

Minimizing Execution Time in MPI Programs on an Energy-Constrained, Power-Scalable Cluster*

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Abstract

Recently, the high-performance computing community has realized that power is a performance-limiting factor. One reason for this is that supercomputing centers have limited power capacity and machines are starting to hit that limit. In addition, the cost of energy has become increasingly significant, and the heat produced by higher-energy components tends to reduce their reliability. One way to reduce power (and therefore energy) requirements is to use high-performance cluster nodes that are frequency- and voltage-scalable (e.g., AMD-64 processors).

The problem we address in this paper is: given a target program, a power-scalable cluster, and an upper limit for energy consumption, choose a schedule (number of nodes and CPU frequency) that simultaneously (1) satisfies an external upper limit for energy consumption and (2) minimizes execution time. There are too many schedules for an exhaustive search. Therefore, we find a schedule through a novel combination of performance modeling, performance prediction, and program execution. Using our technique, we are able to find a near-optimal schedule for all of our benchmarks in just a handful of partial program executions.

Categories and Subject Descriptors D.4.8 [Performance]: Modeling and Prediction

General Terms Measurement, Experimentation

Keywords Power, Energy, Modeling, Prediction, MPI

1. Introduction

Recently, power-aware computing has gained traction in the high-performance computing (HPC) community. There are two primary reasons for this. First, decreasing power consumption leads to greater reliability (temperature decreases and mean time between failures increases) and maintainability. It also has significant secondary benefits because of the corresponding reduction in heat generated, such as lower cooling costs and increased machine density. Even relatively new centers that house large clusters are having trouble staying within power and cooling constraints [27]. Second,

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because HPC applications rarely achieve peak efficiency, much of the power that is used is actually wasted.

As a result, low-power, high-performance clusters, such as BlueGene/L [1], have been developed to satisfy the ever-increasing demand for energy, while maintaining good performance. Blue Gene/L and similar systems solve this problem by utilizing low-power processors. However, since the processors are only designed to use one voltage, the system uses the same amount of energy under load, regardless of the characteristics of that load. Our previous work has shown this can be inefficient for some applications [14].

Our research focuses on using *power-scalable clusters*, which utilize processors that are each frequency and voltage scalable—*i.e.*, their clock speed and therefore power consumption can be changed dynamically. In this paper, we refer to the different available frequencies as *energy gears*. Such clusters can potentially deliver good energy efficiency because an increase in CPU frequency generally results in a smaller increase in application performance. The reason for this is that the CPU is frequently not the bottleneck resource.

However, while the CPU frequency of a node (in our case, a node is a single processor) can be scaled down to save energy, such scaling primarily saves CPU energy. A much greater savings is possible by simply not using a node; *i.e.*, using only a subset of the available nodes. Hence, given a power-scalable cluster, there are two primary ways to save energy: (1) power down a subset of the nodes, and (2) on the nodes that are actively participating in the computation, scale down the CPU frequency. This paper synthesizes these two approaches.

The problem we address in this paper is: given a target program, power-scalable cluster, and an upper limit for energy consumption, choose a schedule that simultaneously satisfies the energy limit and minimizes execution time. In this paper the term *schedule* means a tuple whose first element specifies the number of nodes to be used; the remaining elements indicate, for each computational phase, the CPU frequency (gear) in which to execute that phase. Because determining the optimal schedule requires (in the worst case) executing all possible schedules, the problem is exponential in the number of phases. Hence, **the goal of this paper is** to determine a near-optimal schedule, while only (partially) executing a given program a small number of times.

The approach we propose uses a combination of performance modeling and performance prediction, backed up by actual program execution. First, we create models for both execution time and energy consumption. Second, we create initial estimates of the key parameters of the model by executing the program a small number of times and subsequently performing regressions. Then, we repeatedly execute the following steps until our algorithm believes it has found a satisfactory schedule: (1) use the model to create predictions for each possible schedule, (2) execute a few iterations of the program using the best predicted schedule, and (3) update the

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estimates of the key parameters using the additional information collected during the executed iterations.

For evaluation, we used a combination of the NAS parallel benchmarks and several synthetic benchmarks. This allows us to give both a real-world evaluation and an exploration of the bounds of the problem space. Using our technique, we are able to find a near-optimal solution in just a handful of partial program executions. For example, for the NAS FT benchmark, by using 11 executions (of just a few iterations), we discovered a schedule that results in a completion time that is within 2.2% of the optimal. An exhaustive search would have required execution of over 100 schedules. In addition, the results are promising not just for FT, but also for the other NAS benchmarks and a set of synthetic programs that cover a range of different application characteristics in terms of parallel speedup and memory pressure.

The rest of this paper is organized as follows. Section 2 describes related work. Section 3 discusses our model and algorithm for finding an effective schedule. Section 4 discusses the measured results on our power-scalable cluster. Finally, Section 5 summarizes and describes future work.

2. Related Work

This section describes some of the closely related research. It divides the related work into two broad categories: performance prediction and tuning and energy-related research in server/desktop and mobile systems.

2.1 Performance Prediction and Tuning

First, underlying this work is the problem of understanding parallel scalability. The work in [32] focuses on finding MPI operations that cause scalability problems. This is done through both machine learning and statistical analysis. A model for understanding the scalability of a class of task and data parallel programs is presented in [31].

Second, several researchers have addressed various parallel programming issues by (1) executing programs, (2) taking measurements, and then (3) analyzing the results. Perhaps the best known of these is ATLAS [37], which uses the *Automated Empirical Optimization of Software* technique. Essentially, a specialized library of linear algebra functions is created by executing the library functions over several days, with many different compile-time options. The ADAPT system took a similar approach [34]. The ATLAS technique was generalized to other high-performance computing kernels in [38]. Other related techniques include executing a few iterations of a high-performance application to predict performance across different platforms [39] and executing MPI routines on each new platform to generate the most efficient implementation [11].

This paper borrows several of these general ideas, but differs in several ways. First, the number of executions that our technique can make is limited, because we are not creating a library, but rather running a program that the user wishes to complete as soon as possible. Second, we address the need to understand program scalability by running a (small) set of iterations of the program and developing time and energy models that encompass both computation and communication.

2.2 Energy-Related Research

Several people have investigated saving energy in server systems. In sites such as hosting centers where there is a sufficiently large number of machines, energy management may become an issue; see [5, 26, 10] for examples of this using commercial workloads and web servers. Such work shows that power and energy management are critical for commercial workloads, especially web servers [22]. Additional approaches have been taken to include dynamic voltage scaling (DVS) and request batching [9]. The work

in [29] applies real-time techniques to web servers in order to conserve energy while maintaining quality of service.

Our project differs from most prior research because it focuses on HPC applications and installations, rather than commercial ones. An HPC installation exists to speed up an application, which is often highly regular and predictable. One approach is to save energy in an application-specific way; the work in [6] used this approach for a parallel sparse matrix application. Another HPC effort that addresses the memory bottleneck is given in [17]. Also, Cameron *et al.* [3] use a variety of different DVS scheduling strategies (for example, both with and without application-specific knowledge) to save energy without significantly increasing execution time. None of this work, however, considers finding a schedule.

In server farms, disk energy consumption is also significant; several have studied reducing disk energy (*e.g.*, [4, 41, 16, 25]). In this paper, we do not consider disk energy, as it is relatively minor compared to CPU energy, especially if scientific programs operate primarily in core.

There are also a few high-performance computing clusters designed with energy in mind. One is BlueGene/L [1], which uses a “system on a chip” to reduce energy. Another is Green Destiny [35], which uses low-power Transmeta nodes. A related approach is the Orion Multisystem machines [24], though these are targeted at desktop users. Unlike our approach, these machines sacrifice performance in order to save energy by using less powerful processors.

While not our focus in this work, there is also a large body of work in saving energy in mobile systems. At the system level, there is work in trying to make the OS energy-aware through making energy a first-class resource [8, 7]. One important avenue of application-level research on mobile devices focuses on collaboration with the OS [23, 36, 40, 12]. Our approach differs in that we are concerned with saving energy in HPC applications, where execution time is the primary consideration.

Our prior work is threefold: an evaluation-based study that focused on exploring the energy/time tradeoff in the NAS suite [14], development of an algorithm for switching CPU frequency (gear) dynamically between phases [13], and leveraging load imbalance to save energy [20].

In [13], we establish the usefulness of varying the energy gear per phase and providing an algorithm for choosing the gear assignment. This paper extends this idea by allowing the number of nodes to vary, which complicates the problem considerably.

Finally, in our work we divide programs into one or more computational phases. There has been a large body of work in phase partitioning. Static techniques, such as [21, 28], appeared in the literature first. More recently, dynamic techniques have been used [19, 30].

3. Implementation

This section describes our implementation. The inputs to our system are a program divided into P phases, an energy limit, and a maximum number of available nodes. Our system will output a $(P + 1)$ -tuple, or *schedule*, the first element of which is the number of nodes to use, and the remainder the CPU frequency (*energy gear*) selected for each phase. To determine a schedule, we use a combination of performance modeling and performance prediction, backed up by small number of program executions (where each execution is only a handful of iterations).

Our system takes as input a program divided into one or more *phases*. For this paper, we used a straightforward phase division technique, which applies primarily to iterative and predictable HPC applications. We first obtain a trace of the application in question (using the fastest gear on each node—highest frequency-voltage setting). The division into phases is done by examining the trace and using an *ad hoc* approach that conforms to the following heuristics. First, any MPI operation demarcates a block boundary.

Second, if the *memory pressure* changes abruptly, a block boundary occurs at this point. (Memory pressure is determined by inspecting performance counters; for this paper we look at operations and cache misses.) We have found in previous work that multiple phases are necessary to obtain good time/energy tradeoffs in several of the NAS benchmarks. For example, in MG, by using multiple phases we were able to save an additional 11% energy compared to using a single phase (and therefore only a single gear). Further details are available in [13] and in Section 4.

This section first describes our assumptions in this paper. Then, it presents our time and energy models. Next, we give our algorithm for finding an effective schedule. Finally, we discuss specific details of our algorithm.

3.1 Assumptions

First, the effectiveness of our system relies on having valid partitionings of phases. We consider the general phase division problem to be orthogonal to our research, but can leverage off of a large amount of related work in the area (described in Section 2).

Second, we assume that we are given an maximum (total) energy constraint (by the user or cluster administrator). While not currently policy on large supercomputers, based on others' experience with large clusters in even modern data centers [27], we can envision a situation in the near future where the cost of energy is charged at least partially to the user. This constraint may be imposed for many reasons; for example, the aggregate mean time to failure of large clusters has fallen into the range of minutes [18]. The Arrhenius equation states that a $10K$ reduction in operating temperature will result in a doubling of expected hardware lifetime [33]. Because energy consumed translates directly into heat dissipated, reducing energy consumption should extend hardware lifetimes.

Third, we assume no load imbalance. In future work we will address load imbalance, but the programs in the NAS suite generally balance the computation between nodes fairly evenly. Extending the model described in the next subsection to handle load imbalance is a nontrivial task. Finally, we assume that program behavior between iterations is consistent, so that it is possible to predict future program behavior by examining current behavior.

3.2 Model

In this section we describe our models of execution time and consumed energy. Later, we discuss the algorithm we use to predict time and energy in as few iterations as possible.

In our previous work [14], we noted that (1) computation time and communication time tend to scale differently as the number of nodes increases, and (2) the power consumed by the system is different when computing than when communicating. Therefore, our model separates execution time and consumed energy into their computation and communication components:

$$\begin{aligned} T &= T_C + T_B \\ E &= T_C P_C + T_B P_B \end{aligned}$$

where T_C is computation time and T_B is the communication time (which we assume is primarily blocking), while P_C and P_B are the corresponding average power consumption levels. Below we show how to model time and energy as a function of the energy gear and the number of nodes; that is, the model produces the functions $T(g, n)$ and $E(g, n)$. Given this model, one can estimate the time and energy for all values of g and n with only a handful of empirical measurements. The four individual terms in the model are discussed below.

Computation time To determine the effect the number of nodes has on T_C , we make use of Amdahl's law. The computation component of a program can be decomposed into parallelizable and

inherently serial fractions (F_p and $1 - F_p$, respectively). Given F_p , computation time in the fastest gear (gear 0) as a function of n is:

$$T_C(0, n) = T_C(0, 1) \left(\frac{F_p}{n} + 1 - F_p \right).$$

Now we address the effect the number of gears has on T_C . Let $S_g = T_C(g, n)/T_C(0, n)$ be the *slowdown* of the computation at gear g relative to top gear. Our data indicates that S_g is independent of n . Putting it together,

$$T_C(g, n) = S_g T_C(0, 1) \left(\frac{F_p}{n} + 1 - F_p \right).$$

Both F_p and S_g are determined experimentally.

Communication time We assume that any time spent in blocking communication calls is unaffected by gear because the CPU is mostly idle. In other words, $T_B(g, n) = T_B(0, n) \forall g$. Using measurements of T_B on a handful of different numbers of nodes, we develop an equation to extrapolate $T_B(0, n)$ for all n (described in the next subsection).

Computation power The model makes two assumptions regarding power consumed during computation. First, it leverages the assumption of no load imbalance to conclude that each node uses the same amount of power, *i.e.*, $P_C(g, n) = P_C(g, 1) \cdot n$. Next, it assumes that per-node power consumption is independent of the total number of nodes. Our previous work has found this is generally true [14]. The exception to this rule occurs when changing the number of nodes causes a material change in the application. One example of this is when an application is out of core on P nodes but in core on Q nodes ($Q > P$). (The CG benchmark has this property; see Section 4 for details). In any case, what is needed to find $P_C(g, n)$ is simply measurements of $P_C(g, 1) \forall g$.

Communication power In order to determine $P_B(g, n)$, we measure $P_B(0, 1)$, and then, similar to the assumption that communication time is independent of gear, we assume that power while communicating is also independent, *i.e.*, $P_B(g, 1) = P_B(0, 1) \forall g$. Therefore, $P_B(g, n) = P_B(0, 1) \cdot n$.

While the above equations are relatively straightforward, there are two situations where they are not fully precise. First, we assumed that $T_B(g, n)$ and $P_B(g, n)$ are independent of the gear g . It turns out that they are actually affected by the gear. We further discuss how we extend the model to improve its accuracy in Section 3.4.

Second, in our earlier work [14], we discussed the effects of *reducible time*, on execution time when changing gears. Reducible time is defined as the time between an send/receive or send/wait pair. It is important because when using a lower gears, computation speed slows but communication speed remains relatively constant. Any reducible work increase, therefore, will result in a corresponding blocked time ($T_B(g, n)$) decrease (unless $T_B(g, n)$ reaches zero).

We analyzed program traces to determine the amount of reducible time for the programs considered for these experiments and found that all but one of them had essentially no reducible time.¹ Thus, we elected not to consider the effects of reducible time in this paper, but we will consider this in future work.

3.3 Algorithm

Broadly speaking, our algorithm repeatedly executes the program for a handful of iterations. On each run, we measure time and energy as well as refine our estimates for a subset of the dependent variables (F_p , S_g , and $P_C(g, 1)$) in our model. This improves our

¹The NAS SP benchmark had 6s of reducible time out of 60s of computation time. Further inspection revealed that any prediction inaccuracy due to reducible time was at most 1s.

overall estimate of execution time and energy consumption. This section provides details of our algorithm.

3.3.1 Step 1: Initialize

The first step is to determine initial values for $P_C(g, 1)$, F_p , and S_g . The minimum number of runs to do this is $g + 2$. The first g runs are required to determine $P_C(g, 1)$ for each energy gear. This is done by executing the program on one node and dividing the observed energy consumption by the execution time. One node is used so that communication does not affect our measurements. In other words, we are only measuring computation power. Note that power is *not* constant over different applications, because their different characteristics lead to different use of the machine.

Combined with the one-node, top gear run, we can create accurate estimates for $T_C(0, n)$, $T_B(0, n)$, and S_g , with just two additional runs. These are performed in top gear. To estimate $T_C(0, n)$, we use a regression on measured values for F_p . Our previous work has shown that for programs without scaled speedup, F_p scales linearly with the number of nodes. Therefore, a linear regression using these values is an accurate way to predict their values at unknown numbers of nodes.

To estimate $T_B(0, n)$, we first note that communication time may scale in different ways depending on the implementation of a specific program. In most cases, communication time scales either logarithmically, linearly, or quadratically. Knowing which of these models best fits the communication of a particular program requires three runs. With the observed data, we fit the data to each of the three functions, and select the function that gives the lowest average error.

We found that the best way to predict S_g was to use micro-ops per data cache miss, *OPM*. Our previous work shows that *OPM* correlates well with memory pressure [15]. Through experimentation, we found that a logarithmic function best fits the relation between *OPM* and S_g . We used this to estimate S_g for unknown numbers of nodes. The reason we use *OPM* to indirectly measure S_g is because S_g is not constant across numbers of nodes; indeed, cache performance (which is directly related to how much pressure is exerted on memory) often improves when nodes are added.

3.3.2 Step 2: Predict and sort all schedules

Because the time taken to predict execution time and consumed energy (as opposed to executing the program) for a given schedule is negligible, we make predictions for every possible schedule. We divide the schedules into two lists: those predicted to satisfy the energy constraint (denoted *satisfying*), and the remainder (denoted *non-satisfying*). Because the power meter has a limited precision (see Section 4.2 for details), a schedule is deemed satisfying if the energy consumed is smaller than the difference of the limit and the error.

Each list is then sorted: the satisfying list in order of increasing execution time, and the non-satisfying list in order of increasing energy. In other words, the first schedule on the satisfying list is the one predicted to be fastest within the energy constraint. Furthermore, the first schedule on the non-satisfying list is predicted to be closest to satisfying the energy constraint.

3.3.3 Step 3: Execute schedule, update estimates

We then select the first schedule on the satisfying list. In this step we do not ever select a test that was previously executed (see below). We execute this schedule for a few iterations (5 in all of our tests). The results are compared to the energy constraint, and if it indeed is below the constraint, we perform validation tests (step 4). Otherwise, we update our estimates of F_p and S_g (using regression as in step 1) and return to step 2.

Run	Schedule	Time		Energy	
		Predicted	Actual	Predicted	Actual
I_1	(1, [0, 0])	—	267	—	28.0
I_2	(4, [0, 0])	—	100	—	38.5
I_3	(9, [0, 0])	—	64	—	53.1
1	(4, [2,1])	108	109	36.9	36.2
2	(4, [1,1])	107	101	37.6	35.1
G	(4, [0,1])	107	110	37.9	37.1
N	(9, [4,4])	73.2	68.4	47.1	42.5
S	(4, [1,1])	107	101	37.6	35.1

Table 1. An illustration of our algorithm on SP with an energy limit of 37 kJ. Boldface entries satisfy the energy limit.

3.3.4 Step 4: Validate schedule

Once we have found a schedule that satisfies the energy constraint, we wish to ensure that the proposed solution is close to the best possible schedule. To do this, we run two further tests: one which differs in gear selection, and the other differs in the number of nodes.

To ensure we are using the right gear, we perform what we call *gear validation*. We consider a schedule using the same number of nodes, but with at least one phase using a faster gear. To do this we use the first such schedule on the non-satisfying list. If this schedule does not satisfy the constraint, it means that any schedule using strictly faster gears and the same number of nodes will fail to satisfy the energy constraint.

This schedule is then executed for a few iterations. If this schedule does not satisfy the constraint, it means that any schedule using strictly faster gears and the same number of nodes will fail to satisfy the energy constraint. If the test *does* satisfy the energy constraint, then we go to step 2 and regenerate new estimates for all schedules. Otherwise, we proceed to *node validation*, which is similar in spirit to gear validation. Specifically, we examine the non-satisfying list for schedules that use a larger number of nodes than the current schedule.² Of those schedules, we choose the one that is predicted to use the least energy and executes faster than the candidate schedule. This schedule is then executed for a few iterations. If it does *not* satisfy the energy constraint, it is unlikely that any solution using more nodes will satisfy the energy constraint or execute in less time.

At this point we have shown that there is likely no better legal schedule if the number of gears *or* nodes is changed, so our algorithm terminates and returns the candidate schedule. Presumably the user will now execute the entire program using this schedule.

On the other hand, if the node validation test does satisfy the constraint, then, as before, it means the candidate solution may be able to be improved with better estimates, and so we return to step 2.

It is possible that a validation test may be skipped: this occurs if either (1) we are using top gear for all phases (so there is no schedule with a faster gear), or (2) we are using the maximum number of nodes (so there is no schedule with more nodes). In either case, that validation test is skipped. In addition, a given schedule is only run once during program execution. We store the results of every execution so that should a schedule be selected twice, the results of the first run will be used.

3.3.5 Example

We illustrate our algorithm for the specific case of SP with an energy limit of 37kJ. Table 1 shows the steps carried out. In the

²The NAS programs do not run on an arbitrary number of nodes, so the closest higher number of nodes may not be simply adding 1 to the current number.

table, the entries in the *Run* column are one of the following: I_1 , I_2 , and I_3 are the initialization tests, an S denotes the accepted schedule, G is a gear validation test, N is a node validation test, and an integer denotes an ordinary test. If the actual energy value is below the limit, then that entry is in bold. A schedule is described by $(P, [g_0, g_1, \dots])$, where P is the number of nodes and g_i is the gear to be used for phase i .

First, we run the initialization tests on different numbers of nodes (I_1 through I_3). (For brevity, we omit the gear-based initialization tests.) Then, we predict energy consumption and execution time for all schedules. Based on the predictions, we select (4, [2, 1]) as the the fastest schedule predicted to satisfy the energy constraint. Then, we execute the program using this schedule for a few iterations and collect the energy consumed. Because it is below the energy limit, we attempt the gear validation test, which uses the schedule (4, [1, 1]). This is the schedule that uses the same number of nodes, but at least one faster gear, and is predicted to be faster than (4, [2, 1]) but to consume more energy than the limit. After execution of this test, we note that, contrary to our predictions, (4, [1, 1]) *did* satisfy the energy limit. Therefore we refine our estimates, return to step 2, and once again predict all schedules.

This time, the best predicted schedule is (4, [1, 1]) and, because it has already been evaluated, we begin gear validation again. The schedule (4, [0, 1]) is selected and executed. The result is that it does *not* satisfy the energy limit. Thus gear validation is successful, and we progress to node validation. For this, we select the schedule (9, [4, 4]). This is the schedule with more nodes that is predicted to be closest to, but not satisfying, the limit. Execution of this schedule showed that it did not satisfy the limit, so node validation is successful. This means that the algorithm terminates, returning (4, [1, 1]) as the selected schedule.

3.4 Implementation Details

This section describes some specific details of our implementation. First, we discuss how we collect data. Then we describe how we estimate $P_B(g, n)$.

3.4.1 Data Collection

To initialize the dependent variables (F_p , S_g , $P_C(g, 1)$) of the model, it is necessary to gather data from program executions. To do so, we utilize a combination of MPI call profiling, hardware performance counters, and inline multimeters. As described above, we need to collect $T_C(0, n)$, $T_B(0, n)$, and OPM in order to estimate the above dependent variables.

To do this, we use our *MPI-JACK* tool, which intercepts MPI calls and allows for arbitrary code to be inserted before and after execution of the call. This was used to gather the duration of each MPI call as well as to inspect the performance counters to obtain micro-operations and cache misses (to determine OPM).

We determine energy consumption by placing a WattsUp wattmeter between the system power supply and the wall; then, Power readings are taken from the multimeter every second. The values are integrated over time to yield energy consumption.

3.4.2 Generalizing $P_B(g, n)$

Earlier, we assumed that any time spent blocking on communication calls (e.g., `MPI_Allgather` and `MPI_Recv`) consumes constant power. Separate results [15] have showed that the time is largely (but not completely) independent of gear. Therefore, we do not concern ourselves with a generalization of $T_B(g, n)$.

However, we found through experiments that the power consumed blocking on communication calls could be significantly more than idle power—and that it varied with gear. This is because there is a *computation* component of communication time (e.g., copying between an MPI buffer and a user buffer) that may be significant. So, it is inaccurate to consider power due to commu-

nication for blocking calls to be identical to power consumed when the system is idle. Because different MPI calls have different computation/communication ratios, we need to determine power due to communication separately for each call.

To address this issue, on any multiple-node run we use *MPI-JACK* to log all message events. We record the computation portion of communication routines as well as the energy consumed. $P_C(0, n)$ is determined experimentally. Then, we determine $P_B(g, n)$ at top gear by first using:

$$P_B(0, n) = \frac{E/n - P_C(0, n)T_C(g, n)}{T_B(g, n)}$$

To calculate $P_B(g, n)$ for an arbitrary gear g , we need to know the percentage difference between CPU power consumption for all g . Because $P_C(g, n)$ represents the combination of CPU and system power, it is necessary to record system-only power by taking readings when idle. Once system power has been measured, the CPU-only power is measured by subtracting the idle power from $P_C(g, n)$. Then, $P_B(g, n)$ can then be computed by multiplying $P_B(0, n)$ by the CPU power at gear g divided by CPU power at top gear.

4. Performance

This section reports our performance results. For all experiments, we used a 10-node AMD Athlon-64 cluster connected by a 100Mbps network. Each node has 1 GB of main memory. The Athlon-64 CPU supports energy gears of 2.0, 1.8, 1.6, 1.4, 1.2, 1.0, and 0.8 GHz, but the 1.0GHz gear was not reliable and so was not used. Each node runs the Fedora Core 2 OS, and gear shifting was done through the `sysfs` interface. All applications were compiled with either `gcc` or the Intel Fortran compiler, using the `-O2` optimization flag. We controlled the entire cluster, so all experiments were run when the only other processes on the machines were daemons.

We first describe the overall results of running the NAS suite [2] on our system. Then we present the results of more detailed examinations of the behavior of both our algorithm and model.

4.1 NAS Parallel Benchmarks

Table 2 displays the results of running the NAS programs on our system. For each program, we selected an energy limit as follows. First, we measured the energy consumed running at top gear (denoted as gear 0) for all phases, using 8 nodes (or 9, for those benchmarks that require it). Then, we subtracted 10% from this amount of energy. This results in a different energy limit for each application because the applications execute for different lengths of time.

In the table, we first show the number of executions incurred by our algorithm (labeled *Necessary*). Next, we show the number of schedules that could be selected by an optimal algorithm (*Optimal*). Any other schedule would never be chosen by an optimal algorithm, because it is dominated by a schedule that takes less time *and* uses less energy. (There is exactly one optimal schedule for any given energy limit, but the optimal schedule may change if the limit changes.) The next column shows number of executions needed for an exhaustive search (*Exhaustive*). Finally, and most importantly, we show the time difference from optimal. The optimal solution was obtained through exhaustive search; of course, in general this is not feasible. Recall that each “execution” is not an execution of the entire program, but rather a small number of iterations (5 in the NAS programs).

The table shows that we are able to produce an optimal or near-optimal schedule in all cases in which a schedule that satisfies the energy limit exists. Furthermore, in all cases the number of executions using our system was small. In particular, BT was the program in the NAS suite that required the largest number of executions—and it only required 16, 8 of which are required initialization runs. Considering that running all schedule permutations requires 108

Program	Energy Limit (kJ)	Executions			Chosen Schedule	Time Difference
		Necessary	Optimal	Exhaustive		
BT	65	16	18	108	(9, [1,1])	0.0%
CG	20	12	7	24	(4, [1])	0.0%
EP	45	11	4	24	None	—
FT	72	11	47	144	(8, [4,4])	2.2%
IS	33	14	16	24	(8, [2])	0.0%
LU	23	15	36	864	(8, [2,4,2])	6.1%
MG	21	13	29	144	(8, [2,3])	2.0%
SP	48	16	15	108	(9, [2,1])	0.0%

Table 2. Results of running our algorithm on NAS parallel benchmarks. The chosen energy limit is 10% less than the energy consumed at top gear for all phases, using 8 nodes (or 9, for BT and SP). The time difference is that between executing the program using our chosen schedule and executing the optimal schedule. Note that the “necessary” executions include eight executions required for initialization.

runs (3×6^2 , as there are three possible node configurations, six gears, and two phases), this is reasonable—and is the worst case over the entire NAS suite in terms of the number of runs. Note that LU requires 864 runs to complete all permutations, and our system only needs 15 to arrive at a schedule just 6.1% from optimal.

In fact, in some cases we achieved the minimum number of runs: 8 initialization runs and 3 subsequent runs (one prediction and then up to two validation tests). This was the case for EP and FT. It is worth noting that the reason that BT required the most executions is because the energy constraint was in a region containing many clustered schedules (*i.e.*, both their time and energy are similar). Based on the observed accuracy of the BT predictions, it is likely that fewer executions would be needed with a different constraint (we verified this with additional experiments). More details on the effect of the energy limit are given in Section 4.2.

We emphasize that the number of initialization runs remains constant as both the number of available nodes and the number of program phases increase—meaning that the initialization runs will be negligible on large clusters executing large-scale programs. Additionally, if the energy limit is later changed, the initialization runs need not be repeated.

Next, we examine the *quality* of the chosen schedule. We deem our system to have chosen a high-quality schedule if it results in an execution time that is close to that of the optimal schedule.

Table 2 shows that our system does indeed select a high-quality schedule in all cases. For BT, CG, IS, and SP, our algorithm selected the optimal schedule. In the case of FT, the chosen schedule produced an execution time that was within 2% of the optimal schedule. The reason we did not select the best schedule is because there are many schedules “near” the chosen schedule in the problem space. In general, this makes choosing the optimal schedule challenging; on the other hand, a suboptimal choice is likely to result in an execution time close to the optimal. In the case of LU, we chose the schedule (8, [2,4,2]). Nevertheless, this is our worst case and is only 6% from optimal. It is important to note that by softening the constraints in our algorithm for what schedules should be accepted, we could explore more of the search space and arrive at a better result. However, the cost would be more program executions for *all* programs, and our system finds a near-optimal schedule in all other cases.

Additionally, in EP no schedule satisfied the 10% energy limit. For this program, 8 nodes at top gear consumes 50kJ, so the energy limit chosen was 45kJ. Because EP gets nearly perfect speedup, the energy consumption is essentially the same on all node configurations, because the time decreases as nodes are added. Also, EP is highly CPU bound. Therefore, reducing the gear has a large time penalty and little energy savings.

Finally, CG is an interesting case. This application presented a potential problem for our system because on our cluster, the one-node program is out of core. This results in superlinear speedup for

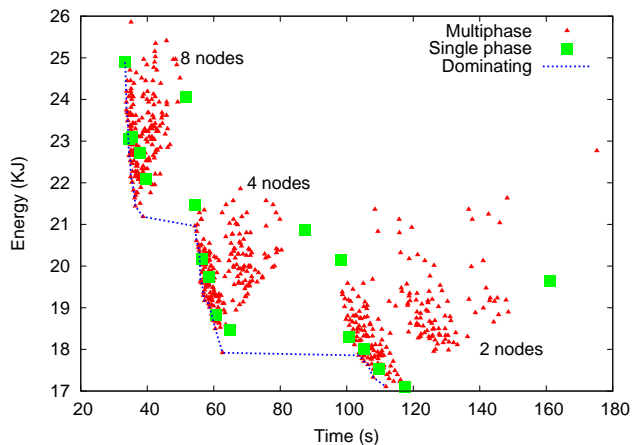


Figure 1. Energy-time scatter plot of every LU schedule. Schedules on the line are not dominated. For readability, the axes do not start at the origin.

the two-, four-, and eight-node programs and results in distorted values of F_p . This in turn can cause the gear and node validation steps to fail because a better schedule arises.

To handle CG, we used a simple filtering technique to remove anomalous results. Specifically, when our system detects superlinear speedup, we compute F_p using the first number of nodes that results in an in-core program. This allowed our system to choose the optimal schedule, which was (4, [1]). Separate tests showed that without filtering, the schedule chosen was (2, [0]), which would have resulted in a 10% slowdown in time as well as two extra executions.

4.2 Detailed Results

In this section, we examine in more detail several aspects of our model as well as the behavior of our algorithm. Specifically, we first examine our assumption that using different gears in different phases is important. Then, we investigate the behavior at the extremes of the problem space, the sources of error, the effect of the choice of energy limit, and the accuracy of our predictions,

4.2.1 Multigear schedules

This work is motivated by the notion that a program has phases with different optimal gears. This section presents some empirical data to support this conjecture. First, it looks at LU in detail, then it shows data for all multiphase benchmarks.

Figure 1 plots the energy and time of every possible LU schedule. The line connects the set of schedules that are not dominated.

	Number of schedules			
	Total	Optimal	Multigear	
BT	72	18	13	72%
FT	108	47	36	77%
LU	648	36	35	97%
MG	108	29	20	69%
SP	72	15	11	73%

Table 3. Total schedules (excluding one-node), number of schedules that are not dominated, and the number and percentage of such schedules that are multigear.

Importantly, if only single gear schedules are considered, then execution time may be much higher. For example, if the energy limit were 22kJ, there are several 8-node multigear schedules that execute in less than 40 seconds. However, the best single-gear schedule under the limit is (4, [0,0]), which takes nearly 60 seconds.

Table 3 shows the overall benefit of using multiple gears on the 5 multiphase NAS benchmarks. The total number of schedules depends on the number of phases, gears, and node configurations, as stated above. Each of these schedules was executed on our cluster. Next, the table shows the number of schedules that are not dominated as well as how many of those schedules are multigear. For NAS, on average, 79% of the schedules that are not dominated are multigear, which we believe shows that a model that allows different gears in different phases is important.

4.2.2 Examining the problem space

In our previous work [14], we showed that the behavior of a parallel program at different gear settings was dependent on program speedup and memory pressure. The better the speedup, the lower the energy premium to run using more nodes. At the limit, if speedup is perfect, then there is no additional energy cost because doubling the nodes halves the execution time. Also, the higher the memory pressure, the greater benefit in running at a lower gear, because the CPU spends a large amount of time waiting on memory. Together, these two factors control the behavior of a program as it relates to our algorithm and model.

To illustrate that our algorithm can support an arbitrary combination of speedup and memory pressure, we constructed a set of six benchmarks. Each consists of two phases. A phase has (1) either poor or excellent speedup and (2) either low or high memory pressure. Assuming we do not care about order and that we want each phase to have different characteristics, this yields six benchmarks. The idea is that these benchmarks are at the extremes of the problem space, and all NAS benchmarks are in the “interior” of the space.

The results of the six benchmarks, each using three different energy limits, are presented in Table 4. The energy limits are chosen by calculating the value, for each program, of 95% of energy consumed by the 8-, 4-, and 2-node versions at top gear for both phases. There are several interesting aspects of these results. First, our system often finds the optimal schedule (12 times out of 15). Second, when we do not find the optimal, we are always within 6%. Third, the schedule (8, [2,0]) is chosen on *all three* energy limits for the fifth benchmark, which has excellent speedup in both phases. This is the case because perfect speedup means that adding extra nodes does not increase the energy limit. In addition, top gear is not chosen in the first phase because memory pressure is high. Fourth, most of the schedules chosen have different gears per phase. Last, all schedules shown in Table 4 use the top three gears. This is due to the limits used; different limits will select schedules with slower gears (as occurred in the NAS programs).

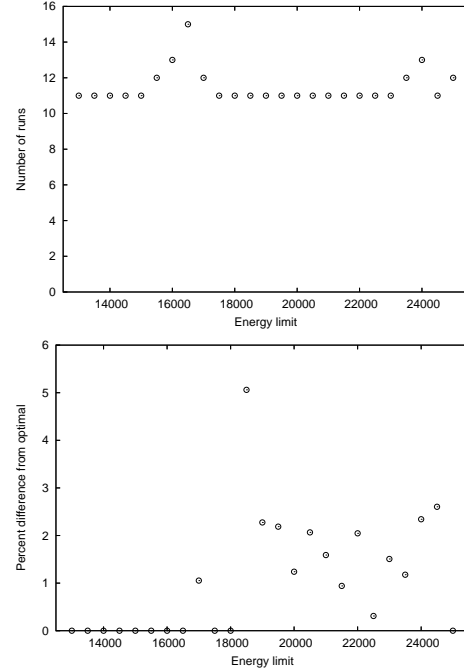


Figure 2. Effect of the energy limit. On the top, the number of executions required. On the bottom, the percentage difference from the optimal schedule.

4.2.3 Sources of error

Here we examine the sources of error in our system. First, we use an external power meter, which is accessed through the serial interface. We found that there is a relatively small variation in measurements of consumed energy. We believe this is a combination of the precision of the meter and that it is accessed through the serial port. Consequently, very small measurements of energy may be unreliable. Considering that a typical NAS program consumes thousands of joules even when running for only a handful of seconds, and inspecting how long our programs run, we estimate the meter error to be less than 1%.

Second, as mentioned earlier, we model idle time assuming that it is independent of gear. As idle time includes blocking communication calls, this is not strictly true. However, our measurements have shown that the time to receive data in MPI is relatively insensitive to gear. We have not yet measured the precise error here, but our initial results suggest that it is quite small.

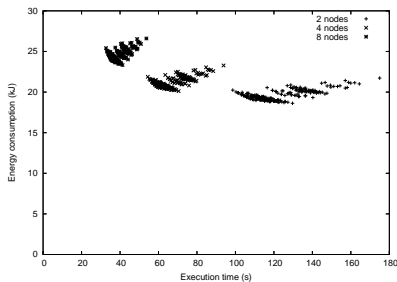
4.2.4 Effect of energy limit

In our NAS programs, we chose an energy limit that was 10% less than the peak energy that each program consumed. Here, we investigate the effect of varying the energy limit for a one-phase synthetic benchmark that has poor speedup and high memory pressure. We vary the limit from 13kJ, which for this program is the minimum needed to find a valid schedule, to 25kJ, where the chosen schedule is to use the maximum number of nodes at the fastest gear.

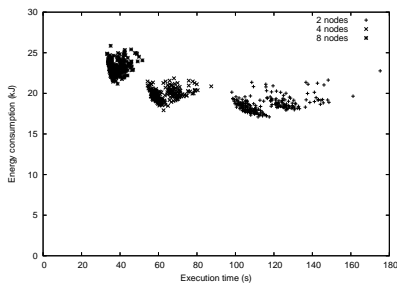
Figure 2 shows the results, including the number of executions as well as the quality of the schedule. Two things are of note here. First, at 16.5kJ, a much greater number of executions is needed. This is due to the fact that there are a large number of schedules whose energy consumption is predicted to be close to the limit. A small error in energy prediction may cause a candidate schedule to exceed the energy limit when it is believed to be within the limit

Program	Chosen Schedules					
	95% of 8	Time Diff.	95% of 4	Time Diff.	95% of 2	Time Diff.
(Poor/High, Excellent/High)	(8, [2,1])	3.7%	(4, [1,1])	0.0%	None	—
(Poor/High, Poor/Low)	(8, [1,2])	0.0%	(4, [1,2])	0.0%	(2, [2,0])	0.0%
(Poor/High, Excellent/Low)	(8, [2,1])	0.0%	(4, [1,1])	0.0%	None	—
(Excellent/High, Poor/Low)	(8, [2,1])	5.1%	(4, [0,1])	0.0%	(2, [2,1])	0.0%
(Excellent/High, Excellent/Low)	(8, [2,0])	0.0%	(8, [2,0])	0.0%	(8, [2,0])	0.0%
(Poor/Low, Excellent/Low)	(8, [2,0])	3.7%	(2, [0,0])	0.0%	None	—

Table 4. Results of running our algorithm on six synthetic benchmarks. Each program is two phases. For example, (Poor/High, Excellent/Low) indicates that the first phase had poor speedup and high memory pressure, and the second phase had excellent speedup and low memory pressure. Each of the six programs is run with three energy limits (95% of energy consumed by the 8-, 4-, and 2-node programs at top gear for both phases). Note that the number of executions for an exhaustive for all programs is 144. The average number of executions of a program (over all 18 experiments) was 13—2 more than the minimum.



(a) Predicted



(b) Actual

Figure 3. Comparison of predictions vs. actual executions for LU.

(or vice versa). This causes “nearby” schedules to be evaluated. Second, at 18.5kJ, our system produces a schedule that has the largest difference from optimal.

4.2.5 Accuracy of our model

In Table 2 we presented the performance of our algorithm combined with our model. The reason we are able to generate near-optimal schedules in few executions is because our model is accurate. To examine this further, we used our time and energy model to make predictions for *all* possible permutations of gears per phase (this totals 864 complete executions) on LU. Then we ran all programs, producing exhaustive results (as described above). The results are presented in Figure 3. Examining the predicted results, distinct clusters can be seen, one for each number of nodes, and the shapes are similar.

5. Conclusion

This paper addresses the problem of finding a schedule that minimizes execution time on a power-scalable cluster and a maximum energy budget. Our approach uses a combination of performance prediction and profiling, backed up by actual program execution. Results show that typically, only a handful of iterations of a given program need to be executed to find a schedule that results in a near-optimal execution time. In particular, over all NAS benchmarks, typically less than 15 executions (of just a few iterations each) are needed to choose a schedule. Equally importantly, the quality of the chosen schedule is in the worst case 6.1% of the optimal schedule that is found by running all schedules exhaustively. Furthermore, the difference is usually less than 2% of optimal.

While we are encouraged by our results, there are still open questions that we intend to address in future work. First, we hope to implement our system on a much larger cluster. This will help us determine the robustness of our system. Second, we would like to relax some of the assumptions that we have made in this paper; in particular, we would like to expand our model to include load imbalance as well as reducible work. Finally, we plan to use the infrastructure created in this work within a general power-aware MPI runtime system.

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