \lambda \geq \lambda_{target}) \vee |G| = R_{max}$
9: Clear worker-group *G*
10: **end while**

3. EVALUATION

In this section, we evaluate the RIDGE framework and present a comprehensive performance comparison of RIDGE against vanilla BOINC. We first describe our experimental setup along with the metrics used, followed by the evaluation results.

3.1 Experimental Setup

We have deployed BOINC/RIDGE on PlanetLab [3], a shared distributed infrastructure consisting of donated machines. Our Grid consists of 120 nodes which serve as the worker nodes. The BOINC/RIDGE server runs on a dedicated machine outside the PlanetLab infrastructure. We used the BLAST (Basic Local Alignment Search Tool) [4] bioinformatics application as our test application. In our

setup, BLAST is run as a BOINC project by writing a BOINC-specific wrapper around it. Each workunit consists of a BLAST database file and an input sequence that has to be compared with each sequence in the database file. BLAST performs the sequence comparison and generates an output file result which is returned to the server. We have used a standard BLAST database file igSeqNt, with sizes of 28MB and 55MB for our experiments. The input sequence was a randomly selected sequence from the database file and is of length 770 bytes. M-first voting is used as the verification technique. To isolate the impact of RIDGE vs. BOINC scheduling, we have disabled 'Re-scheduling' in the initial results presented (later, we re-enable it). Thus, in our first set of experiments, a workunit whose validation is not successful the first time is deemed to have failed and is discarded from the work queue. Each experiment is run for 2 hours and repeated 3 times to smooth the effects of the underlying load fluctuations in PlanetLab.

3.2 Evaluation Metrics

To compare the performance of RIDGE against BOINC, we use the following metrics:

• *Success-Rate*: The success-rate for a run is defined as the ratio of the number of successful workunit completions (without re-scheduling) to the total number of workunits allocated.

• *Throughput* : The throughput for a run is defined as the total number of workunits completed.

• *Makespan*: The makespan of a workunit is defined as the difference between the completion time of the workunit and the dispatch time of the workunit's first task.

Here are some additional metrics we use to quantify the resource utilization of BOINC and RIDGE schedulers:

• *Group-Size*: The Group-Size of a workunit is defined as the number of workunit tasks that are assigned to workers.

• *Quorum-Size*: The Quorum-Size of a workunit is defined as the number of workunit tasks completed when the validation succeeds.

Note that at the time of validation, some tasks may not have been scheduled yet, which are discarded. The number of tasks scheduled at the time of validation corresponds to the Group-size, while the number of tasks that return by the time of validation corresponds to the Quorum-size.

3.3 Correctness Evaluation of Reliability

We first evaluate the performance of BOINC and RIDGE w.r.t. to the correctness behavior of workers in a throughput-oriented environment, where the primary objective is to obtain correct results. In this environment, all the results returned by the workers are considered to be 'timely'. Thus, the reliability of a worker reduces to the probability of returning a correct result. The goal of this set of experiments is to evaluate the following: given a desired success-rate, how effectively do BOINC and RIDGE achieve it with respect to resource consumption and throughput.

Since the nodes in the PlanetLab testbed are completely reliable w.r.t. correctness, we emulate the reliabilities of the nodes using synthetic distributions in this set of experiments. M-first voting, with M=2 is used as the verification technique, and TSRate was set to 0.75. While a success-rate of 0.75 may appear to be a relatively lax requirement, note that this corresponds to the desired proportion of successful first-time validations. Moreover, selecting this value allows us to explore the success rate-throughput tradeoff more clearly in our experiments, as we will show below. In fact, our results show that a high success rate target may not always be desirable in a throughput-oriented environment. To emulate various real-world reliability scenarios, we generated individual worker reliabilities from three different probability distributions:

• HighRE: An environment where a majority of the workers are reliable was emulated using the complement of a heavy-tailed distribution (1-Pareto(a,b) with parameters a=1, b=0.1).

• LowRE: An environment where a majority of the workers are unreliable was emulated using a heavy-tailed distribution (Pareto(a,b) with parameters a=1, b=0.2).

• ModRE: An environment with a mix of reliable and unreliable workers was emulated using a Uniform distribution with mean=0.5.

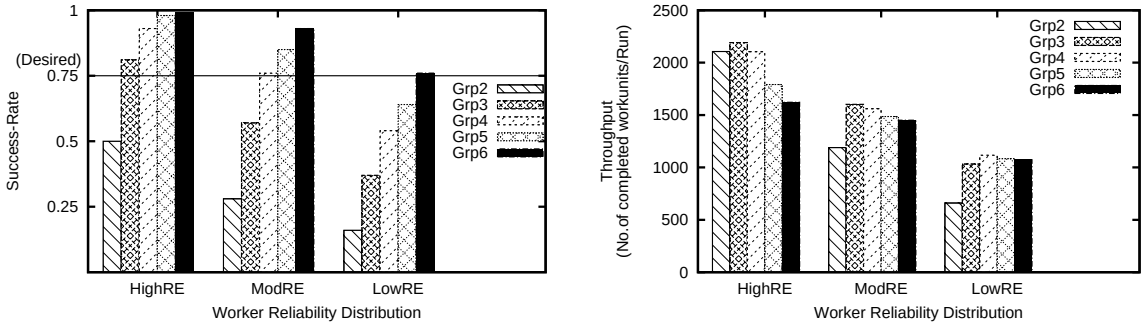
3.3.1 Impact of BOINC Replication Factor

We begin by evaluating the performance of BOINC, using various fixed replication factors, for the three reliability environments described above. The replication factor is varied, from a minimum of 2 to a maximum of 6, to determine the best static BOINC configuration that achieves the desired success-rate for each reliability distribution.

Figures 3(a) and 3(b) show BOINC's performance in terms of success-rate and throughput, respectively. Figure 3(a) shows that for a given reliability environment, the success-rate monotonically increases with the replication factor. This is expected, since the greater the number of replicas, the higher the probability of receiving at least M(=2) results that match. However, from Figure 3(b), we observe that as the replication factor increases, the throughput initially increases, but then decreases beyond a point. The low throughput for small replication factors is a consequence of the low success-rate for these values, as too little replication results in too many failures and hence low throughput. However, beyond a certain degree of replication, the increase in success-rate comes at the cost of a drop in throughput. This is because resources are being overprovisioned, leading to poor resource utilization and thus reduced throughput. Moreover, we observe that for a desired success-rate of 0.75, the 'optimal' replication factors for HighRE, ModRE, and LowRE are 3, 4, and 6, respectively, providing (success-rate, throughput) combinations of (0.81, 2191), (0.76, 1560) and (0.76, 1073). Thus, our results show that *given a desired success-rate, there is an 'optimal' fixed replication factor, which further depends on the underlying reliability distribution.*

Since the reliability of the underlying environment may not be known a priori and also the environment might change over time, it is difficult for a BOINC application writer (user) to select a suitable replication factor. A conservative user might select a large replication factor that achieves the desired success-rate in the worst environment possible. However, such a conservative value (6 in the above scenario) results in degraded throughput if the underlying environment is more reliable than expected. Conversely, an optimistic choice would be to select a small replication factor that achieves high throughput in most scenarios. However, such a choice (3 in our experiments) results in a low success-rate if the actual environment is worse than expected. Thus, the *same fixed replication factor does not perform well in all reliability environments.*

Another observation we can make from these results is that for a given reliability environment, even the 'optimal' fixed replication factor might not match the desired success-rate. In fact, it could be much greater than the desired success-rate leading to a compromise in throughput. For example, for HighRE, the 'optimal' replication factor of 3 results in a success-rate of 0.81, which is higher than the desired value of 0.75. This is a limitation of using *a static replication factor for all workunits*. By dynamically adjusting the replication factor on a per-workunit basis, the throughput can be improved while closely matching the desired success-rate. This is precisely the strategy used by RIDGE to schedule work for increased throughput while maintaining the desired success-rate.



(a) Success-Rate

(b) Throughput

Figure 3: Performance Comparison of different BOINC configurations

3.3.2 BOINC vs. RIDGE Comparison

We now compare the performance of RIDGE to that of BOINC under the three reliability environments. The RIDGE server is configured with TSRate set to 0.75, MinClients to 2 and MaxClients to 6, corresponding to the static replication factors used for BOINC. For our initial set of experiments, we assume that the RIDGE server already has the actual worker reliability ratings. Note that under normal execution, RIDGE would learn these ratings first. We omit the learning phase here to separate the effects of the learning algorithm from the performance benefits of the RIDGE scheduling algorithm (We show the learning phase in the next section).

The goal of these experiments is to evaluate how well RIDGE uses knowledge of the underlying characteristics of the worker population to dynamically size redundancy groups to meet the TSRate. We compare the performance of RIDGE to BOINC's best static configuration (referred to as BOINC^{Bst}) for each particular reliability environment. For example, for the HighRE distribution, RIDGE is expected to perform close to or dominate the performance achieved by BOINC configured with a replication factor of 3, since that is the 'optimal' for that distribution.

Performance Comparison: Figures 4(a) and 4(b) compare the performance of RIDGE with BOINC^{Bst} and a conservative BOINC configuration (BOINC^{Con}), which uses a replication factor of 6 to achieve the desired success-rate for all three reliability environments. The goal is to determine how close RIDGE performs to BOINC^{Bst} and how much of an improvement RIDGE offers over BOINC^{Con}. We observe that the success-rate achieved by RIDGE is at least 0.75 for all three environments. Thus, RIDGE is able to meet the TSRate. Also, the throughput achieved by RIDGE is comparable to that of BOINC^{Bst}, for all three cases. We also notice that RIDGE performs at least as well or better than BOINC^{Con} in all cases. The small throughput gap between RIDGE and BOINC^{Bst} is due to the following:

• The slightly higher resource consumption of RIDGE when compared to BOINC^{Bst} as discussed below.

• There is a small overhead in the RIDGE server due to the fact that workers must check-in with the scheduler and wait for a scheduling decision before receiving work. This overhead is evident in the total number of tasks scheduled by RIDGE, which was about 2% less than BOINC^{Bst} in all cases.

Resource Utilization Comparison: To understand how closely RIDGE tunes the group-sizes to that of BOINC^{Bst}, we compare the resource utilization of RIDGE against BOINC^{Bst} in Table 1. From Table 1, we observe the following for each reliability environment:

	Group Size		Quorum Size	
Distr	BOINC^{Bst}	RIDGE	BOINC^{Bst}	RIDGE
HighRE	2.85	3.06	2.37	2.42
ModRE	3.74	4.20	2.86	3.05
LowRE	5.52	5.54	3.89	3.75

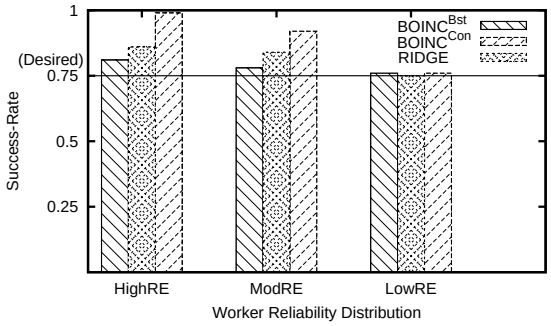
Table 1: BOINC^{Bst} vs RIDGE Resource Utilization

• The average group-size of BOINC^{Bst} is slightly less than the pre-specified fixed replication factor (3, 4, and 6 respectively for HighRE, ModRE, and LowRE). This is because even though BOINC replicates each workunit to a fixed number of tasks, not all of them are scheduled to workers. In BOINC, a worker could pick up any task from the workpool, resulting in a small degree of randomization in scheduling (that is, it is not serial). Moreover, as soon as a workunit is validated successfully, its unscheduled tasks are taken off the work queue, resulting in lower resource-consumption in some cases.

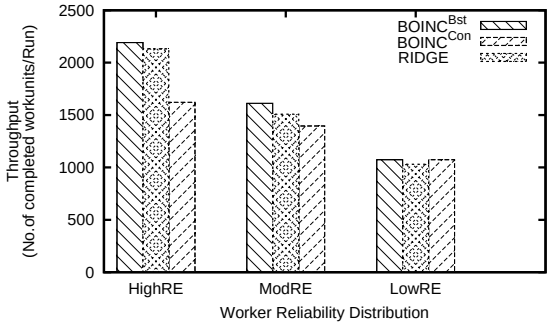
• The Group-size of RIDGE is slightly greater than BOINC^{Bst} for two reasons. First, RIDGE serially schedules work, so there is a high probability that all the tasks for a workunit are assigned to workers. Second, the reputation-based scheduling algorithms used in RIDGE ensure that each group formed strictly surpasses the TSRate. This conservative approach results in additional workers being added to a group even if the group is very close to meeting the TSRate.

• The average quorum-sizes for RIDGE and BOINC^{Bst} are very close (with RIDGE having a smaller quorum-size for LowRE). This indicates that RIDGE requires about the same number of workers to return results for a successful validation. This result could potentially help in improving the overall utilization if previously allocated tasks could be pre-empted.

Makespan Comparison: Makespan is an important metric when the time taken to complete a number of workunits or tasks must be bounded, such as in a service-oriented environment. Figure 5 compares the average makespan of each workunit in RIDGE with BOINC^{Bst} for the three reliability environments. We notice that RIDGE has an approximate 35% decrease in makespan when com-



(a) Success-Rate



(b) Throughput

Figure 4: Comparison of RIDGE with best (BOINC^{Bst}) and conservative (BOINC^{Con}) configurations of BOINC

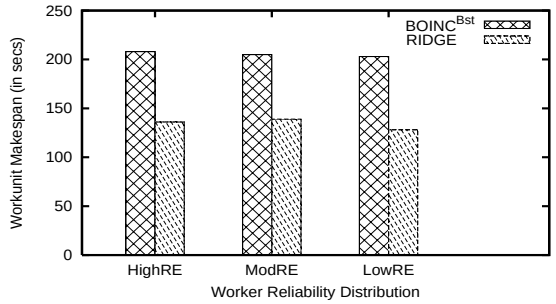


Figure 5: Makespan Comparison

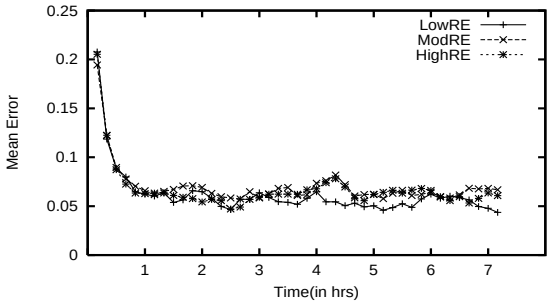


Figure 7: Learning Behavior of RIDGE

pared to BOINC^{Bst}. This is a consequence of the serial scheduling in RIDGE vs. the randomized scheduling of BOINC.

In summary, the results in this section show that *despite the minor overheads incurred, RIDGE performs comparable to BOINC^{Bst}, using* **automatic dynamic replication**, *and is superior to the conservative BOINC^{Con}.*

3.4 Timeliness Evaluation of Reliability

In this section, we evaluate the performance of BOINC and RIDGE w.r.t. the timeliness of workers in an environment where getting work done within certain time-constraints is the primary objective. Here, we assume that every worker is 100% reliable w.r.t. correctness and hence the reliability of a worker reduces to the probability that it returns a result in a 'timely' manner. The timeliness of a task is determined by the ExecThrld parameter, which is defined as the maximum task execution time beyond which a task is considered late and discarded. The ultimate goal is to use these reliability ratings to do sophisticated scheduling to support deadline-oriented service environments.

Since all nodes are assumed to be correct in this scenario, a workunit is said to be completed as soon as one scheduled task returns within the ExecThrld time. In other words, M-first voting with M=1 is used as the verification technique. Since M is 1, comparably higher success-rates can be achieved for smaller replication factors, so we use a desired success-rate of 0.90 for these experiments.

3.4.1 Emulation of Reliability Environments

In this set of experiments, instead of using synthetic reliability distributions, we used the actual execution times of the results returned by nodes in the PlanetLab testbed to determine nodes' reliability ratings. To emulate different reliability environments, we used different values of ExecThrld, so that higher values of ExecThrld correspond to more reliable environments and vice-versa. Figures 6(a),6(b) and 6(c) show the reliability distributions produced using ExecThrld of 120s, 180s and 240s respectively. We refer to these distributions as LowRE, ModRE and HighRE respectively (not to be confused with the synthetic distributions in the previous section). These graphs are obtained by running the server for 3 hours and calculating the reliabilities of the workers based on their performance during that period. From these graphs, we observe that most of the nodes are either highly reliable or unreliable w.r.t. a given ExecThrld. This implies that given an ExecThrld, learning the reliability of nodes is indeed useful since the node reliabilities are relatively stable over time intervals on the order of a few hours.

3.4.2 Learning Behavior of RIDGE

We first evaluate the learning behavior of RIDGE for worker reliability estimation for the three reliability environments described above. For this evaluation, the RIDGE server was run for approximately 7 hours while the actual execution times and reliability ratings estimated by RIDGE for each worker were logged every 10 minutes. The actual reliability of a worker at time *t* was approxi-

(a) LowRE:ExecThrld=120s (b) ModRE:ExecThrld=180s (c) HighRE:ExecThrld=240s

Figure 6: Different reliability environments

mated by the average reliability of the worker through the 1 hour time interval around *t*. The mean error at time *t* is then calculated as the difference between the actual reliability and the estimated reliability averaged over all workers. Figure 7 shows the mean error over the 7-hour period. From the figure, we observe that the error converges within 1 hour to less than 0.1 for all three environments.

3.4.3 Performance of BOINC

In this section, we evaluate the performance of BOINC, using various fixed replication factors, for the reliability environments described above. The replication factor is varied, from a minimum of 1 to a maximum of 6, to determine the 'optimal' replication factor for a desired success-rate. Due to time constraints, BOINC was not run to completion for each combination of reliability distribution and replication factor. Instead, we only evaluated the 'optimal' case and the two cases on either side of the 'optimal' in detail for each reliability environment.

Figures 8(a) and 8(b) show the performance of BOINC for different replication factors under each reliability environment. We observe similar trends w.r.t. success-rate and throughput metrics for varying replication factors as observed in the results for reliability w.r.t. correctness. The same explanations for the observed trends hold here. We observe that the 'optimal' replication factor values in this case are 2, 3, and 5, respectively, for HighRE, ModRE and LowRE with corresponding (success-rate, throughput) combinations of (0.95, 2378), (0.96, 1723) and (0.91, 1020). However, as discussed before, since the underlying distribution may not be known a priori, a conservative application designer might select a fixed replication factor of 5, to ensure a minimal success-rate of 0.90 for all reliability environments.

3.4.4 BOINC vs. RIDGE Comparison

We now compare the performance of RIDGE and BOINC. Each run of BOINC was carried out for 2 hrs, while RIDGE was run for 3 hrs with 1 hr for the learning period. The RIDGE server is configured with a TSRate of 0.90, and MinClients and MaxClients were set to 1 and 5, respectively.

Performance Comparison: Figures 9(a) and 9(b) illustrate the performance comparison of BOINC^{Bst}, RIDGE and BOINC^{Con} (that uses a replication factor of 5). We observe that RIDGE meets the TSRate of 0.90 in all three environments. Also, from the Throughput comparison graph, we notice that RIDGE has higher throughput

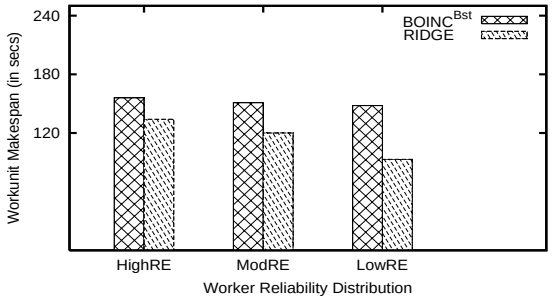


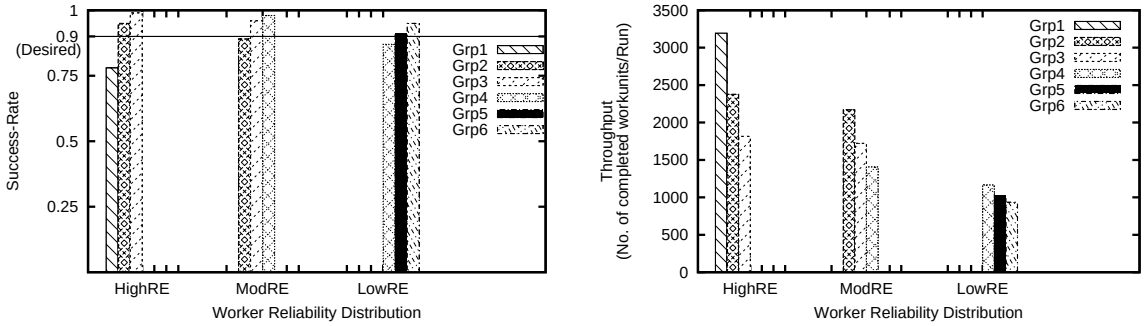
Figure 10: Makespan Comparison

than BOINC^{Bst}. There are two reasons for this. First, RIDGE can form groups of size 1, which is not possible in BOINC (discussed in detail in the following section). This increases the resource utilization, and hence throughput, when compared to BOINC^{Bst}. Second, RIDGE does fast serial scheduling. Since only one result is needed for validation, serial scheduling increases the likelihood that the workunit could be completed faster, thus increasing throughput.

	Group Size		Quorum Size	
Distr	BOINC^{Bst}	RIDGE	BOINC^{Bst}	RIDGE
HighRE	1.67	1.46	1.05	1.01
ModRE	2.31	1.89	1.12	1.03
LowRE	3.68	3.22	1.41	1.08

Table 2: BOINC^{Bst} vs RIDGE Resource Utilization

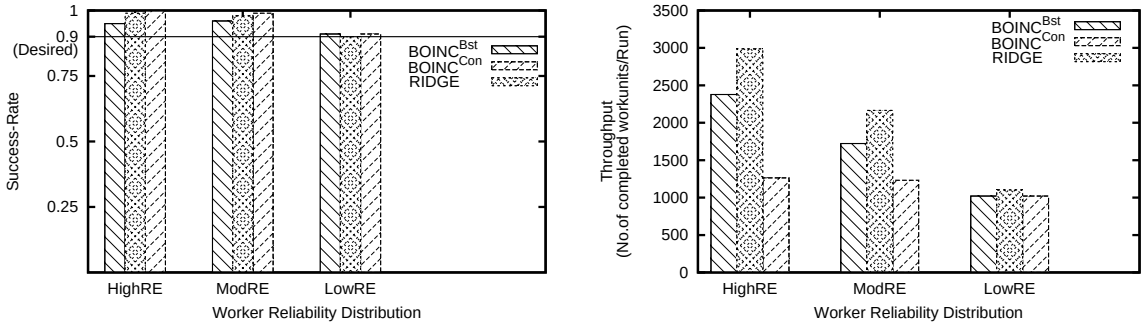
Resource Utilization Comparison: Table 2 illustrates the resource utilization of BOINC^{Bst} and RIDGE for the three reliability environments. An interesting observation is that the Group-Size of RIDGE is *less than* that of BOINC^{Bst}. This is because, depending on the value of ExecThrld, there is a high percentage of highly reliable workers in all three reliability environments. RIDGE will create groups of size 1 using these highly reliable workers, which results in a lower average group-size. Depending on the reliability of the environment, there may be a large number of such single-worker groups, resulting in a positive performance impact,



(a) Success-Rate

(b) Throughput

Figure 8: Comparison of different BOINC configurations



(a) Success-Rate

(b) Throughput

Figure 9: Comparison of RIDGE with the best and conservative configurations of BOINC

despite the minor overheads imposed by RIDGE. Forming such small groups is not possible for BOINC^{Bst}, since it uses a fixed replication factor for all workunits (with a replication factor of at least 2 in all cases).

Makespan Comparison: Figure 10 compares the average makespan of a workunit in BOINC^{Bst} with that of RIDGE for the three reliability environments. We notice that RIDGE has a lower makespan when compared to BOINC^{Bst} for all of the environments. The reasons for this result are similar to those for results corresponding to reliability w.r.t correctness. Another interesting observation from the figure is that in the case of RIDGE, the makespan of a workunit is bounded by the given ExecThrld. Thus, by having a bound on the execution time on a per-task basis, we are able to achieve an upper bound on the makespan of the entire workunit. On the other hand, BOINC provides no such bound on the makespan, as is evident in the LowRE environment, where it exceeds the ExecThrld of 120s. This is due to the randomization in its scheduling, which prevents any upper bound on workunit makespan.

3.5 Service-Oriented Environments

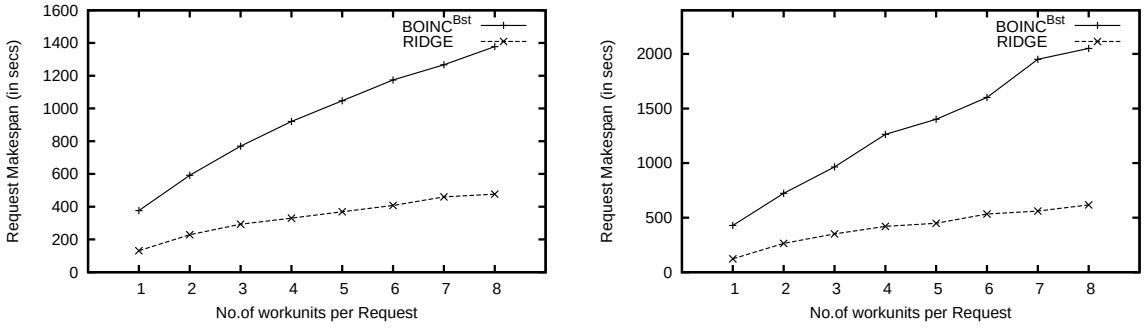
In this section, we evaluate how BOINC and RIDGE perform in service-oriented environments. We characterize such environments by a high-level unit of work, a *service request*, that is defined as a set of workunits. A request is said to be completed when all its constituent workunits are completed successfully. For this set of experiments, we enable the 'Re-scheduling' component of BOINC and RIDGE, so that a workunit that has failed in its first validation is not discarded, but is re-scheduled until it is successfully completed. The definition of some of the metrics used in the previous set of experiments are extended to the 'Request' level as follows:

• *Throughput* : Throughput during a run is defined as the number of requests completed.

• *Makespan*: The makespan of a request is defined as the difference between the completion time of its last workunit and the dispatch time of its first workunit .

We reconsider the scenario mentioned in Section 3.3, with a TSRate of 0.75. Since the 'optimal' BOINC configuration BOINC^{Bst} has already been identified, we compare only the performance of BOINC^{Bst} against RIDGE. To emulate service request behavior, each set of consecutive workunits in the workpool are bundled to model a service request. The performance comparison is shown for two reliability environments, HighRE and LowRE. The results for ModRE are similar and are omitted due to space constraints.

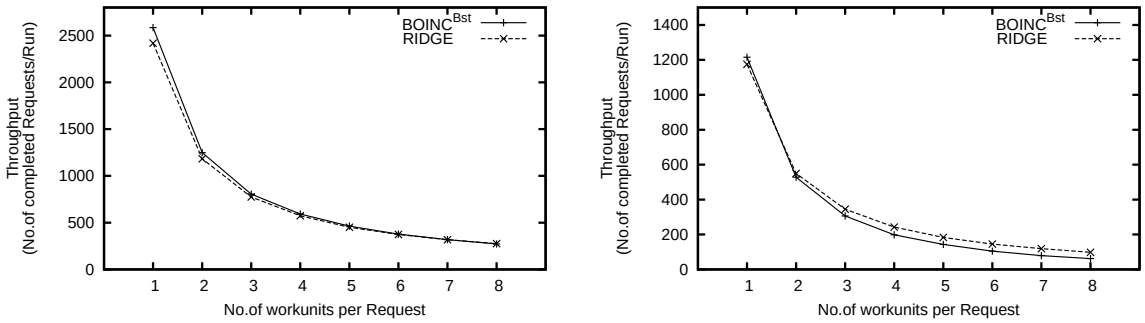
Makespan Comparison: Request makespan is a key metric in a service-oriented environment since a service request is not complete until all of its component workunits are complete. Figures 11(a)



(a) HighRE Makespan

(b) LowRE Makespan

Figure 11: Comparison of Request Makespan for different reliability environments



(a) HighRE Throughput

(b) LowRE Throughput

Figure 12: Comparison of Request Throughput for different reliability environments

and 11(b) show the request makespan for BOINC^{Bst} and RIDGE as the number of workunits per request is varied from 1 to 8. We observe that as the request size is increased, the makespan for BOINC^{Bst} increases much more rapidly when compared to RIDGE. This is explained by the way BOINC and RIDGE schedule and re-schedule work. As mentioned, randomization in scheduling is one factor. Another is that when a validation fails, BOINC puts the additional task in the workpool and no explicit preference is given to the pending tasks. However, since RIDGE gives preference to pending work, RIDGE achieves better request makespans. This is another factor that supports RIDGE in a service-oriented environment.

Throughput Comparison: Figures 12(a) and 12(b) show the throughput comparison of BOINC^{Bst} and RIDGE as the number of workunits per request is varied, for two different reliability environments. From both graphs, we observe that the request throughput is comparable to BOINC^{Bst}. This is a consequence of both serial scheduling and preference to pending workunits adapted by RIDGE.

Our results indicate that *RIDGE not only minimizes the request makespan but also maintains the request throughput*.

4. RELATED WORK

The primary challenge faced by volunteer distributed computing infrastructures, such as BOINC [1] is the inherent unreliability of the participant nodes. While redundant task allocation combined with voting is a popular technique used to deal with such unreliability, the major drawback of such a solution is the low resource utilization due to task replication. Several techniques have been proposed to minimize such redundant task execution and increase resource utilization. Golle and Mirnov [10, 8] present a verification technique that inserts pre-computed images of special spot-checks into distributed tasks to verify results returned by a worker and identify cheaters. Another verification technique [18, 22] employs pre-computed tasks called 'quizzes' that are embedded into a batch of (otherwise indistinguishable) tasks allocated to a worker. Such verification techniques avoid the need for replication to validate the correctness of the results. The concept of reducing the redundancy factor in a volunteer computing environment has been proposed in [18] by spot-checking and blacklisting volunteer resources. Another technique that is popularly used is to employ Reputation Systems to gauge the reliability of nodes based on the past interactions. Zhao and Lo [22] propose augmenting peer-to-peer cycle sharing systems with a reputation system to reduce the degree of replication required to verify results. All of these techniques deal with unreliability w.r.t correctness alone.

On the other hand, there have been techniques that have emerged to deal with unreliability w.r.t. timeliness alone. [12] uses host and

CPU availability information of the participant workers to propose techniques for resource selection and design scheduling heuristics based on them, for rapid turn-around times for short-lived applications in Desktop Grid environments. [6] uses a similar mechanism to develop a fault tolerant scheduling mechanism in desktop grid environments. [16] presents methods for resource availability predictions in cycle-sharing systems that could be used for designing fault-tolerant scheduling mechanisms in such environments. With a similar motive, [11] discusses methods to predict resource availability using a resource life-cycle model. Also, there have been a number of statistical techniques [5, 13, 14] that have emerged independently, discussing ways to estimate a node's CPU/host availability, that could be used for designing effective scheduling mechanisms. While most of the techniques concentrate on either correctness or timeliness, a desirable method would be to learn the behavior of a node with respect to both timeliness and correctness and use this information in scheduling. One such technique is [21] that characterizes a node's behavior w.r.t. both correctness and timeliness and uses this information to prune the unreliable nodes to ensure performance guarantees. Also, [17] proposes techniques to calculate local trust values to participant nodes, based on their past execution history and uses this information in worker selection so as to meet end user SLAs. Our work uses a more general approach to combine correctness and timeliness. In particular, our approach provides the user freedom to emphasize either of these properties as desired within a single framework. Moreover, our scheduling techniques [20] provide flexibility while explicitly exposing performance-reliability tradeoffs [19].

5. CONCLUSIONS AND FUTURE WORK

In this paper we have presented the design and implementation of RIDGE, a reliability-aware scheduling system that exploits prior node history to size redundancy groups and select workers effectively. We have implemented RIDGE on top of the BOINC distributed computing infrastructure and have evaluated its performance on a live testbed consisting of 120 PlanetLab nodes. Our experimental results showed that RIDGE is able to match or surpass the throughput of the best vanilla BOINC configuration under different reliability environments, by automatically adapting to the characteristics of the underlying environment. In addition, RIDGE is able to provide much lower workunit makespans compared to BOINC, which indicates its desirability in service-oriented environments with time constraints. In the future, we intend to explore the interactions between correctness and timeliness in more detail, and explore other systems issues such as the impact of SchedThrld and node selection ordering on the system overheads.

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