An Autonomic Performance Environment for Exascale

***Kevin A. Huck*[1], *Allan Porterfield*[2], *Nick Chaimov*[1], *Hartmut Kaiser*[3], *Allen D. Malony*[1], *Thomas Sterling*[4], *Rob Fowler*[2]**

Exascale systems will require new approaches to performance observation, analysis, and runtime decision-making to optimize for performance and efficiency. The standard "first-person" model, in which multiple operating system processes and threads observe themselves and record first-person performance profiles or traces for offline analysis, is not adequate to observe and capture interactions at shared resources in highly concurrent, dynamic systems. Further, it does not support mechanisms for runtime adaptation. Our approach, called APEX (Autonomic Performance Environment for eXascale), provides mechanisms for sharing information among the layers of the software stack, including hardware, operating and runtime systems, and application code, both new and legacy. The performance measurement components share information across layers, merging first-person data sets with information collected by third-person tools observing shared hardware and software states at node- and global-levels. Critically, APEX provides a policy engine designed to guide runtime adaptation mechanisms to make algorithmic changes, re-allocate resources, or change scheduling rules when appropriate conditions occur. *Keywords: ParalleX, HPX, exascale, performance measurement, adaptive runtimes.*

1. Introduction

The transition to extreme-scale computing poses new challenges in performance analysis and optimization because of the anticipated high concurrency and dynamic operation that will be required to make extreme-scale systems operate efficiently. Increasingly heterogeneous hardware, deeper memory hierarchies, reliability concerns, and constraints posed by power limits will contribute to a dynamic environment in which hardware and software performance may vary considerably during an application's execution. Furthermore, emerging exascale programming models will emphasize message-driven computation and finer-grained parallelism, resulting in more asynchronous computation. It is no longer reasonable to expect that a *post-mortem* performance measurement and analysis methodology will suffice to optimize applications in such an environment.

Rather, there is a strong need for runtime performance observation that merges in real time *first-person* (application perspective) with *third-person* (resource perspective) introspection, and for *in situ* performance analytics to identify bottlenecks and their impact on specific sections of code. This information can drive online dynamic feedback and adaptation techniques that can be integrated with an exascale software stack. The goal is to create an autonomic capability in the exascale system that can direct the application performance to more productive execution outcomes. In this paper, we describe our prototype implementation of an *Autonomic Performance Environment for eXascale (APEX)* that is part of the *OpenX* integrated software stack being developed in the DOE XPRESS project [9] (see Section 2). The APEX prototype supports both introspection and policy-driven adaptation for performance and power optimization objectives. We describe the APEX design and development in Section 3. Section 4 shows several examples that demonstrate the effects of APEX-enabled execution. These focus on making guided adjust-

[1]Performance Research Laboratory, University of Oregon, Eugene, OR 97405, USA
[2]Renaissance Computing Institute, University of North Carolina, Chapel Hill, NC 27517, USA
[3]The STE||AR Group, Louisiana State University, Baton Rouge, LA 70803, USA
[4]Center for Research in Extreme Scale Technologies, Indiana University, Bloomington, IN 47408, USA

ments to thread-scheduling controls for different policy objectives. Section 6 discusses the next steps in our research work.

2. XPRESS Project

The XPRESS project is organized into four major elements: system software; programming models and languages; applications; and cross-cutting issues. The HPX-3 runtime system [17, 33, 3] serves as a starting point as a programming tools and operating system target at the beginning of the XPRESS project. This has been complemented by the development of HPX-5, which is being developed to add functionality for fault tolerance and power management and to provide a robust open-source runtime system. The LXK lightweight kernel operating system, based on the advanced Kitten operating system [35, 7], is being developed in response to the new requirements for billion-way concurrency, introspective management of faults and power, and management of a protected and dynamic global virtual name space. It targets projected future directions of system architectures while running efficiently on near term systems, LXK is co-designed with HPX around the centerpiece of the RIOS interface between the runtime and operating system software. This interface will share information in both directions between the two major software layers for performance, reliability, and control of power consumption. The Open-X software stack is shown in Figure 1.

Two programming methods are employed to provide early means of conducting application- and kernel-driven experiments, as well as to facilitate ease of programming and portability. In addition to the native programming API provided by HPX-3 and HPX-5 and potentially wrapped by Domain Specific Languages (DSLs), a low-level imperative programming interface, XPI, is being developed to expose the semantic constructs comprising the ParalleX execution model [17] embodied in the experimental HPX runtime systems. The project is exploring legacy mitigation to ensure the seamless transition to the OpenX software stack of codes written using MPI or OpenMP. The approach is to develop XPI interfaces for these programming models, thus providing interoperability between software modules in both forms, and providing a path for incrementally extending parallelism within the MPI and OpenMP frameworks. APEX provides performance instrumentation interfaces compatible with XPI, DSL, and legacy codes.

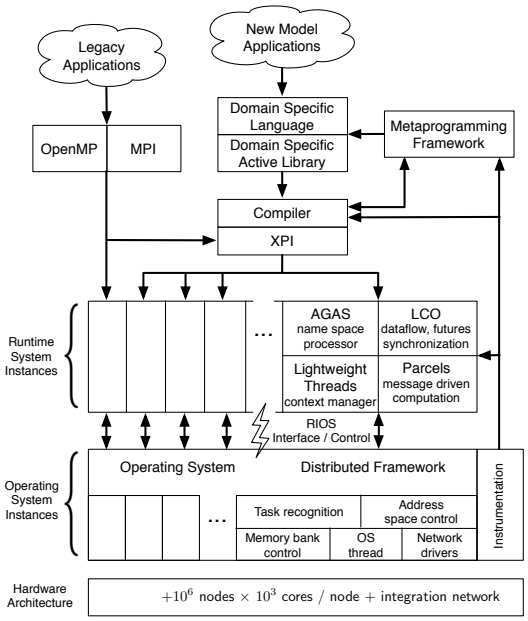


Figure 1. Major components of the OpenX architecture stack. APEX is the cross-cutting *instrumentation* component.

Essential cross-cutting functions includes automatic control and introspection, resilience, power management and heterogeneity. Power-management software in combination with anticipated energy-efficient hardware will achieve much greater resource utilization per joule while dramatically reducing data movement, a major source of power consumption, through active locality management. APEX represents the initial research prototype for introspection and dynamic control required for the XPRESS project.

3. APEX Design

3.1. Overview

APEX aims to enable autonomic behavior in software by providing the means for applications, runtimes, and operating systems to observe and control their performance. Autonomic behavior requires performance awareness (introspection), and performance control/adaptation. APEX is designed around these two main components. APEX provides introspection from both top-down and bottom-up perspectives, including node-wide resource utilization data, energy consumption, and health information, all accessed in real-time. The introspection results are combined and associated with policy rules in order to provide the feedback control mechanism.

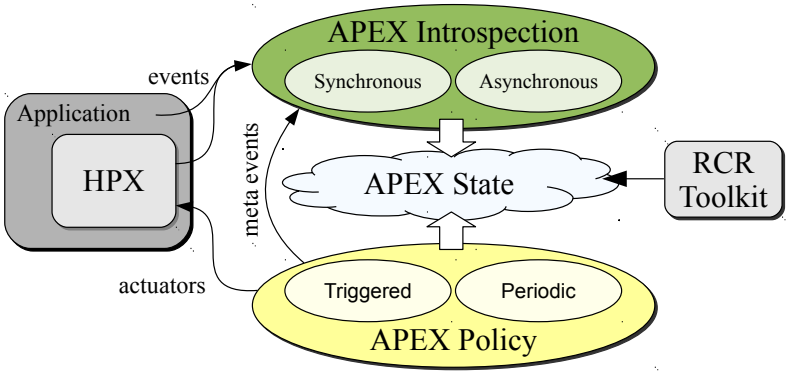


Figure 2. APEX design.

3.2. Introspection

APEX collects *top-down* introspection data from a runtime system, library, or high-level application through an event-based *inspector* API. The software to be controlled is instrumented with this event API. APEX recognizes several types of logistic events such as initialization, termination, setting a process rank (*e.g.,* an MPI rank, or HPX locality ID), and creating a new thread. For measurement, APEX has instrumented timer-start and timer-stop calls, as well as sampled counter values (*e.g.,* bytes transferred, queue length, idle rate). These API calls enter APEX as events. Internally, APEX has several event *listeners* that perform actions based on the types of events that are passed in to APEX. Events are either handled by listeners immediately using synchronous code execution or are handled using asynchronous method invocation. For the asynchronous processing, the event is stored internally on a queue for background processing, and execution control is quickly returned to the code that called the APEX API. Custom events are also available to trigger specific policy engine rules. Further explanation of this behavior is presented in Section 3.4.

Bottom-up introspection data is collected from the operating system and hardware using periodic sampling. These measurements do not use events, but rather additional OS threads are spawned to periodically read values directly from available sources. On Unix-like systems, the `/proc` virtual filesystem files provide access to CPU, memory, network, disk, process, and operating system statistics. Resource Centric Reflection (RCR) [20, 21] provides a user-level API to access any counter available through PAPI, PERF_EVENTS, or a hardware instruction. RCRdaemon runs on protection ring 0 and supplies information about hardware resources shared by more than one core (*e.g.,* energy consumption, Last Level Cache events, or memory-controller usage) in a data structure that can be read at user-level. RCRdaemon uses a self-describing

hierarchical data structure in a shared memory region to transmit protected counter values in an application-agnostic manner. The power interface reads these values and can be used by any application to acquire power/energy information. RCR calipers can be placed around any code region (up to the entire application) to measure energy used by that region. On Cray systems protection level 0 access is denied, but the Cray PM Counters [22] facility is available. RCRdaemon was therefore modified to get its data from this source. The values were then placed into the same data structure previously used. The user API was unchanged. Updates occur at the same rate as Cray updates /proc.

3.3. Event Listeners

As mentioned in Section 3.2, APEX events are processed by event listeners. Each listener is implemented as a C++ class, and as events pass through APEX, each instantiated listener is given access to the event object. The listeners implement handler methods for each event type available in the system. Notable event listeners in APEX include the *Profiling Listener*, the *Concurrency Listener*, the *Policy Engine Listener*, and the *TAU Listener*.

The profiling listener implements timer and counter measurement back-end processing in APEX. The salient events processed by the profiling listener include the `timer_start`, `timer_stop` and `sample_value` events. When the profiling listener gets a `timer_start` event, it creates a profiler object, generates a timestamp, and returns a handle to the profiler object. When the profiling listener gets a `timer_stop` event, it takes a second timestamp, puts the profiler object in a single-producer-single-consumer (spsc) queue for back-end processing, and returns. Each OS thread in the process has its own spsc queue to avoid contention. Similarly, when the profiling listener gets a `sample_value` event, it creates a profiler object, puts it in the spsc queue for back-end processing, and returns. The profiling listener has a background *consumer* thread that waits for a signal that indicates that data has been pushed onto one of the queues. When the consumer thread has been signalled, it clears all of the spsc queues of pending work by removing a profiler object from the queue, and updates the per-thread and per-process statistical profile for the running application. The currently executing profile can be queried subsequently at runtime through an introspection API. The optional TAU listener is similar to the profiling listener, with the exception that all processing is done synchronously through the TAU measurement library in order to generate a detailed profile or trace for offline, post-mortem performance analysis.

The concurrency listener works as follows. The salient events processed by the profiling listener are the `timer_start` and `timer_stop` events. When the concurrency listener gets a `timer_start` event, it pushes the timer ID onto a thread-specific stack, and returns. When the profiling listener gets a `timer_stop` event, it pops a timer ID off of the thread-specific stack. The concurrency listener also has a background consumer thread that periodically examines the top of each thread's timer stack and builds a histogram reporting the task currently being executed by each thread during that time quantum. At the end of execution, the histograms are written to files on disk and `gnuplot` [37] is used to visualize a concurrency graph of the application. Figures 3 through 7 are examples of concurrency graphs. The concurrency listener does not have a role in runtime adaptation, and is instantiated only when concurrency graphs are desired.

3.4. The Policy Engine

The most important listener component in APEX is the Policy Engine. The policy engine provides autonomic controls to an application, library, runtime, or operating system using the introspection measurements described in Section 3.2. Policies are rules that decide on outcomes based on the observed state captured by APEX. The rules are encoded as callback functions that are registered with APEX, and are either *triggered* or *periodic*. Triggered policies are invoked by an APEX event, whereas periodic policies, by definition, are executed at set intervals. The policy rule functions have access to the APEX API in order to request profile values from any measurement collected by APEX. Using these values to make logical decisions, the functions can change the behavior of the application by whatever means available, such as throttling threads, changing task granularity, or triggering data movement such as mesh refinement or repartitioning. In this way, the policy engine enables runtime adaptation using introspection data, engages actuators across stack layers, and can be used to invoke online auto-tuning support.

3.5. Global Performance Views

Thus far in the discussion performance introspection has been limited to local node observations. No performance information from remote nodes or processes is available implicitly to the local policy functions. However, there are situations in which global performance information is necessary to make runtime adaptation decisions for problems such as load balancing. In those cases, APEX provides a skeleton interface for exchanging local information in a distributed application scenario. The global exchange of local performance data in APEX is similar to that provided by TAUg [15], in which TAU performance data collected by an MPI application was exchanged using MPI functions. Rather than be tied directly to a specific communication infrastructure, APEX provides a skeleton interface to be populated using the distributed communication library used in the application to be controlled. Examples implemented so far include HPX-3, HPX-5 and MPI. The interface that the runtime has to implement includes two functions; `action_apex_get_value()` – each node gets local data to be reduced and performs an optional *put* (if implementing a push model); and `action_apex_reduce()` - each node performs an optional *get* (if implementing a pull model), all remote node data is aggregated at root node, and an optional push broadcasts the aggregated result back out to the non-root nodes. Ideally, puts and gets are performed using one-sided communication such as remote distributed memory accesses (RDMA) or by using a Global Address Space (PGAS or AGAS).

3.6. HPX Integration

APEX is integrated with operating systems, runtime systems, libraries, and applications by instrumenting the code with calls to the APEX introspection API, as well as by registering desired policy functions and global communication. Because both HPX-3 and HPX-5 are task-based runtime systems, we added the instrumentation in the respective task schedulers, placing timer start/stop calls just before and after task functions are executed, taking special care to avoid measuring internal lightweight tasks such as "no-op". `Sample_value()` calls were added to capture internal runtime statistics (*i.e.,* number of yields, steals, spins, *etc.*) and we added other instrumentation for initialization, thread creation and termination. Where applicable, we wrote policy functions and added the code to register the policy functions to perform adaptation of the runtime system. All the examples described in Section 4 modify runtime behavior in the same

way, by setting a cap on the maximum number of active worker threads, so we also modified the HPX thread scheduler loop for worker threads to check the cap value and de-activate a worker thread if the number of active threads is greater than the thread cap. Even though we are measuring nearly every task executed by the runtime, our measurements show that the overhead introduced by APEX does not exceed 2%, and is usually less than 1%, depending on the granularity of the executed tasks. We believe that this is due to our asynchronous profile-processing combined with the small but sufficient amount of available processing capacity headroom when executing on many-core nodes. Global performance data is exchanged in HPX using the Active Global Address Space (AGAS).

4. Experimental Results

In order to demonstrate the features and capabilities of APEX, we integrated it with two distinct but related runtimes, HPX-3 and HPX-5. We implemented a variety of policy rules, and we present a selection of them here, along with the applications that best demonstrate them. In this section, we present the following examples:

- HPX-3 1-D stencil code, runtime optimized for best performance
- HPX-5 Single-source, shortest-path benchmark, runtime optimized for highest throughput
- HPX-5 LULESH kernel, runtime modified to stay under a user-specified power cap
- HPX-3 miniGhost kernel, runtime modified to stay under a user-specified power cap

All of the experiments described below were conducted on Edison, a Cray XC30 system deployed at NERSC [36]. Edison has 5576 nodes with two 12-core Intel "Ivy Bridge" processors operating at 2.4 GHz, with a total of 48 threads per node (24 physical cores w/hyperthreading). The network on Edison is a Cray Aries interconnect with Dragonfly topology, with 23.7 TB/s global bandwidth. As LXK was not yet integrated with HPX, the applications were executed on the Compute Node Linux (CNL) operating system.

4.1. HPX-3 1-D Stencil Code

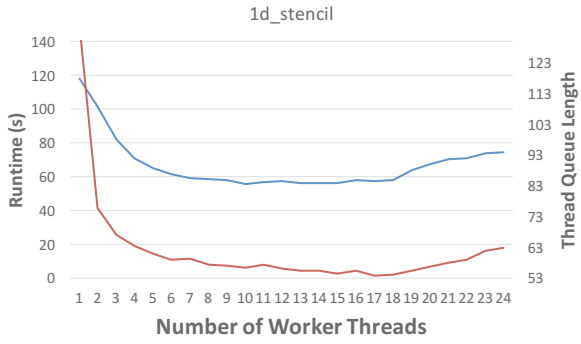
The 1D stencil code is a simple, iterative heat-diffusion solver using a 3-point stencil, used as an example code for HPX-3, and for which multiple versions are available with different optimizations applied. The simplest version represents the computation for each data point as an individual future, but the performance of this version is extremely poor as the task granularity is far too small. The version with good performance partitions the data into a user-configurable number of equally-sized chunks, with the computation on each chunk being represented as a future. Within a node, performance initially increases with an increasing number worker threads, but then decreases.

Figure 3a shows the runtime (blue line) of the 1D stencil code as function of number of worker threads from 1 to 24, which is the number of physical cores available on Edison nodes. It also shows that runtime is highly correlated with the average thread queue length (red line), which is a counter exposed by the HPX-3 runtime representing the number of tasks waiting to execute on worker threads. APEX can query the thread queue length while the program is executing and adjust dynamically the number of worker threads allocated to minimize runtime.

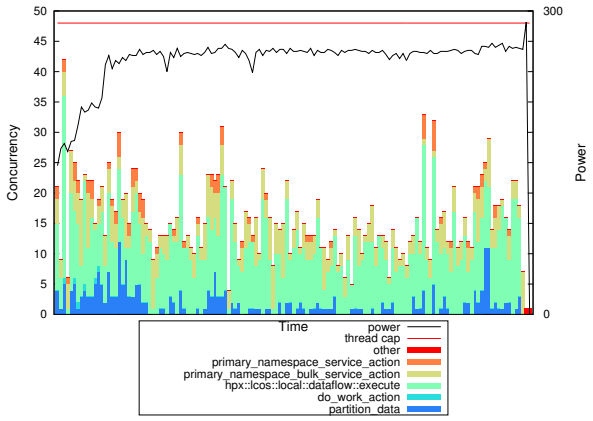
Figure 3b shows the concurrency graph for the execution of the 1D stencil code run on 100,000,000 elements partitioned into 1000 chunks with 48 worker threads, which is the number of logical cores available on an Edison node with hyperthreading enabled. Actual concurrency

is substantially lower, as many tasks are waiting on dependencies to complete before becoming eligible to run, and there is substantial variability in actual concurrency over time. This execution takes 138 seconds to run. Figure 3c shows the concurrency graph for an execution of the same problem size but with 12 worker threads, which produces the shortest runtime of any number of worker threads. That execution takes 61 seconds to run.

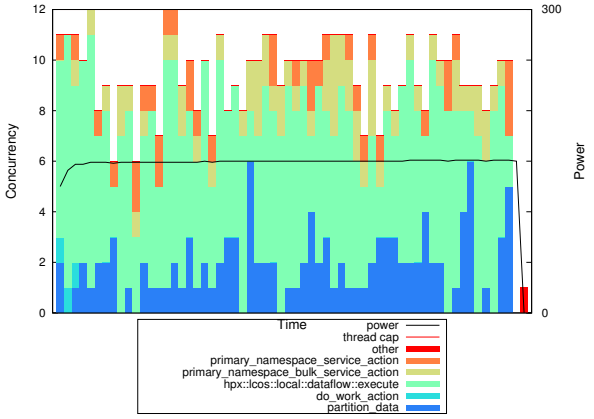
Figure 3d shows the concurrency graph for the same problem size and an initial number of worker threads of 48, but using discrete hill-climbing search to minimize the average thread queue length. This converges on 13 worker threads (*vs.* the optimal value of 12) and does so quickly enough that the overall runtime is nearly as fast (64 seconds) as starting with the optimal number.



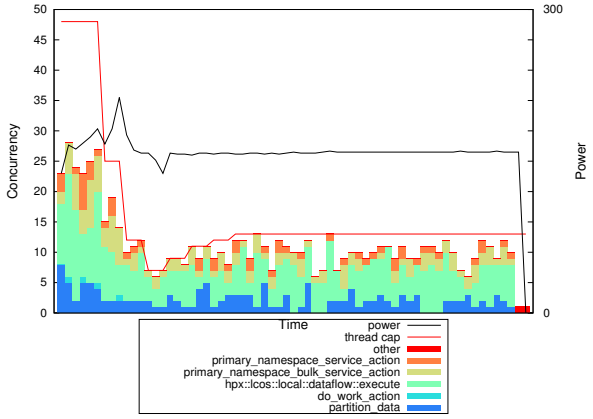
(a) 1D stencil strong scaling. This chart shows the correlation between the execution time (blue line) and the queue lengths (red line) when running with different numbers of threads on Edison.



(b) 1D Stencil unthrottled. This concurrency chart shows a stacked bar chart with the periodic (1 Hz) status of each OS thread. The max number of threads is 48, and the instantaneous power for each sample is the black line.



(c) 1D Stencil with ideal number of threads. This concurrency chart shows the periodic (1 Hz) status of each OS thread. The number of threads is fixed at 12, and the instantaneous power for each sample is the black line.



(d) 1D Stencil throttled by APEX. This concurrency chart shows the periodic (1 Hz) status of each OS thread. The number of active threads starts at 48, but is throttled while APEX searches for an optimal number of active threads to minimize execution time. The evolving thread cap is the red line, and the instantaneous power draw is the black line.

Figure 3. 1D Stencil.

4.2. HPX-5 SSSP benchmark

The Single Source, Shortest Path graph search benchmark (SSSP) [5] is a candidate for inclusion in the Graph500 [6] benchmark kernels. Given an initial graph, the SSSP benchmark computation finds the shortest distance from a given starting vertex to every other vertex in the graph. In the HPX-5 implementation, a large graph is loaded and distributed across localities, a point is selected at random, and the shortest path between it and all other points is found. The search runs for a fixed length of time, and terminates when the accumulated time performing searches exceeds the specified length of time. Key constraints of the benchmark are that only one initial vertex search is performed at a time, and no memoization between searches is allowed. The dataset used in this example is the Random4-n.10 dataset, executed for 60 seconds worth of timed searches. For this benchmark, the metric of interest is total throughput, not time to completion. The code was run on 10 nodes, using 24 threads per node (no hyperthreading).

The APEX Policy rule used for optimization of SSSP was the maximization of the number of calls to `_handle_queue_action()`, used as proxy for the "throughput" metric. The primary metric for this benchmark is Traversed Edges Per Second (TEPS), and the queue contains vertices to be explored. The policy function adjusts the thread concurrency to maximize throughput, using the *Parallel Rank Order* search strategy provided by the auto-tuning and optimization search framework *Active Harmony* [34]. The initial value for the thread cap was set at 24, with a minimum value of 6. The policy function was registered to execute on a periodic basis (1Hz), adjusting the thread cap to a new value as specified by the optimization search.

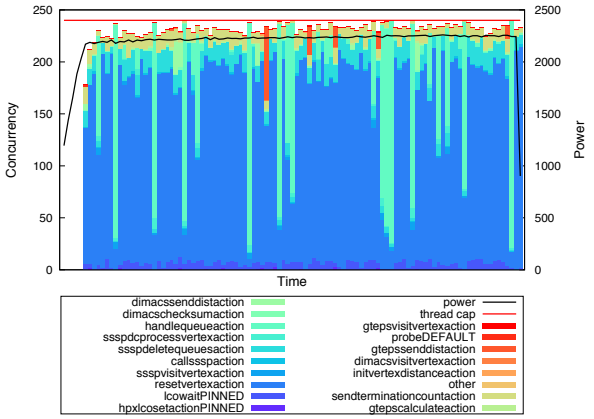
Figure 4a shows the cumulative concurrency graph across all 10 nodes for the baseline execution. The concurrency charts show a stacked bar chart with the periodic (1Hz) instantaneous status of all threads. The red line indicates the maximum total number of threads (fixed at 240), and the instantaneous power measurement for each sample is the black line. In this run, 1962 searches are performed in 60 seconds. The graph shows that nearly all 240 threads are busy, and power consumption is about 240 W per node.

Figure 4b shows the cumulative concurrency graph across all 10 nodes for the throttled execution, using the policy engine. The total maximum number of threads starts at 240, but is throttled while Active Harmony searches for an optimal number of active threads to maximize transaction throughput. As in the baseline figure, the evolving thread cap is the red line and the instantaneous power for each sample is the black line. In this execution, 6929 searches were performed in 60 seconds. When the search converges, only 61 (6 threads on 9 nodes, 7 threads on one node) threads are active. As a side-effect, power consumption is much lower, about 150 W per node. Most importantly, the number of searches done in the 60 seconds is several times higher. Figure 4c shows the correlation between the throughput (total calls to `_handle_queue_action()`) and the evolving thread cap.

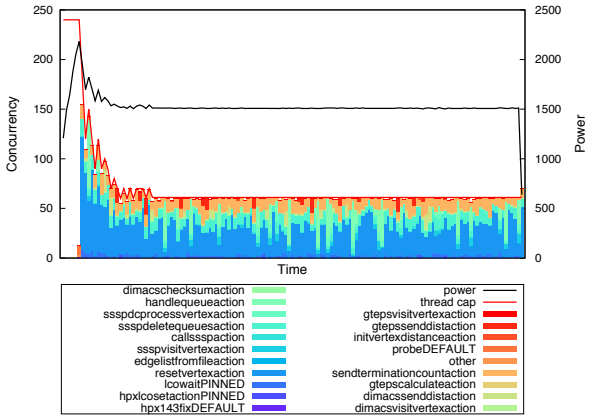
Table 4d shows a comparison of key metrics between the baseline and the runtime optimized executions of SSSP. In the throttled execution, the total cycles and instruction counts are reduced, while the number of L2 cache misses increases slightly. Because the graph is distributed, visiting remote vertices requires network communication. The network request causes a worker thread to yield the task waiting on the network request to perform other work, rather than block and wait on the result. The yield process is implemented using locks, so increased requests for the network lead to lock contention in the runtime. The yield algorithm also includes a small

[5] `http://hpx.crest.iu.edu/applications`
[6] `http://www.graph500.org`

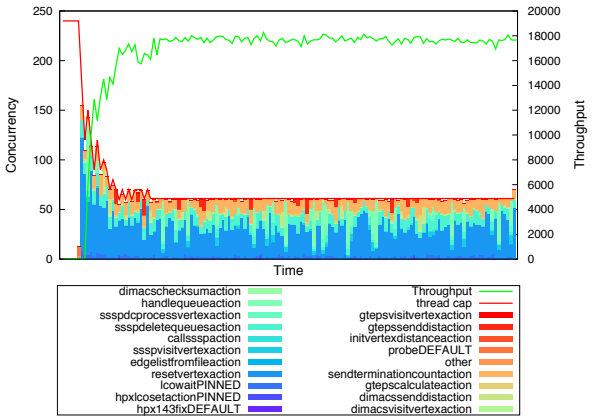
amount of "busy work", which explains the reduction in instructions. Essentially, this application implementation appears to be network-bound, so reducing the number of active worker threads decreases the contention for yielded tasks. As can be seen in the table, the TEPS metrics are increased considerably by throttling, resulting in greater throughput. It is important to note that the problem is not with the runtime, but with the nature of the implementation. Because the graph is distributed, the threads contend while waiting on remote actions.



(a) SSSP Baseline.



(b) SSSP Throttled, with power consumption side effect.



(c) SSSP Throttled, with throughput metric correlation to thread cap.

Metric	Baseline	Throttled
Searches	1962	6929
Cycles	$6.9E+12$	$2.8E+12$
Instructions	$3.2E+12$	$2.0E+12$
L2TCM	$8.0E+9$	$8.6E+9$
IPC	0.45896	0.71626
INS/L2TCM	397.52	235.23
min. TEPS	$7.2E+04$	$9.5E+04$
med. TEPS	$1.4E+05$	$5.0E+05$
max. TEPS	$2.5E+05$	$7.6E+05$

(d) Metric comparison between the baseline and throttled executions of SSSP.

Figure 4. SSSP Benchmark.

4.3. HPX-5 LULESH kernel

The Livermore Unstructured Lagrangian Explicit Shock Hydrodynamics (LULESH) benchmark is one of the proxy applications for the US Department of Energy co-design efforts for exascale. LULESH is an application from the Lawrence Livermore National Laboratory (LLNL) that is used to model and study hydrodynamics, the motion of materials relative to each other when subject to forces. The HPX-5 LULESH implementation was written by the HPX-5 researchers at Indiana University. Because LULESH is CPU bound in most implementations, it is an interesting test case to demonstrate what happens when executed under a power cap. Because it is CPU bound, reducing the power consumption typically involves using fewer threads or slowing down the CPU clock speed, which will affect performance.

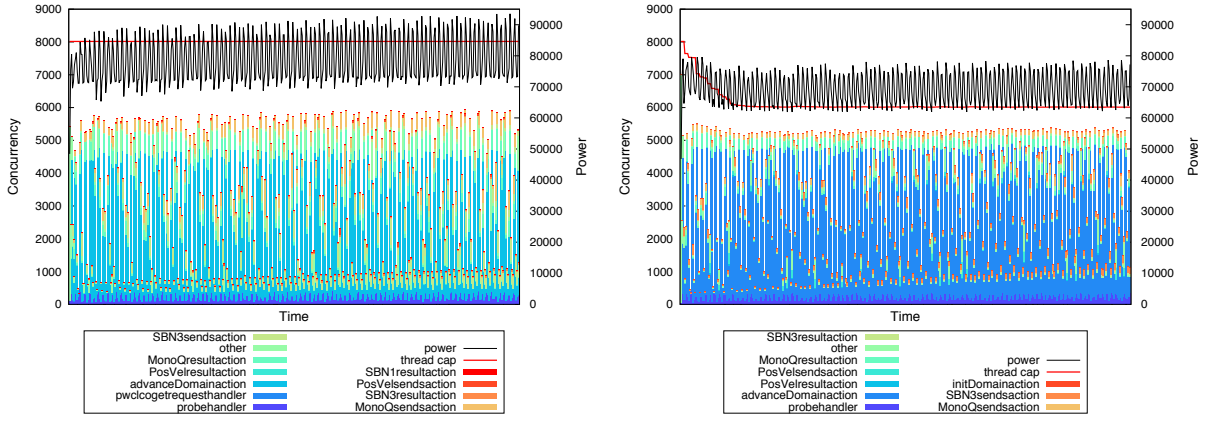
For this example, we developed an APEX policy for maintaining power draw within a high/low range. The policy will periodically check the power draw, and if the current power

draw is greater than the high power cap, the thread cap will be reduced. If the power draw is lower than the low power cap, the thread cap will be increased. The policy rule is a simple hill-climbing algorithm with hysteresis, using a running average of the last N observations. In our tests, we set $N = 3$. We modified the HPX-5 thread scheduler algorithm to check the thread cap on every iteration of the main worker loop. If a thread is not holding any resources and the number of active workers is greater than the current thread cap, the thread goes into an idle state until signaled to resume work. If the number of active workers is less than the cap, an active worker signals an idle thread to resume working. A quiescent node of Edison draws approximately 40W, whereas a fully loaded node draws as much as 300W. We used a high power cap of 220W, and a low cap of 200W. We executed LULESH with 8000 sub-domains, $nx = 64$, for 100 iterations on 334 nodes of Edison (8016 total cores).

Figure 5a shows the cumulative concurrency graph across all 334 nodes for the baseline execution. The total runtime of the application is 118 seconds. The red line shows the maximum concurrency, 8000 threads (fixed). The black line shows the cumulative power draw across all 334 nodes. The power consumption has peaks around 9.3kW, about 278W per node. The average power draw per node was around 236W. The total energy usage was measured as 9.327MJ (megajoules). The stacked bar chart shows which tasks were executing when APEX sampled them with a 4Hz period.

Figure 5b shows the cumulative concurrency graph across all 334 nodes for the throttled execution, using the policy engine. The key difference between the two executions is that the total energy draw for the throttled execution was only 8.180MJ (approximately 12.3% less) while the execution time was not affected. The red line shows the thread cap as it is modified by the policy. The black line shows the reflected reduction in power draw, with some localized fluctuations. The average power draw per node for this run was 207 W. Once the search converged, this execution used less than 1/4 the number of threads, but runtime was unaffected.

Like the SSSP benchmark, the throttled version of LULESH does not yield tasks as much as the original. A sampled TAU profile showed much less time spent in yielding activity when a worker thread surrenders its task in order to stay busy while waiting on a remote result. Our conclusion is that the assignment of sub-domains to localities in HPX does not maintain spatial locality, but rather assigns them round-robin to distribute the work. The HPX-5 implementation is being rewritten in order to exploit spatial locality, and put less pressure on the network.



(a) LULESH Baseline.

(b) LULESH Throttled.

Figure 5. LULESH Benchmark.

4.4. HPX-3 miniGhost kernel

MiniGhost [5], developed as part of the Mantevo project [13], is a finite difference miniapp simulating heat diffusion over a three-dimensional domain. The original version uses OpenMP intra-node and MPI inter-node. It has been ported to HPX-3 [2]; this version uses HPX for both intra- and inter-node parallelism. The HPX version provides better performance than the original OpenMP version.

Figure 6 shows that there are diminishing returns from allocating additional worker threads to MiniGhost. This suggests than we can throttle the application by cutting back on the number of worker threads to reduce energy usage while avoiding substantial performance degradation. Figure 7a shows the concurrency with 48 worker threads, the number of logical cores on an Edison node. While not all available worker threads are used, the application will often use slightly more than the 24 physical cores available. With 48 worker threads, MiniGhost runs in 92 seconds and uses about 275 Watts of power. Figure 7b shows the concurrency when the initial number of worker threads is set to 48 but the thread cap is dynamically adjusted to keep power at or below 200 Watts. APEX converges on a thread cap of 20, yielding 200 Watts of power usage, a 33% reduction in power, and a runtime of 103 seconds, a 12% increase in runtime.

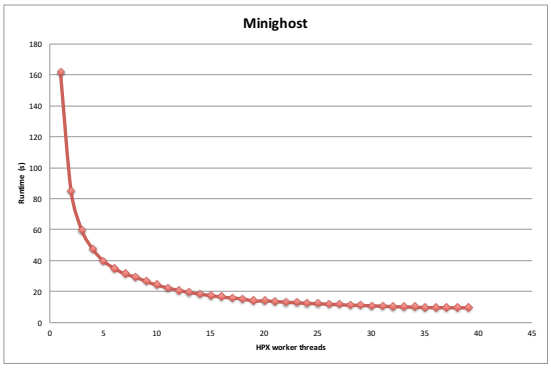
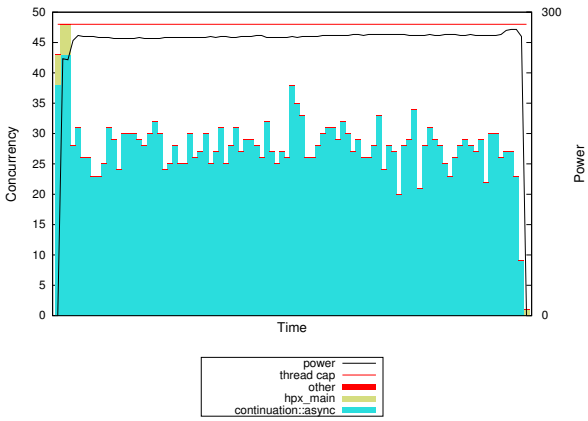
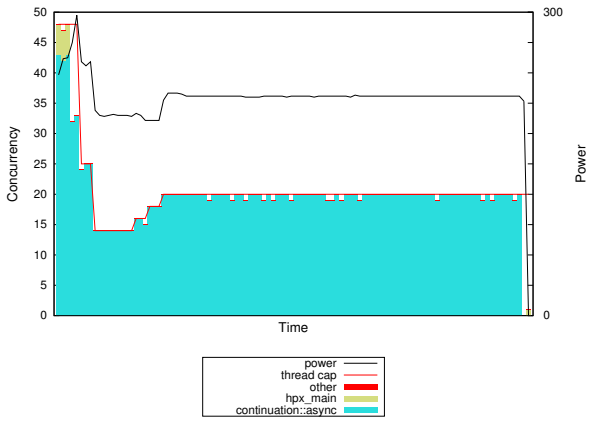


Figure 6. miniGhost strong scaling.



(a) miniGhost Baseline. This concurrency chart shows a stacked bar chart with the periodic (1Hz) status of each thread. The max number of threads is 48 (red line), and the instantaneous power for each sample is the black line.



(b) miniGhost Throttled. This concurrency chart shows a stacked bar chart with the periodic (1Hz) status of each thread. The max number of threads starts at 48, but is throttled while APEX searches for an optimal number of active threads to keep under the power cap. The evolving thread cap is the red line and the instantaneous power for each sample is the black line.

Figure 7. miniGhost Benchmark.

5. Related Work

Several performance tools use measurement for the purposes of offline performance analysis, including TAU [30], HPCToolkit [1], Scalasca [38], Vampir [19], Extrae [26] and others. All are powerful and capable tools in their own right. These tools, however, were designed for offline performance analysis and tuning, focusing on first-person performance measurement of tied tasks on a per-thread (OS thread) basis. New and emerging exascale programming models present technical challenges that the designers of those measurement systems had not considered, such as untied task execution and migration, runtime thread control and execution, third-person observation, and runtime performance tuning. Also, because these tools are inescapably intrusive, they are not designed to be integrated permanently into an application for continuous performance introspection, but rather, to be used in an iterative execute-analyze-tune cycle. In contrast, APEX is designed to perform asynchronous first- and third-person measurement for the sole purpose of supporting runtime introspection and performance adaptation.

One of the most active research areas in HPC is to reduce energy consumption while maintaining and even improving performance. For example, Curtis-Maury *et al.* [10] demonstrated the ability to build a runtime-adaptable optimization that both converges on the best performing configuration and reduces power consumption. This result is due to the observation that some parallel applications have diminishing returns with respect to scalability, and additional hardware merely consumes more power without improving performance. Rountree *et al.* [28] demonstrate the use of dynamic voltage scaling to save energy while minimizing impact on performance. Their *Adagio* approach attempts to scale computation and communication in distributed MPI applications using only local information acquired and applied at runtime in order to eliminate slack at synchronization points. Rountree *et al.* [29] have subsequently explored the inherent variation among processors and the range of effects that placing a hard power cap has on applications with different characteristics.

With respect to runtime thread scheduling, Olivier *et al.* [25] demonstrated that a hierarchical, cache-aware thread scheduler performs better than a flat task scheduling in conjunction with load balancing (via task stealing) within cache and/or NUMA domains. While this is a form of runtime adaptation, it is an approach targeting one issue and does not react to runtime measurements, but rather uses thread affinity and memory hierarchy information at startup. Similarly, Charm++ [18, 39] has mechanisms for distributed dynamic load-balancing based on runtime information. Other researchers have used Charm++ as a platform for developing additional runtime load-balancing strategies [16] both between nodes and within a node using cache/memory hierarchical information. PICS [32] allows runtime adaptivity in Charm++ by allowing the application to register *control points* [11] specifying what effect application parameters have on various categories of performance-effecting properties. For example, the application can register that a variable controlling the size of a subproblem will change the grain size and degree of parallelism. Based on runtime performance measurement, the system selects a property to adjust and adjusts registered control points accordingly.

The OmpSs runtime system has demonstrated the ability to schedule an appropriate kernel implementation based on available heterogeneous hardware choices [12, 27]. In this implementation, DGEMM tasks are scheduled on either CPU or GPU resources depending on the input size, available hardware and prior performance results.

The Open Tool for Parameter Optimization [8] tunes parameters exposed by the OpenMPI runtime. In OpenMPI, many runtime tasks are delegated to modules, which implement different

versions of communication algorithms (such as collectives) and map MPI operations onto lower-level network operations (such as for TCP, InfiniBand, Cray Gemini/Aries, etc.). These modules expose a set of tunable parameters, called MCA parameters, of which a typical installation will have several hundred. OTPO searches for parameters giving the best performance, as measured by latency or bandwidth of network operations.

The AutoTune project [23] is developing the Periscope Tuning Framework, an extension to the earlier Periscope [6] performance analysis and diagnosis tool which allows plugins to provide new functionality. PTF has been used for runtime energy tuning using DVFS and for tuning of MPI runtime parameters [24], and has been integrated with several parallel pattern libraries to tune parameters such as how many CPU cores and acclelerators to use in heterogenous codes and what scheduling policies to use [4]. APEX differs from PTF in being more deeply integrated with runtimes and in providing tuning capabilities based on a global performance view.

Hoffman *et al.* [14] have developed an interface for diverse applications to report a performance measure in a generic way so that operating systems and runtimes can adapt themselves to optimize application performance. In their *Application Heartbeats* framework, applications signal a "heartbeat" as they make progress in a computation; for example, a video-encoding application could signal a heartbeat each time it processes a frame. The system then tries to optimize the observed "heart rate". They provide examples of optimizations purely within an application, such as a video encoder switching algorithms and altering parameters to algorithms to meet a target frame rate, and outside applications, such as a computer-vision application that adjusts the number of cores that it uses to find the smallest number of cores necessary to achieve real-time video processing.

6. Conclusion

The quest for exascale brings fundamentally new challenges to performance and to productivity. The solutions that will likely usher in the exascale era will require software designers and users to embrace performance heterogeneity and variability. We believe that any successful implementation will have to integrate performance introspection, *in situ* analysis, and adaptation in an exascale system stack. The XPRESS project has developed a prototype of APEX integrated with HPX-3 and HPX-5 for use in OpenX. We have demonstrated APEX with several benchmark examples, and we believe that the APEX framework is generally applicable to other X-stack runtime efforts.

There is considerable work that can be done with respect to APEX. In the short term, we would like to conduct more robust application experiments and to explore behavior larger scales on different platforms. As more applications are developed using HPX, we hope to have a greater opportunity to demonstrate the APEX capabilities for runtime adaptation. With that in mind, new applications will present more and better policy (optimization) rules, both for specific applications and to generalize these in the operating system and runtime libraries. In particular, we are interested in possible policy rules that address heterogeneous HPX-3 code that can be executed on GPGPUs, as well as many-core architectures such as the Intel Phi. We plan to develop more policy rules that specifically address the SLOWER design principles of the ParalleX model [31]. We soon will be exploring the multi-objective optimization opportunities available in the development branch of Active Harmony. With that support, we can tune with respect to both performance and energy efficiency, as well as to any other application-specific metrics. Finally, we believe that APEX has applications outside of the XPRESS project, and that

it can be successfully integrated into other runtime systems and parallel execution models with controllable parameters, including OpenMP, MPI, and OmpSs. It can serve as a framework for triggering application-specific optimizations such as adaptive mesh refinement, load balancing, and other dynamic behavior.

Support for this work was provided through the X-Stack Software Research and Scientific Discovery through Advanced Computing (SciDAC) programs funded by the U.S. Department of Energy, Office of Science, Advanced Scientific Computing Research (and Basic Energy Sciences/Biological and Environmental Research/High Energy Physics/Fusion Energy Sciences/Nuclear Physics) under award numbers DE-SC0008638, DE-SC0008704, DE-FG02-11ER26050 and DE-SC0006925. Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. DOEs National Nuclear Security Administration under contract DE-AC04-94AL85000. This research used resources of the National Energy Research Scientific Computing Center, a DOE Office of Science User Facility supported by the Office of Science of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

References

[1] L. Adhianto et al. "HPCTOOLKIT: tools for performance analysis of optimized parallel programs http://hpctoolkit.org". In: *Concurr. Comput. : Pract. Exper.* 22 (6 Apr. 2010), pp. 685–701. DOI: http://dx.doi.org/10.1002/cpe.v22:6.

[2] V. C. Amatya. "Parallel Processes in HPX: Designing an Infrastructure for Adaptive Resource Management". PhD thesis. Louisiana State University, 2014.

[3] M. Anderson et al. "An Application Driven Analysis of the ParalleX Execution Model". In: *CoRR* abs/1109.5201 (2011). http://arxiv.org/abs/1109.5201.

[4] E. Bajrovic et al. "Autotuning of Pattern Runtimes for Accelerated Parallel Systems." In: *PARCO 2013, September 2013, Munich, Germany*. Sept. 2013.

[5] R. F. Barrett, C. T. Vaughan, and M. A. Heroux. *MiniGhost: a miniapp for exploring boundary exchange strategies using stencil computations in scientific parallel computing.* Tech. rep. SAND2012-10431. 2011.

[6] S. Benedict, V. Petkov, and M. Gerndt. "Periscope: An online-based distributed performance analysis tool". In: *Tools for High Performance Computing 2009*. Springer, 2010, pp. 1–16.

[7] R. Brightwell and K. Pedretti. "An Intra-Node Implementation of OpenSHMEM Using Virtual Address Space Mapping". In: *Fifth Partitioned Global Address Space Conference*. Oct. 2011.

[8] M. Chaarawi et al. "A Tool for Optimizing Runtime Parameters of Open MPI". In: *Recent Advances in Parallel Virtual Machine and Message Passing Interface*. Lecture Notes in Computer Science 5205. Springer Berlin Heidelberg, 2008, pp. 210–217.

[9] S. Corporation. "eXascale PRogramming Environment and System Software (XPRESS)". http://xstack.sandia.gov/xpress/. Apr. 2015.

[10] M. Curtis-Maury et al. “Online Power-performance Adaptation of Multithreaded Programs Using Hardware Event-based Prediction”. In: *20th Annual International Conference on Supercomputing*. ICS ’06. Cairns, Queensland, Australia: ACM, 2006, pp. 157–166. DOI: 10.1145/1183401.1183426.

[11] I. J. Dooley. “Intelligent runtime tuning of parallel applications with control points”. PhD thesis. University of Illinois at Urbana-Champaign, 2011.

[12] A. Duran et al. “OmpSs: A Proposal For Programming Heterogeneous Multi-Core Architectures”. In: *Parallel Processing Letters* 21.02 (2011), pp. 173–193. DOI: 10.1142/S0129626411000151.

[13] M. Heroux and R. Barrett. *Mantevo Project*. 2011.

[14] H. Hoffmann et al. “Application Heartbeats: A Generic Interface for Specifying Program Performance and Goals in Autonomous Computing Environments”. In: *7th International Conference on Autonomic Computing*. ICAC ’10. Washington, DC, USA: ACM, 2010, pp. 79–88. DOI: 10.1145/1809049.1809065.

[15] K. A. Huck et al. “TAUg: Runtime Global Performance Data Access Using MPI”. English. In: *Recent Advances in Parallel Virtual Machine and Message Passing Interface*. Vol. 4192. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2006, pp. 313–321. DOI: 10.1007/11846802_44.

[16] E. Jeannot et al. “Communication and topology-aware load balancing in Charm++ with TreeMatch”. In: *Cluster Computing (CLUSTER), 2013 IEEE International Conference on*. Sept. 2013, pp. 1–8. DOI: 10.1109/CLUSTER.2013.6702666.

[17] H. Kaiser, M. Brodowicz, and T. Sterling. “ParalleX: An Advanced Parallel Execution Model for Scaling-Impaired Applications”. In: *Parallel Processing Workshops*. Los Alamitos, CA, USA: IEEE Computer Society, 2009, pp. 394–401. DOI: http://doi.ieeecomputersociety.org/10.1109/ICPPW.2009.14.

[18] L. V. Kale and G. Zheng. “Charm++ and AMPI: Adaptive Runtime Strategies via Migratable Objects”. In: *Advanced Computational Infrastructures for Parallel and Distributed Applications*. Wiley-Interscience, 2009, pp. 265–282.

[19] A. Knüpfer et al. “The Vampir performance analysis tool-set”. In: *Tools for High Performance Computing*. Springer, 2008, pp. 139–155.

[20] A. Mandal, R. Fowler, and A. Porterfield. “Modeling Memory Concurrency for Multi-Socket Multi-Core Systems”. In: *2010 IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS2010)*. IEEE. White Plains, NY, Mar. 2010, pp. 56–75.

[21] A. Mandal, R. Fowler, and A. Porterfield. “System-wide introspection for accurate attribution of performance bottlenecks”. In: *Second International Workshop on High-perfromance Infrastruture for Scalable Tools*. 2012.

[22] S. J. Martin and M. Kappel. “Cray XC30 Power Monitoring and Management”. In: *Cray User Group Conference Proceedings*. 2014.

[23] R. Miceli et al. “AutoTune: A Plugin-Driven Approach to the Automatic Tuning of Parallel Applications”. In: *Applied Parallel and Scientific Computing*. Lecture Notes in Computer Science 7782. Springer Berlin Heidelberg, 2013, pp. 328–342.

[24] Y. Oleynik et al. “Recent Advances in Periscope for Performance Analysis and Tuning”. English. In: *Tools for High Performance Computing 2013*. Springer International Publishing, 2014, pp. 39–51. DOI: 10.1007/978-3-319-08144-1_4.

[25] S. L. Olivier et al. “Scheduling Task Parallelism on Multi-socket Multicore Systems”. In: *International Workshop on Runtime and Operating Systems for Supercomputers*. ROSS ’11. Tucson, Arizona: ACM, 2011, pp. 49–56. DOI: 10.1145/1988796.1988804.

[26] V. Pillet et al. “Paraver: A tool to visualize and analyze parallel code”. In: *Proceedings of WoTUG-18: Transputer and occam Developments*. Vol. 44. mar. 1995, pp. 17–31.

[27] J. Planas et al. “Self-Adaptive OmpSs Tasks in Heterogeneous Environments”. In: *Parallel Distributed Processing (IPDPS), 2013 IEEE 27th International Symposium on*. May 2013, pp. 138–149. DOI: 10.1109/IPDPS.2013.53.

[28] B. Rountree et al. “Adagio: Making DVS Practical for Complex HPC Applications”. In: *23rd International Conference on Supercomputing*. ICS ’09. Yorktown Heights, NY, USA: ACM, 2009, pp. 460–469. DOI: 10.1145/1542275.1542340.

[29] B. Rountree et al. “Beyond DVFS: A first look at performance under a hardware-enforced power bound”. In: *Parallel and Distributed Processing Symposium Workshops & PhD Forum (IPDPSW)*. IEEE. 2012, pp. 947–953.

[30] S. Shende and A. D. Malony. “The TAU Parallel Performance System”. In: *International Journal of High Performance Computing Applications* 20.2 (Summer 2006), pp. 287–331.

[31] T. Sterling et al. “SLOWER: A performance model for Exascale computing”. In: *Supercomputing frontiers and innovations* 1.2 (2014), pp. 42–57.

[32] Y. Sun, J. Lifflander, and L. V. Kalé. “PICS: A Performance-analysis-based Introspective Control System to Steer Parallel Applications”. In: *International Workshop on Runtime and Operating Systems for Supercomputers*. ROSS ’14. Munich, Germany: ACM, 2014, 5:1–5:8. DOI: 10.1145/2612262.2612266.

[33] A. Tabbal et al. “Preliminary Design Examination of the ParalleX System from a Software and Hardware Perspective”. In: *SIGMETRICS Performance Evaluation Review* 38 (Mar. 2011), p. 4.

[34] C. Ţăpuş, I.-H. Chung, and J. K. Hollingsworth. “Active Harmony: Towards Automated Performance Tuning”. In: *2002 ACM/IEEE Conference on Supercomputing*. SC ’02. Baltimore, Maryland: IEEE Computer Society Press, 2002, pp. 1–11.

[35] *The Kitten Lightweight Kernel*. https://software.sandia.gov/trac/kitten. Sandia National Laboratories.

[36] The National Energy Research Scientific Computing Center (NERSC). “Edison”. https://www.nersc.gov/users/computational-systems/edison/. Apr. 2015.

[37] T. Williams and C. Kelley. “Gnuplot Homepage”. http://www.gnuplot.info. Apr. 2015.

[38] F. Wolf et al. “Usage of the SCALASCA toolset for scalable performance analysis of large-scale parallel applications”. In: *Tools for High Performance Computing*. Springer Berlin Heidelberg, 2008, pp. 157–167.

[39] G. Zheng et al. “Hierarchical Load Balancing for Charm++ Applications on Large Supercomputers”. In: *Parallel Processing Workshops (ICPPW), 2010 39th International Conference on*. Sept. 2010, pp. 436–444. DOI: 10.1109/ICPPW.2010.65.