The Case For Prediction-based Best-effort Real-time Systems

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Abstract. We propose a prediction-based best-effort real-time service to support distributed, interactive applications in shared, unreserved computing environments. These applications have timing requirements, but can continue to function when deadlines are missed. In addition, they expose two kinds of adaptability: tasks can be run on any host, and their resource demands can be adjusted based on user-perceived quality. After defining this class of applications, we describe a significant example, an earthquake visualization tool, and show how it could benefit from the service. Finally, we present evidence that the service is feasible in the form of two studies of algorithms for host load prediction and for predictive task mapping.

1 Introduction

There is an interesting class of interactive applications that could benefit from a real-time service, but which must run on conventional reservation-less networks and hosts where traditional forms of real-time service are difficult or impossible to implement. However, these applications do not require either deterministic or statistical guarantees about the number of tasks that will meet their deadlines. Further, they are adaptable in two ways: their components are distributed, so a task can effectively be run on any available host, and they can adjust the computations tasks perform and the communication between tasks, trading off user-perceived degradation and the chances of meeting deadlines.

We propose a best-effort real-time service that uses history-based prediction to choose how to exploit these two levels of adaptation in order to cause most tasks to meet their deadlines and for the application to present reasonable quality to the user. We believe that such a service is feasible, and, while providing no guarantees, would nonetheless simplify building responsive interactive applications and greatly improve user experience.

The paper has two main thrusts. The first is to define the class of resilient, adaptable, interactive applications we have described above and to show that it contains significant real applications. As an example of typical user demands and application adaptivity we analyze QuakeViz, a distributed visualization system for earthquake simulations being developed at CMU. We are also studying OpenMap, a framework for interactively presenting map-based information, developed at BBN [4]. The extended version of this paper [10] covers OpenMap in more detail.

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The second main thrust of the paper is to support the claim that history-based prediction is an effective way to implement a best-effort real-time service for this class of applications. We present two pieces of supporting evidence here. The first is a trace-based simulation study of simple algorithms for predicting on which host a task is most likely to meet its deadline based on a history of past running times. One of the algorithms provides near optimal performance in the environments we simulated. The second piece of supporting evidence is a study of linear time series models for predicting host load that shows that simple, practical models can provide very good load predictions. Because running time is strongly correlated with the load experienced during execution, the fact that load is predictable suggests that information that can be collected in a scalable way can be used to make decisions about where to execute tasks. Together, these two results suggest that prediction is a feasible approach to implementing a best-effort real-time service.

2 Application characteristics

The applications we are interested in supporting have the following four characteristics. First, they exhibit **interactivity** — computation takes the form of tasks that are initiated or guided by a human being who desires responsiveness and predictable behavior. Research has shown that people have difficulty using an interactive application which does not achieve timely, consistent, and predictable feedback [12, 16]. Our mechanism for specifying interactive performance is the task deadline. The second application characteristic is **resilience** in the face of missed deadlines — such failures do not make these applications unusable, but merely result in lowered quality. Resilience is the characteristic that suggests a best-effort real-time approach, instead of traditional "soft" (statistically guaranteed) [21, 6, 15] and "hard" (deterministically guaranteed) real-time approaches [20]. The third characteristic is **distributability** — we assume that the applications are implemented in a distributable manner, with data movement exposed for scheduling purposes. Finally, our applications are characterized by **adaptability** — they expose controls, called *application-specific quality parameters*, that can be adjusted to change the amount of computation and communication resources a task requires.

3 QuakeViz

The Quake project developed a toolchain capable of detailed simulation of large geographic areas during strong earthquakes [2]. Thorough assessment of the seismicity associated with a geographic region requires accurate, interactive visualization of the data produced by the simulation. Visualization of this data is complex because the full data for even a small region such as the San Fernando Valley requires approximately 6TB of data. Even selective output results in tens of gigabytes of data. Nevertheless, with proper management of the visualization data, it is possible to achieve reasonable quality in a resource-limited environment.

The visualization toolchain is shown in Figure 1(a). The raw simulation data is typically read from storage, rather than from the running application, because of the simulation's high cost, scheduling complexities, and the lack of any runtime tunable parameters in the simulation. The raw irregular mesh data is first interpolated onto a regular grid to facilitate processing and downsampled to a more manageable size. The resulting grid is then used to calculate isosurfaces corresponding to various response intensities. The displacement and density isosurfaces are combined with topology information to produce a 3D image, which is then drawn on the user's desktop display.

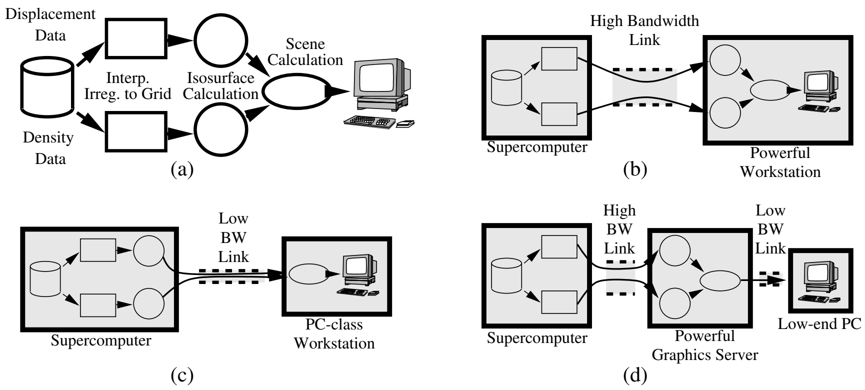


Fig. 1. QuakeViz Application. (a) Stages of the Quake visualization toolchain. Different placements of toolchain tasks corresponding to different resource situations: (b) A high performance network and workstation are available for the visualization. (c) A low-bandwidth network and PC with a 3D graphics accelerator are used. (d) A low-end PC is used as a framebuffer displaying the result of a completely remote visualization process.

Because the Quake visualization is done offline, the user's input consists of controlling the parameters of the visualization. These operations may include rotating the display, removing surface layers, zooming in and out, and adjusting the parameters for isosurface calculation.

In the visualization diagram shown in Figure 1(a), we generally expect the resources to retrieve and do the initial interpolation to be available on only a few high-performance machines, such as those commonly used at remote supercomputing facilities. Because the output device is determined by the user's location, the isosurface calculation and scene calculation are the two components which can be freely distributed to optimize performance.

3.1 Task location

The location of these two phases is governed by the combination of network bandwidth, and computing and graphics resources available to the user. In fact, there are reasons to divide the pipeline at any of the three remaining edges, depending on predicted processor and network capacity. Three examples are shown in Figure 1(b)-(d).

Figure 1(b) is the ideal case where resources allow the full regular mesh produced by the interpolation phase to be sent directly to the user's desktop. This situation is unlikely in all but the most powerful environments, but may offer the best opportunity for interactive use. In Figure 1(c), the isosurface calculation is performed in the supercomputer doing the interpolation. The scene calculation is done in the user's desktop machine. The isosurface calculation is also fairly expensive, whereas the scene calculation can be done quite effectively by a variety of commodity graphics cards currently available. A very limited case is shown in Figure 1(d), where the user's desktop is acting only as a framebuffer for the images. This setup may be useful if the size of the final pixmap is smaller than the size of the 3D representation, which depends on the complexity of the scene, or if the user's workstation does not have 3D hardware.

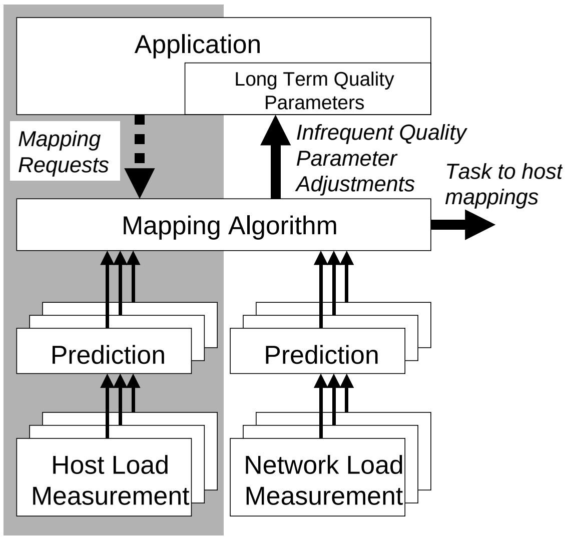


Fig. 2. Structure of best-effort real-time system. The shaded portion is discussed.

3.2 Quality parameters

Frame rate, resolution, and interactive response time are the primary quality parameters which can be adjusted to meet the user's requirements. Because it may take some time for adjustments to these parameters to be propagated through the pipeline, other mechanisms may be used to maintain responsiveness. For example, resolution can be lowered along any edge in the toolchain. Similarly, zooming in on the image can be accomplished along edges, while waiting for the greater detail to be propagated from the beginning of the pipeline. Finally, even if only a pixmap of the image is available on the user's workstation, that image can be used for temporary adjustments, providing the effects of zooming and rotation, while waiting for actual data to fill in the unavailable information.

4 Structure of a best-effort real-time system

Figure 2 illustrates the structure of our proposed best-effort real-time system. The boxes represent system components. Thin arrows represent the flow of measured and predicted information, thick arrows represent the control the system exerts over the application, and the dotted arrow represents the flow of application requests. We have shaded the parts of the design that we discuss in this paper.

The system accepts requests to run tasks from the application and then uses a mapping algorithm to assign these tasks to the hosts where they are most likely to meet their deadlines. A task mapping request includes a description of the data the task needs, its resource requirements (either supplied by the application programmer or predicted based on past executions of the task), and the required deadline. The mapping algorithm uses predictions of the load on each of the available hosts and on the network to determine the expected running time of the task on each of the hosts, and then runs the task on one of the hosts (the target host) where it is likely to meet its deadline with high confidence. If no such host exists, the system can either map the task suboptimally, hoping that the resource crunch is transient behavior which should soon disappear, or adjust the quality parameters of the application to attempt to reduce the task's computation and/or communication requirements or to add more slack to the deadline.

The choice of target host and the choice of application-specific quality parameters are adaptation mechanisms that are used at different time scales. A target host is chosen for every task, but quality parameters are only changed when many tasks have failed to meet their deadlines, or when it becomes clear that sufficient resources exist to improve quality while still insuring that most deadlines can be met by task mapping. Intuitively, the system tries to meet deadlines by using adaptation mechanisms that do not affect the user's experience, falling back on mechanisms that do only on failure. Of course, the system can also make these adjustments pre-emptively based on predictions.

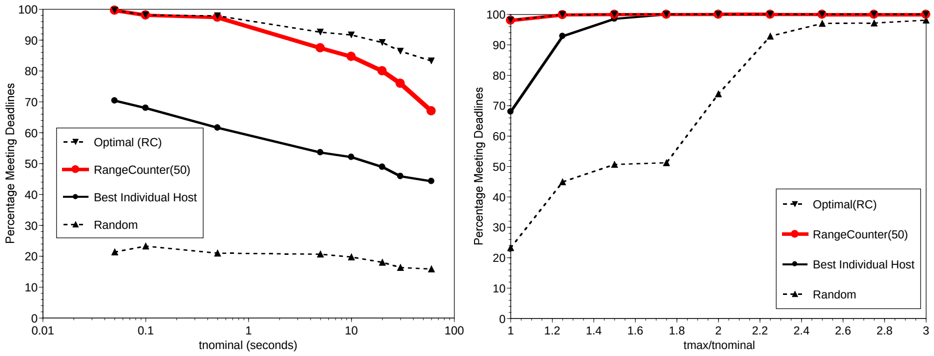
The performance of the system largely reflects the quality of its measurements and predictions. The measurement and prediction stages run continuously, taking periodic measurements and fitting predictive models to series of these measurements. For example, each host runs a daemon that measures the load with some periodicity. As the daemon produces measurements, they are passed to a prediction stage which uses them to improve its predictive model. When servicing a mapping request, the mapping algorithm requests predictions from these models. The predictions are in the form of a series of estimated future values of the sequence of measurements, annotated with estimates of their quality and measures of the past performance of the predictive model. Given the predictions, the mapping algorithm computes the running time of the task as a confidence interval whose length is determined by the quality measures of the prediction. Higher quality predictions lead to shorter confidence intervals, which makes it easier for the mapping algorithm to choose between its various options.

5 Evidence for a history-based prediction approach

We present two pieces of evidence that suggest history-based prediction is a feasible approach to implementing a best-effort real-time service for distributed, interactive applications. The first is a trace-based simulation study of simple mapping algorithms that use past task running times to predict on which host a task is most likely to meet its deadline. The study shows that being able to map a task to any host in the system exposes significant opportunities to meet its deadline. Further, one of the algorithms provides near optimal performance in the environments we simulated. The second piece of evidence is a study of linear time series models for predicting host load. We found that simple, practical models can provide very good load predictions, and these good predictions lead to short confidence intervals on the expected running times of tasks, making it easier for a mapping algorithm to choose between the hosts. Network prediction is of considerable current interest, so we conclude with a short discussion of representative results from the literature.

5.1 Relationship of load and running time

The results in this section depend on the strong relationship that exists between host load and running time for CPU-bound tasks. We measured the host load as the Unix five second load average and sample it every second. We collected week-long traces of such measurements on 38 different machines in August 1997 and March 1998. We use these extensive traces to compute realistic running times for the simulation experiments of Section 5.2. In Section 5.3 we directly predict them with an eye to using the predictions to estimate running times. A detailed statistical analysis of the traces is available in [9]. Considering load as a continuous signal $z(t)$ the relationship between load and running



(a) (b)

Fig. 3. Representative data from our study of simple prediction-based mapping algorithms: (a) the effect of varying nominal execution time, (b) the effect of increasing deadline slack.

time $t_{running}$ is $\int_0^{t_{running}} \frac{1}{1+z(t)} dt = t_{nominal}$ where $t_{nominal}$ is the running time of the task on a completely unloaded host. Notice that the integral simply computes the inverse of the average load during execution. Further details on how this relationship was derived and verified can be found in [11].

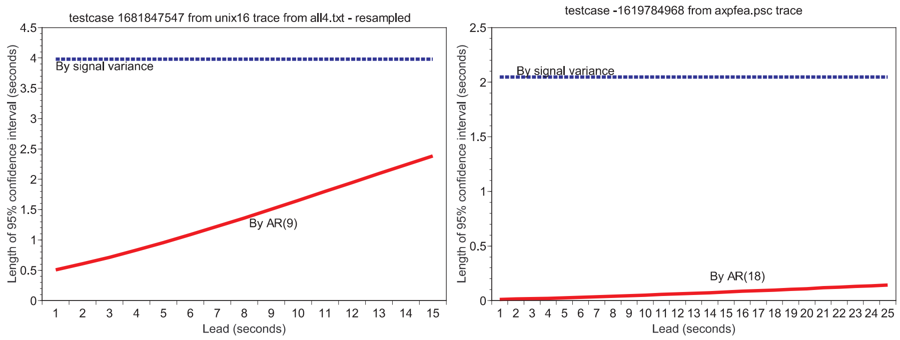
5.2 Simple prediction-based mapping algorithms

We developed and evaluated nine different mapping algorithms that use a past history of task running times on the different hosts to predict the host on which the current task's deadline is most likely to be met. These algorithms included several different window-average schemes, schemes based on confidence intervals computed using stationary IID stochastic models of running times, and simple neural networks. Due to space limits, we will focus on the performance of *RangeCounter(W)*, the most successful of the algorithms, and only describe the evaluation procedure at a high level. For more details on the algorithms and how we evaluated them, consult the extended version of this paper [10].

We evaluated the mapping algorithms with a trace-driven simulator that uses the load traces described in Section 5.1 to synthesize highly realistic execution times. The simulator repeatedly requested that a task with a nominal execution time $t_{nominal}$ be completed in t_{max} seconds and counted the number of successful mapping requests. Communication costs were ignored—the task is entirely compute-bound and requires no inputs or outputs to be communicated. In addition to simulating the mappings chosen by the algorithm being tested, the simulator also simultaneously simulated a random mapping, the best static mapping to an individual host, and the optimal mapping.

Figure 3(a), which is representative of our overall results, illustrates the effect of varying the nominal time, $t_{nominal}$ with a tight deadline of $t_{max} = t_{nominal}$. Notice that there is a substantial gap between the performance of the optimal mapping algorithm and the performance of random mappings. Further, it is clear that always mapping to the one host does not result in an impressive number of tasks meeting their deadlines. These differences suggest that a good mapping algorithm can make a large difference. We can also see that *RangeCounter(W)* performs quite well, even for fairly long tasks.

Even with relaxed deadlines, a good mapping algorithm can make a significant difference. Figure 3(b), which is representative of our results, illustrates the effect of relax-



(a) (b)

Fig. 4. Benefits of prediction: (a) server machine with 40 users and long term load average of 10, (b) interactive cluster machine with long term load average of 0.17.

ing the deadline t_{max} (normalized to $t_{nominal}$ on the x-axis) on the percentage of tasks that meet their deadlines. Notice that there is a large, persistent difference between random mapping and optimal mapping even with a great deal of slack. Further, using the best single host is suboptimal until the deadline is almost doubled. On the other hand, *RangeCounter(W)* presents nearly optimal performance even with the tightest possible deadline.

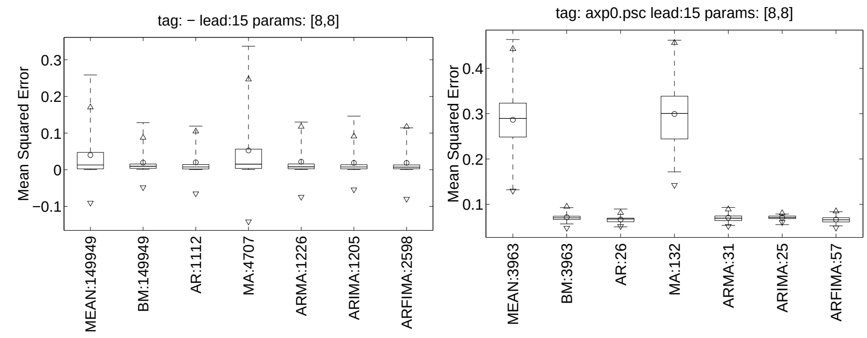
In a real system, the cost of communication will result in fewer deadlines being possible to be met and will tend to encourage the placement of tasks near the data they would consume, and thus possibly reduce the benefits of prediction. Still, this study shows that it is possible to meet many deadlines by using prediction to exploit the degree of freedom that being able to run a task on any host gives us.

5.3 Linear time series models for host load prediction

Implicitly predicting the current task's running time on a particular host based on previous task running times on that host, as we did in the previous section, limits scalability because each application must keep track of running times for every task on every node, and the predictions are all made on a single host.

Because running time is so strongly related to load, as we discussed in Section 5.1, another possibility is to have each host directly measure and predict its own load and then make these predictions available to other hosts. When mapping a task submitted on some host, the best-effort real-time system can use the load predictions and the resource requirements of the task to estimate its running time on each of the other hosts and then choose one where the task is likely to meet its deadline with high confidence.

Load predictions are unlikely to be perfect, so the estimates of running time are actually confidence intervals. Better load predictions lead to smaller confidence intervals, which makes it easier for the mapping algorithm to decide between the available hosts. We have found that very good load predictions that lead to acceptably small confidence intervals can be made using relatively simple linear time series models. Due to space limits, we do not discuss these models here, but interested readers will find Box, et al. [8] to be a worthy introduction. Figure 4 illustrates the benefits of such models on (a) a heavily loaded server and (b) a lightly loaded interactive cluster machine. In each of the graphs we plot the length of the confidence interval for the running time of



(a) (b)

Fig. 5. Performance of 8 parameter host load prediction models for 15 second ahead predictions: (a) All traces, (b) Moderately loaded interactive host.

a one second task as a function of how far ahead the load predictions are made. Figure 4(a) compares the confidence intervals for a predictive AR(9) model and for the raw variance of the load. Notice that for short-term predictions, the AR(9) model provides confidence intervals that are almost an order of magnitude smaller than the raw signal. For example, when predicting 5 seconds ahead, the confidence interval for the AR(9) model is less than 1 second while the confidence interval for the raw load signal is about 4 seconds. Figure 4(b) shows that such benefits are also possible on a very lightly loaded machine.

The prediction process begins by fitting a *model* to a history of periodically sampled load measurements. As new measurements become available, they are fed to the fitted model in order to refine its predictions. At any point after the model is fitted, we can request predictions for an arbitrary number of samples into the future. The quality of predictions for k samples into the future is measured by the *k-step ahead mean squared error*, which is the average of the squares of the differences between the k-step ahead predictions and their corresponding actual measurements. After some number of new samples have been incorporated, a decision is made to refit the model and the process starts again. We refer to one iteration of this process as a *testcase.*

A good model provides *consistent predictability* of load, by which we mean it satisfies the following two requirements. First, for the average testcase, the model must have a considerably lower expected mean squared error than the expected raw variance of the load. The second requirement is that this expectation is also very likely, or that there is little variability from testcase to testcase. Intuitively, the first requirement says that the model provides good predictions on average, while the second says that most predictions are close to that average.

In a previous paper [11], we evaluated the performance of linear time series models for predicting our load traces using the criterion of consistent predictability discussed above. Although load exhibits statistical properties such as self-similarity (Beran [5] provides a good introduction to self-similarity and long-range dependence) and epochal behavior [9] that suggest that complex, expensive models such as ARFIMA [14] models might be necessary to ensure consistent predictability, we found that relatively simple models actually performed just about as well.

Figure 5(a) shows the performance of 8 parameter versions of the models we studied for 15 second ahead predictions, aggregated over all of our traces, while Figure 5(b) shows the performance on the trace of a single, moderately loaded interactive host. Each of the graphs in Figure 5 is a Box plot that shows the distribution of 15-step-ahead (predicting load 15 seconds into the future) mean squared error. The data for the figure comes from running a large number of randomized testcases. Each testcase fits a model to a random section of a trace and then tests the model on a consecutive ection of random length. In the figure, each category is a specific model and is annotated with the number of testcases used. For each model, the circle indicates the expected mean squared error, while the triangles indicated the 2.5th and 97.5th percentiles assuming a normal distribution. The center line of each box shows the median while the lower and upper limits of the box show the 25th and 75th percentiles and the lower and upper whiskers show the actual 2.5th and 97.5th percentiles.

Each of the predictive models has a significantly lower expected mean squared error than the expected raw variance of the load (measured by the MEAN model) and there is also far less variation in mean square error from testcase to testcase. These are the criteria for consistent predictability that we outlined earlier. Another important point is that there is little variation in the performance across the predictive models, other than that the MA model does not perform well. This is interesting because the ARMA, ARIMA, and especially the long-range dependence capturing ARFIMA models are vastly more expensive to fit and use than the simpler AR and BM models. An important conclusion of our study is that reasonably high order AR models are sufficient for predicting host load. We recommend AR(16) models or better.

5.4 Network prediction

Predicting network traffic levels is a challenging task due to the large numbers of machines which can create traffic over a shared network. Statistical models are providing a better understanding of how both wide-area [1, 18] and local-area [22] network traffic behave. Successes have been reported in using linear time series models to predict both long term [13] and short term [3] Internet traffic. These results and systems such as NWS [23] and Remos [17] are being developed to provide the predictions of network performance that are needed to provide best effort real-time service. For applications which are interested in predicting the behavior of a link on which they are already communicating on, passive monitoring may be appropriate [7, 19].

6 Conclusion

We have identified two applications (QuakeViz, which we analyzed here, and OpenMap, analyzed in [10]) which can benefit from a best-effort real-time service. Without such a service, people using such interactive applications would face a choice between acquiring other, possibly reserved or dedicated resources or running the application at degraded quality.

The success of best-effort real-time depends on the accuracy of the predictions of resource availability. We have shown that CPU load can be predicted with a high degree of accuracy using simple history-based time series models. When combined with currently available network information systems, these resources allow decisions to be made for locating tasks and selecting application parameters to provide a usable system.

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