

ENERGY EFFICIENT JAVA APPLICATION - EMPIRICAL STUDIES AND
RUNETIME DESIGN

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DISSERTATION

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ABSTRACT

Energy efficiency is increasingly becoming critical for computer systems for at least two reasons. First, widely used platform such as, Android phones, Apple Watch and drones, are powered by battery and battery life has a direct impact on the usability of these systems. On the higher end, electricity bills are significant part of operational cost for data centers.

A growing interest is to study energy consumption on the application level. Unlike lower-level energy management strategies that often happen “under the hood,” application-level energy management has some unique advantages, applications and its runtime systems are viewed as a white box, whose structural features may be considered for energy optimization.

First, we study the energy impact of alternative data management choices by programmers, such as data access patterns, data precision choices, and data organization. we further attempt to build a bridge between application-level energy management and hardware-level energy management, by elucidating how various application-level data management features respond to Dynamic Voltage and Frequency Scaling (DVFS). Finally, we apply our findings to real-world applications, demonstrating their potential for guiding application-level energy optimization.

Second, we conducted an empirical investigation of 16 collection implementations (13 thread-safe, 3 non-thread-safe) grouped under 3 commonly used forms of data structures (lists, sets, and mappings). Using micro- and real world-benchmarks, we show that small design decisions can greatly impact energy consumption. For example, different implementations of the same thread-safe collection can have widely different energy consumption behaviors. This variation also applies to the different operations that each collection implements, e.g. a collection implementation that performs traversals very efficiently can be more than an order of magnitude less efficient than another implementation of the same

collection when it comes to insertions.

Third, we introduce VINCENT¹, a novel JVM-level solution for improving the energy efficiency of Java applications. The key insight of VINCENT is that the programming abstraction of methods may serve as an ideal granularity for phase-based energy management, and specifically, Dynamic Voltage and Frequency Scaling (DVFS). VINCENT is a multi-pass feedback-directed optimizer with a focus on applying DVFS to hot methods.

¹“I have tried to express the terrible passions of humanity by means of red and green.”
— Letter from Vincent van Gogh to Theo van Gogh, Arles, 8 September 1888

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Chapter 1

Introduction

Energy efficient computing is an active direction of research with results from many computer science areas. The most established area is hardware solutions. For example, how to save energy by designing low power CPUs and caches? Further up on the compute stack, there are also many other system level solutions. For example, there are some mobile device operating systems designed for smart energy management. In recent years, a growing interest is to study energy consumption on the application level. Real word applications are often very large with very complex structures. First, applications are viewed as a white box, whose structural features may be considered for energy optimization. Second, the knowledge of software developers and their design choices can influence energy efficiency. Programmers need to understand the energy behaviors at different levels of software granularities in order to make judicious design decisions in order to improve the energy efficiency. If energy aware programmers wish to make their applications more energy efficient, where should they start?

First, an emerging direction in programming is approximate programming. The premise is programmers can accept different versions of the same program but with different quality of service. For example, the programmer is willing to use single floating point numbers when the battery is low. Otherwise double should be used. To effective, a crucial question that needs to be answered is how much energy savings could there be when the data type is switched from double to float.

Second, despite Java thread-safe collections of characteristics of the performance, scalability and thread-safety are widely discussed by software developers. The energy effi-

ciency of those collections are still not widely considered in the application design and implementation. That is, the performance is not always the only indicator for even the energy consumption of different implementation of the same collection. For some cases, power consumption plays an important role in the energy consumption. This is especially true for the thread-safe collections – the synchronized locks are commonly used in the collection implementations, which could cause the other threads to wait for the resources and turn to be idle state so the power consumption of the core would be reduced.

Finally, energy optimization should not be studied in isolation. What are the cross layer effects? For example: a classic hardware level energy management technique is dynamic voltage and frequency scaling (DVFS). The unknown is how hardware features interact with application level energy management features. The application runtime, e.g. JVM, Android runtime and etc. serve the excellent candidate for the cross layer between the lower layers and the higher layers. That is, the runtime has accessibility of method specific information and its respective invocation frequency. As a result, unlike its neighbor layers, the runtime has ability to manage the energy consumption with the boundary of programming method.

1.1 Contributions

To understand the energy consumption behavior of the applications to better serve the application level energy optimization at runtime. We have developed a energy profiling Java APIs to let us enable to refine the energy analysis. We further discuss the interactive energy consumption behaviors between application and hardware. As a result, we propose a novel application runtime energy optimization solution.

Data-Oriented Characterization of Application-Level Energy Optimization: we have designed a new methodology of energy measurement – jRAPL¹ It is an open source fined grained energy measurement java library running on Intel CPUs with Running Average Power Limit (RAPL) [26]. Instead of traditional meter-based energy profiling, which is

¹<http://kliu20.github.io/jRAPL/>

hard to synchronize the beginning/end of measurement with the specific program execution stage, jRAPL enables us to profile the energy consumption behavior of the program with finer granularity without synchronization needed. We collect the energy profiling information to show: (i) How the application-level data management impact energy consumption (ii) How does application-level energy management interact with hardware-level energy management. We apply the energy optimization strategies to the real-world benchmarks, SUNFLOW and XALAN, from the well-known DaCapo suite² [12]. It shows the energy consumption can be reduced by 4.29% without performance loss.

A Comprehensive Study on the Energy Efficiency of Java Thread-Safe Collections:

We further explore the energy optimization space on the choice of Java thread-safe collections. By energy profiling of 13 thread-safe collections, we talk the impact of energy consumption base on four points. (i) Different implementation of the same collection (ii) Different operations in the same implementation of a collection (iii) Energy consumption scalability of collections in the aspect of multithreading. (iv) Energy consumption of different collection configurations and usages. With the knowledge of the energy optimization space, we made the small changes in both micro-benchmarks and DaCapo benchmark suite by replacing the collections to be more energy efficient collections. We got energy consumption improved by 2x in our micro-benchmarks, and by 10%, in DaCapo benchmark suite.

Vincent: Energy-Efficient Hot Methods for Java Applications: We propose a novel application runtime-based energy optimizer in a JVM, called Vincent. Instead of the existing application runtime-based energy profiling and optimization methodology, which applies for the specific service of application runtime [1], [89], [44], Vincent built on top of JVM is aware of the programming abstraction of methods. It would allow Vincent can align the method-grained energy profiling with the boundary of methods optimization. Thanks to the Just-In-Time (JIT) design, Vincent is aware of the method-grained hotspot to limit the overhead of the energy profiling and optimization.

²<http://www.dacapobench.org/>

1.2 Outline

Rest of the dissertation is organized as follows. In Chapter 2, We present the Intel RAPL technique. The energy profiling technique that jRAPL built on top of. We further discuss Dynamic Voltage and Frequency Scaling (DVFS), the classic energy management strategy. Then we would introduce the JIT componnet of JikesRVM [3, 2], and Adaptive Optimization System (AOS) [5] of JikesRVM for the background of the instrumentation and hot method selection Vincent built on top of. In Chapter 3, we present the related work. In Chapter 4, we present data-Oriented characterization of application-level energy optimization. In Chapter 5, we present the energy efficiency impact of Java thread-safe collections. In Chapter 6, we present Vincent, a JVM-based energy-efficient system for Java application. In Chapter 7, we conclude the dissertation and discuss the future directions.

Chapter 2

Background

Energy profiling and management strategies are the most basic questions of energy efficient computing that need to be answered. In this chapter, we introduce the background concepts related to the energy profiling and management strategy we use. Furthermore, we introduce one JVM component called AOS which uses in JikesRVM to recognize the hot methods. Optimization compilers and Intermediate Representation layers in JIT.

2.1 RAPL

RAPL is an Intel technology which collects accumulated energy information and places it in a set of non-architectural registers called Machine-Specific Register (MSRs). As Figure 2.1 ¹ (edit from Intel Power Governor Documentation) shows, it records the energy consumption from three different domains, e.g. CPU core, CPU uncore(L3 cache, on-chip GPUs, and interconnects), package and DRAM. RAPL has ability to do energy management through writing the bits to some certain domains of registers. Since this dissertation only uses energy profiling part of RAPL. When we talk about jRAPL, it would be equivalent to energy profiling.

2.2 DVFS

DVFS [43] is a common CPU feature where the operational frequency and the supply voltage of the CPU can be dynamically adjusted. DVFS is a classic and effective power

¹<https://software.intel.com/content/www/us/en/develop/articles/intel-power-governor.html>

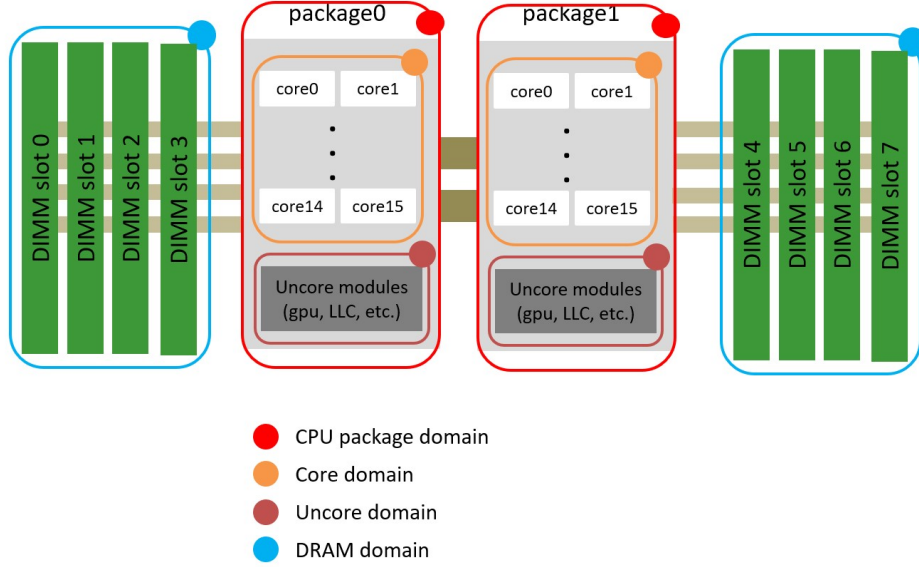


Figure 2.1: RAPL Domains

management strategy. The dynamic power consumption of a CPU, denoted as P , can be computed as $P = C * V^2 * F$, where V is the voltage, F is the frequency, and C is a (near constant) factor. The energy consumption E is an accumulation of power consumption over time t , *i.e.*, through formula $E = P * t$.

2.3 Hot Method Selection

Hot method selection is the essential component of JIT which is commonly supported by JVM-based platform. As Figure 2.2 from [5] shows, AOS serves as a online feedback-directed optimization component in JikesRVM [3, 2] that is used for hot method selection and optimization recompilation decision making. In order to profile the method execution with low cost, AOS takes samples of the method execution and push the count to the corresponding priority queue. When the threshold reached, only the high prioritized methods would be considered as the hot method for the optimizing recompilation uses.

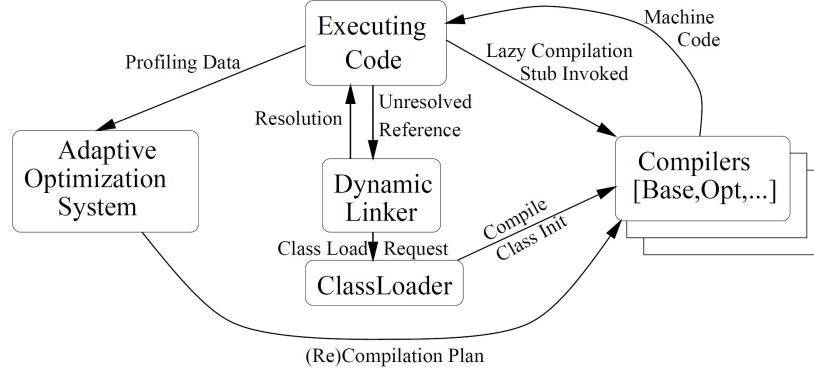


Figure 2.2: Methods Compilation Workflow

2.4 Instrumentation In JIT

Instrumentation has been widely used to add to the existing program in profiling and tracing. Instrumentation can be injected in the source code directly or in the different compilation stages with IR or binary. Different with instrumentation injection in the static compiler or interpreter, instrumentation injection in JIT can get the profiling information on-the-fly and makes advantage of the hot methods selection features in JIT. As Figure 2.3² shows, JikesRVM has three levels of IR, High Level IR (HIR), Low Level IR (LIR) and Machine Specific IR (MIR). Each level would optimize and translate the method from higher level IR to the lower level IR. In JikesRVM, the instrumentation can be injected to any level of IR dynamically. In this dissertation, we injected our energy profiling and energy optimization instrumentation to HIR to LIR. Once the method is picked as hot method, the instrumentation would be injected and carried all the way to the program ends.

²<https://www.jikesrvm.org/Resources/Presentations/> (Jikes RVM Optimizing Compiler Intermediate Code Representation)

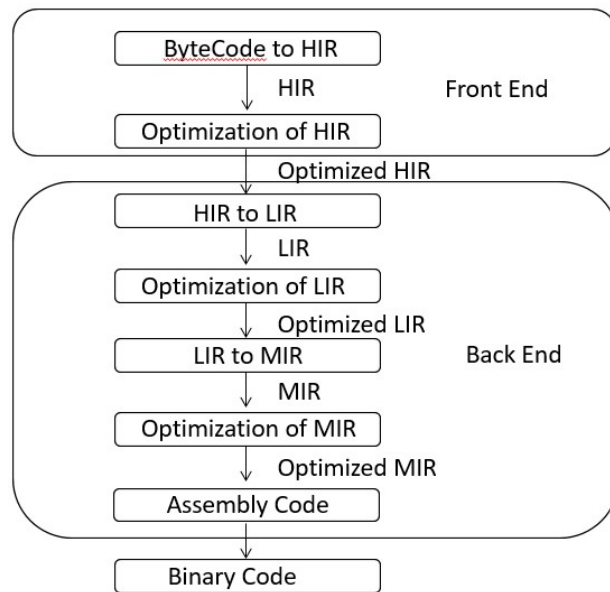


Figure 2.3: Optimizing Compiler Architecture

Chapter 3

Related Work

Energy-efficiency is an active research area many layers of compute stack. This chapter, we overview energy efficiency techniques in other layers.

3.1 Application-Level Energy Management.

In recent years, a number of studies have explored energy management strategies at the application level as an attempt to empower the application programmer to take energy-aware decisions. Some focus on the design of new programming models, with examples such as Green [7], Energy Types [23], and Eco [93]. In these systems, recurring patterns of energy management tasks are incarnated as first-class citizens. Approximated programming [19] trades and reasons about occasional “soft errors”, *i.e.*, errors that may reduce the accuracy of the results, for a reduction in energy consumption. The relationship between this line of work and our work is complementary: existing work provides language support to facilitate energy optimization, whereas our work experimentally and empirically establishes the room of the energy optimization space.

3.2 Energy Profiling

Energy profiling is a broad area of research. Prior work has attempted to model energy consumption at the individual instruction level [86], system call level [30], and bytecode level [80]. Recent progress also includes fine-grained profiling for Android programs [39, 51], with detailed energy profiling of different hardware components such as camera, Wi-Fi

and GPS. RAPL-based energy profiling has appeared in recent literature (*e.g.*, [46, 84]); its precision and reliability has been extensively studied [38].

Energy profiling is more commonly conducted at the system level (*e.g.*, [64, 34]), rather than at the boundary of programming abstractions such as methods. Chappie [6] supports method-grained energy profiling. It adopts an approach with fixed time intervals, a necessary design choice when there is no JVM modification. VINCENT is fundamentally a JVM-centric approach. It takes advantage of the JVM support such as instrumentation to enable delimited sampling. To VINCENT, energy profiling is an intermediate step for energy optimization, which Chappie does not support.

3.3 Empirical Studies

Existing research that dealt with the trade-off of comparing individual components of an application and energy consumption has covered a wide spectrum of applications. These studies vary from concurrent programming [67], VM services [17, 46], cloud offloading [48], and refactoring [77]. To the best of our knowledge, our study is the first in exploring how different choices of fine-grained data manipulation impact on the energy consumption of different hardware sub-systems, and how application-level energy management and lower-level energy management interact.

Empirical studies often illuminate the energy consumption (and performance) of managed language runtimes. An early study by Vijaykrishnan et al. [89] focuses on the energy consumption impact on the memory hierarchy (cache and main memory) by JIT-enabled Java applications. Esmailzadeh et al. [32] studies energy efficiency with a focus on diverse configurations of workload and hardware. Sartor and Eeckhout [79] illuminates the performance of Java applications, with a focus on mapping Java application threads and JVM threads to multi-core hardware. Despite that their focus is on performance, DVFS is extensively used in their design space exploration, such as running GC threads at different CPU frequencies. Pinto et al. [71] studies the impact of energy consumption when alternative thread management designs in Java are used, such as different settings of the thread pool. Specific to ForkJoin [50], a study [68] also explored the impact of work stealing

on the performance and energy trade-off in Java runtimes. The energy impact of different choices of Java collection classes — such as an `ArrayList` or a `HashMap` — were also a subject of studies [37, 73]. Kambadur [?] takes a cross-layer approach to surveying the energy management solutions, studying the interface and interaction of different hardware/OS/compiler configurations. Li *et al.* [52] presented an evaluation of a set of programming practices suggested in the official Android developers web site. They observed that some practices such as the network packet size can provide impressive energy savings, while others, such as limiting memory usage, had minimal impact on energy usage. Vallina-Rodriguez *et al.* [88] surveys the energy-efficient software-centric solutions on mobile devices, ranging from operating system solutions to energy savings via process migration to the cloud and protocol optimizations.

Java collections are the focus of several studies [90, 74, 55], although only few of them are interested in analyzing their energy consumption [69, 60, 40]. In a previous effort, we have presented a preliminary study on the energy consumption of the Java thread-safe collections [69]. This current study greatly expands the previous study, attempting to answer four different research questions. The preliminary paper only addressed two of these research questions. Also, in this current submission, we employ two different energy profiling methods in two different machines, instead of just one, as reported in the initial study. Finally, we also applied our findings into two real-world, non-trivial benchmarks.

To the best of our knowledge, two other studies intersect with our goal of understanding the energy consumption of Java collections [60, 40]. SEEDS [60] is a general decision-making framework for optimizing software energy consumption. The authors demonstrated how SEEDS can identify energy-inefficient uses of Java collections, and help automate the process of selecting more efficient ones. The focus of their work is the methodology itself, not the energy footprint of Java collections. The closest study was conducted by Hasan *et al.* [40]. In this study, the authors also investigated collections grouped with the same interfaces (`List`, `Set`, and `Map`). However, they do not focus on concurrent collections neither perform experiments in a multi-core environment. Therefore their study can be seen as complementary to ours.

3.4 JVM-Centric Solutions

A relatively small number of JVM-centric solutions exist for energy optimization. Chen et al. [22] relies on garbage collection tuning to save memory system energy consumption in JVMs. Cao et al. [18] improves the energy efficiency of JVM by assigning JVM services to small cores on asymmetric hardware. DEP+BURST [1] is a performance predictor and energy management system where JVM features such as synchronization, inter-thread dependencies, and store bursts, are taken into account for performance/energy prediction. Hussein et al. [44] investigates the energy impact of garbage collector design in the Android runtime. They proposed some extensions to improve the energy efficiency of asynchronous GC in Android. Overall, a common theme in existing work is to focus on JVM services (such as GC and thread management), but none considers energy optimization at the granularity of programming abstractions. Our work complements existing work with a fine-grained method-based approach for energy optimization. For unmanaged language runtimes, Hermes [76] is an energy-efficient solution built on top of Cilk. It performs DVFS based on the dependencies between thief threads and victim threads in a work stealing runtime. Zhang *et al.* [92] presented a mechanism for automatically refactoring an Android app into one implementing the on-demand computation offloading design pattern, which can transfer some computation-intensive tasks from a smartphone to a server so that the task execution time and battery power consumption of the app can be reduced significantly. Cao *et al.* [17] described how different VM services (such as the Just-In-Time compiler, interpretation and/or the garbage collector) impact energy consumption.

Chapter 4

Data-Oriented Characterization of Application-Level Energy Optimization

Modern computing platforms are experiencing an unprecedented diversification. Beneath the popularity of the Internet of Things, Android phones, Apple iWatch and Unmanned Aerial Vehicles, a critical looming concern is energy consumption. Traditionally addressed by hardware-level (*e.g.*, [43, 26]) and system-level approaches (*e.g.*, [33, 75]), energy optimization is gaining momentum at the level of application development [7, 19, 23, 48, 58, 93]. These *application-level energy management* strategies complement lower-level strategies with an expanded *optimization space*, yielding distinctive advantages: first, applications are viewed as a white box, whose structural features may be considered for energy optimization; second, the knowledge of programmers and their design choices can influence energy efficiency. Recent studies [66] show application-level energy management is in high demand among application developers.

The grand challenge ahead is the lack of systematic guidelines for application-level energy management. Unlike lower-level energy management strategies that often happen “under the hood,” application-level energy management requires the participation of application software developers. For example, programmers need to understand the energy behaviors at different levels of software granularities in order to make judicious design decisions, and thus improve the energy efficiency. As indicated in recent studies, the devil often lies with the details [17, 67], and the guidelines are often anecdotal or incorrect [66]. Should we pessimistically accept that the optimization space of application-level energy management as unchartable waters, or is there wisdom we can generalize and share with application developers in their energy-aware software development?

This chapter is aimed at exploring this important yet largely uncharted optimization space. Even though the energy impact of arbitrary developer decisions — *e.g.*, using encryptions when the battery level is high and no security otherwise — is impossible to generalize and quantify, we believe a sub-category of such design decisions — those related to *data* — have interesting and generalizable correlations with energy consumption. With Big Data applications on the rise, we believe the data-oriented perspective on studying application-level energy management may in addition have the forward-looking appeal on future energy-aware software development. In particular, we attempt to answer the following research questions:

RQ1 How does the choice of application-level data management features impact energy consumption?

RQ2 How does application-level energy management interact with hardware-level energy management?

For **RQ1**, we consciously look into features “middle-of-the-road” in granularity: they are coarser-grained than instructions [86] or bytecode [39, 51] to help retain the high-level intentions of application developers, yet at the same time finer-grained than software architectures or frameworks to facilitate reliable quantification. Specifically, we study the impact of energy consumption over different choices of:

- *data access pattern*: For a large amount of data, does the pattern of access (sequential vs. random, read vs. write) impact energy consumption?
- *data organization and representation*: Do different representations of the same data (unboxed vs. boxed data, a primitive array vs. an `ArrayList`, an array of objects vs. multiple arrays of primitive data) have impact on energy consumption?
- *data precision*: Do precision levels (*e.g.*, short, int, and long) of data have impact on energy consumption?
- *data I/O strategies*: For I/O-intensive applications, do different choices of data processing — such as buffering — have impact on energy consumption?

To answer **RQ2**, we are aimed at connecting application-level energy management and its lower-level counterparts. It is our belief that energy consumption is the combined effect of interactions through application software, system software, and hardware; the best energy management strategy should be the harmonious coordination of all layers of the compute stack. Concretely, we reinvestigate the aforementioned data-oriented application features in the context of Dynamic Voltage and Frequency Scaling (DVFS) [43], arguably the most classic hardware-based energy management strategy. This exploration expands the energy optimization space where “software meets hardware,” over a frontier where software engineering research joins forces with hardware architecture research.

Overall, this chapter makes the following contributions:

- It performs the first empirical study that systematically characterizes the optimization space of application-level energy management, from the fresh perspective of *data*. The multi-dimensional study ranges from data access pattern, data organization and representation, data precision, and data I/O intensity.
- It conducts experiments to bridge application-level and hardware-level energy management, and constructs a unified optimization space connecting hardware and application software.
- It reports the release of jRAPL, an open-source library to precisely and non-invasively gather energy/performance information of Java programs running on Intel CPUs.

4.1 Methodology

In this section, we introduce our research methodology and the details of our experimental environment.

4.1.1 The Open-Source jRAPL Library

We have developed a set of APIs for profiling Java programs running on CPUs with Running Average Power Limit (RAPL) [26] support. Originally designed by Intel for enabling chip-level power management, RAPL is widely supported in today’s Intel architectures,

including Xeon server-level CPUs and the popular i5 and i7. RAPL-enabled architectures monitor the energy consumption information and store it in Machine-Specific Registers (MSRs). Such MSRs can be accessed by OS, such as the `msr` kernel module in Linux. RAPL is an appealing design, particularly because it allows energy/power consumption to be reported at a fine-grained manner, *e.g.*, monitoring CPU core, CPU uncore (L3 cache, on-chip GPUs, and interconnects), and DRAM separately.

Our library can be viewed as a software wrapper to access the MSRs. The RAPL interface itself has broader support for energy management, whereas our library only uses its capability for information gathering, a mode in RAPL named “energy metering.” Since the `msr` module under Linux runs in privileged kernel mode, jRAPL works in a similar manner as system calls.

The user interface for jRAPL is simple. For any block of code in the application whose energy/performance information is to the interest of the user, she simply needs to enclose the code block with a pair of `statCheck` invocations. For example, the following code snippet attempts to measure the energy consumption of the `doWork` method, whose value is the difference between `beginning` and `end`:

```
double beginning = EnergyCheck.statCheck();  
doWork();  
double end = EnergyCheck.statCheck();
```

Additional APIs also allow time and other lower-level hardware performance counter information (for diagnostics) to be collected. The API can flexibly collect either CPU time, User Mode time, Kernel Mode time, and Wall Clock time. If not explicitly specified, all time reported in the paper is Wall Clock time. When a CPU consists of multiple cores, jRAPL can report data either individually or combined. Throughout the paper, all energy/power data for multi-core CPUs are reported as combined.

Compared with traditional approaches based on physical energy meters, the jRAPL-based approach comes with several unique advantages:

- *Refined Energy Analysis*: thanks to RAPL, our library can not only report the over-

all energy consumption of the program, but also the breakdown (1) among hardware components and (2) among program components (such as methods and code blocks). As we shall see, refined hardware-based analysis allows us to understand the relative activeness of different hardware components, ultimately playing an important role in analyzing the energy behaviors of programs. In meter-based approaches, hardware design constraints often make it impossible to measure a particular hardware component (such as CPU cores only, or even DRAMs because they often share the power supply cable with the motherboard).

- *Synchronization-Free Measurement*: in meter-based measurements, a somewhat thorny issue is to synchronize the beginning/end of measurement with the beginning/end of the program execution of interest. This problem is magnified for fine-grained code-block based measurement, where the problem *de facto* becomes the synchronization of measurement and the program counter. With jRAPL, the demarcation of measurement coincides with that of execution; no synchronization is needed.

One drawback of the jRAPL-based approach is the energy data collection itself may incur overhead. Fortunately, the time overhead for MSR access is in the microseconds, orders of magnitude lower than the execution time of our experiments.

4.1.2 Experimental Environment

We run each experiment in the following machine: a 2×8 -core (32-cores when hyper-threading is enabled) Intel(R) Xeon(R) E5-2670, 2.60GHz, with 64GB of DDR3 1600 memory. It has three cache levels (L1, L2 and L3) with 64KB per core (128KB total), 256KB per core (512KB total) and 3MB (smart cache), respectively. It is running Debian 6 (kernel 3.0.0-1-amd64) and Oracle HotSpot 64-Bit Server VM (build 20.1-b02, mixed mode), JDK version 1.6.0_26. The processor has the capability of running at several frequency levels, varying from 1.2, 1.4, 1.6, 1.8, 2.0, 2.2, 2.4 and 2.6 GHz.

For the JVM, the parallel garbage collector is used, and just-in-time (JIT) compilation is enabled to be realistic with real-world Java applications. The initial heap size and maximum heap size are set to be 1GB and 16GB respectively. We run each benchmark 6 times

within the same JVM; this is implemented by a top-level 6-iteration loop over each benchmark. The reported data is the average of the last 4 runs. We chose to report the last 4 runs because JIT execution tends to stabilize in the later runs [67]. If the standard deviation of such 4 runs is greater than 5%, we executed the benchmark again until results stabilize. All experiments were performed with no other load on the OS. Unless explicitly specified in the paper, the default ondemand governor of Linux is used for OS power management. Turbo Boost feature is disabled.

4.2 Application-Level Energy Management

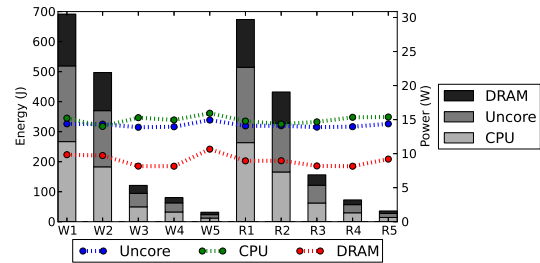
This section explores the optimization space of application-level energy management through five data-oriented characterizations.

4.2.1 Data Access Patterns

We first examine how energy consumption differs under sequential and random access. By access, we consider both read and write operations. The read micro-benchmark traverses a large int array (of size $N=50,000,000$) and retrieves the value at each position, while the write counterpart micro-benchmark assigns integer 1 to each position.

To construct a fair comparison between sequential and random access, we resort to an “index array” preloaded with index numbers: numbers from 1 to N in that order for sequential access, and a random permutation of numbers between 1 and N for random access. Thanks to the index array, the program logic is identical for sequential and random access. The reported results do not consider index array preloading.

The figure on the right shows¹ the benchmarking results, with bars for energy data and lines for power data. We do not explicitly show the execution time, which by physics, can be derived as the division of energy and power. There are 10 bars



¹Throughout the paper, all bar charts follow the same legends as those in this figure.

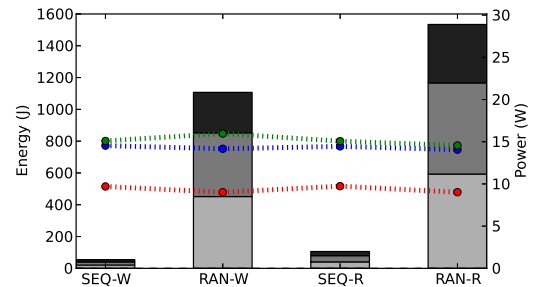
for each figure, the first five of which (with prefix W) indicate write access, and the remaining five (with prefix R) indicate read access. In each group, suffix 1 represents 100% randomness in access, 2 for 25% randomness, 3 for 1% randomness, and 4 for 0.1% randomness, and 5 for 0% randomness, *i.e.*, sequential access. The level of randomness is controlled by index range: *e.g.*, we imitate 1% random access by allowing random permutation within each $N \times 1\%$ interval of the array.

The data reveals the significant impact of access randomness on energy consumption. The more random data access is, the more energy is consumed. This is consistent with hardware behaviors due to cache locality. Further observe that read vs. write accesses make little difference on energy consumption. The conventional folklore is that writes are often more expensive than reads, but this effect, if any, appears to be small on energy consumption. In fact, in one combination R3 vs. W3, the opposite is true.

4.2.2 Data Representation Strategies

Let us now investigate the impact of different data representation strategies on energy consumption. First, we look into the difference between representing a sequence of integers as a primitive array and as an `ArrayList`. We construct a similar experiment as one described in Section 4.2.1, by traversing an `ArrayList` of `Integer`'s of a large size ($N = 50,000,000$). We mimic “read” through the `List.get(int i)` method, and “write” through the `List.set(int i, Object o)` method.

The results of the `ArrayList` implementation are shown the figure on the right, where SEQ/RAN/R/W labels denote sequential, 100% random, read, and write access, respectively. Compared with Section 4.2.1, energy consumption is much higher: the RAN-R configuration with prim-

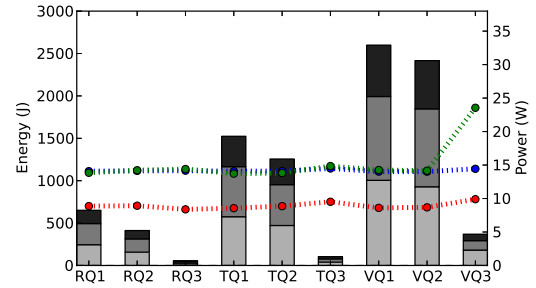


itive array representation consumes around 670J, whereas its counterpart result here is around 1550J. This does not come as a surprise. `ArrayList` uses boxed data (of `Integer` type) whereas our primitive array implementation uses unboxed data (of `int` type). Furthermore, the getter/setter required by `ArrayList` are method invocations, more expensive than primitive array read/write.

This experiment motivated us to answer a more general question related to object-oriented languages: when we say an object is accessed, which representation of the object is being accessed: a reference to it, a value it holds, or the type it has? Do they have the same effect on energy consumption? We construct the next experiments, in three groups:

- *Reference Query (RQ)*: accesses the reference of an `Integer` object;
- *Type Query (TQ)*: accesses the type held by an `Integer` object;
- *Value Query (VQ)*: accesses the value that an `Integer` object holds;

The result on the right is divided into three groups as above. In each group, postfix 1 denotes 100% random access, 2 denotes 25% random access, and 3 denotes sequential access. For the TQ experiment, our benchmark applies `instanceof` operator to the object. To avoid source-level compiler optimization performed by modern Java compilers such as transforming expression `x instanceof Integer` to a no-op if `x` is only assigned to hold an `Integer` object, our micro-benchmark assigns objects of different types to reference `x`, and the `instanceof` operator cannot be optimized away through standard points-to analysis.



RQ and TQ are both more efficient than VQ. According to the runtime semantics of object-oriented programs, RQ only entails a stack access, whereas VQ includes access to

```

class Grouped {
    int a, b, c, d, e = ...;
}
class Main {
    Grouped[] group = ...;
    void calc() {
        for (int i = 0; i < N; i++) {
            group[i].e = group[i].a * group[i].b * group[i].c * group[i].d;
        }
    }
}

```

Figure 4.1: Object-Centric Data Grouping

```

class Main {
    int[] a = ..; int[] b = ..; int[] c = ..; int[] d = ..; int[] e = ..;
    void calc() {
        for (int i = 0; i < N; i++) {
            e[i] = a[i] * b[i] * c[i] * d[i];
        }
    }
}

```

Figure 4.2: Attribute-Centric Data Grouping

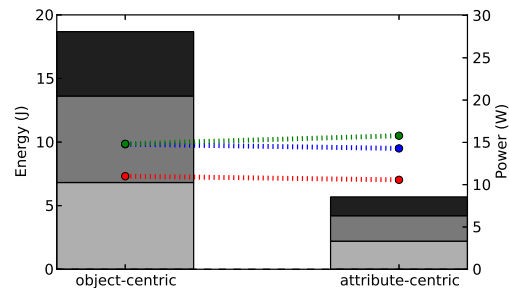
the heap, a much more expensive operation.

Less obvious is the case of TQ. On one hand, the type of an object is stored as object metadata, whose access also requires heap access. As a result, TQ is more expensive than RQ. On the other hand, all objects of the same type share the same metadata representing the type, and repeated queries of the same type yield high cache hits. As a result, TQ is cheaper than VQ.

4.2.3 Data Organization

In the next experiment, we consider two programs in Figure 4.1 and Figure 4.2. Functionally equivalent, the first *object-centric* program accesses a large array (of size $N=50,000,000$) of objects with 5 fields, and the second *attribute-centric* program accesses 5 primitive arrays.

As shown here, the object-centric data grouping consumes about 2.62x energy. The results here may reveal a trade-off between programming productivity and energy efficiency. Object-oriented encapsu-

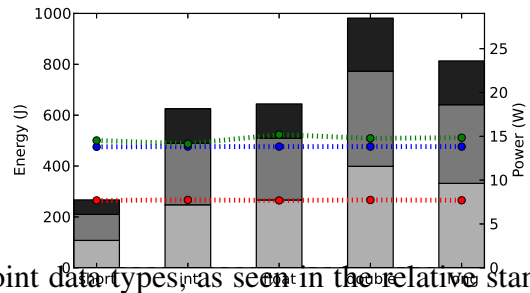


lation is known to have many benefits, such as modularity, information hiding, and maintainability. That being said, it does pay a toll on energy consumption, likely due to garbage collection. Another plausible cause is that there is no guarantee that objects in the array are allocated in contiguous space on the heap. As a result, even though Fig. 4.1 may be cache-friendly for retrieving the 5 fields for the same object, it may incur more cache misses when the entire array is traversed.

4.2.4 Data Precision Choices

We next analyze the impact of data precision choices on energy consumption. Our micro-benchmark performs the multiplication of two 1000×1000 matrices. For our experiments, we vary the matrix element type, declared with the `short`, `int`, `float`, `double`, and `long` types respectively for each variation of the benchmark. In our environment, `short/int/float/double/long` data types are 16/32/32/64/64 bits respectively. To set a fair comparison, we pre-fill matrices with `double` values through random number generation. All other variations of the benchmark pre-fill their matrix data through data conversion from the `double` matrix. In other words, all experiments operate on matrices of comparable values, only with different precisions. Our reported results exclude the pre-filling/converting stage above.

Our experiments show that energy consumption grows with the number of bits (a) among the non-floating point data types, as reflected by the relative standings between `short`, `int`, and `long`. (b) among floating point data types, as seen in the relative standings between `float` and `double`. Both are consistent with architecture-level comparisons, where instructions operating on more bytes/words are more expensive.

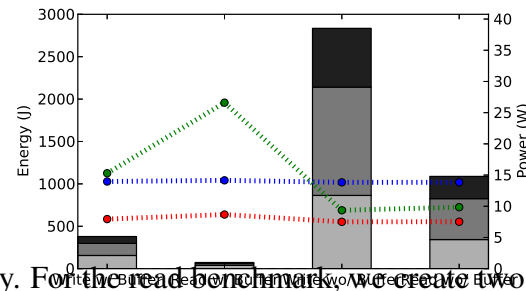


It is however unreliable to use the number of bits to cross-compare between non-floating

point types and floating point types. Programs with floating point types involve the use of FPUs. Based on our experience, one must be cautious to draw generalizations from cross-comparisons between FPU-intensive programs and those otherwise. For instance, the two 32-bit types used in our benchmarking — `int` and `float` — appear to incur similar amounts of energy consumption. As we shall see in the Section 4.4 however, the two may also lead to drastically different consumptions. It is a reminder for energy-conscious programmers who wish to save energy by modifying their float-precision program to one with `int` precision — the strategy may or may not be effective.

4.2.5 Data I/O Configurations

Finally, we analyze the energy behaviors of I/O operations. We construct two micro-benchmarks that read and write 50MB data from/to a file, using `FileInputStream` and `FileOutputStream` objects respectively. For the read benchmark, we create two variations, one with buffering through the use of the `BufferedInputStream` object, and the other without. Similarly, the write benchmark has two variations. The one with buffering uses the `BufferedOutputStream` object.



As the figure reveals, buffering has significant impact on improving energy efficiency. Indeed, buffer removal in essence disables bulking of I/O operations, so its effect on energy consumption is dramatic. Furthermore, observe that data output is significantly more energy-consuming than data input. Third, the power consumption of unbuffered file access (about 10W) is lower than that of buffered access. Unbuffered file access leads to a much higher level of I/O intensity. As a result, CPU is more likely to remain idle, and more likely to be scaled down by Linux’s default power management strategy, the `ondemand` governor.

RQ1 Summary: *Random access, object-centric data organization, unbuffered I/O consume significantly more energy. The energy consumption for memory read and write are on par, but file write is significantly more expensive than file read. Data types with more bits tend to consume more energy, but there is no simple generalization to cross-compare FPU-intensive types and those that are not.*

4.3 Unifying Application-Level Optimization with DVFS

This section places application-level energy management in a broader context, investigating its combined impact with hardware-based energy management.

Background. DVFS [43] is a common CPU feature where the operational frequency and the supply voltage of the CPU can be dynamically adjusted. DVFS is a classic and effective power management strategy. The dynamic power consumption of a CPU, denoted as P , can be computed as $P = C * V^2 * F$, where V is the voltage, F is the frequency, and C is a (near constant) factor. The energy consumption E is an accumulation of power consumption over time t , *i.e.*, through formula $E = P * t$.

Result Summary. We have conducted the same experiments reported in the previous section, except that the executions are conducted at different CPU frequencies. Due to page limit, we defer the complete data set in the online repository (see Section 4.6 for information). Figure 4.3 and Figure 4.4 report selected results. All figures are represented as heat map matrices.

A common trend among these experiments is that downscaling CPU often leads to less “favorable” results: in the majority of experiments, not only there will be a performance loss, but also increased energy consumption. The root cause is that DVFS only directly influences the CPU power consumption. The power consumptions for the Uncore and the DRAM sub-systems remain roughly constant. Thus, since time increases as frequency decreases, energy consumption for these sub-systems increases as well when a lower CPU frequency is selected. This is a sober reminder of the applicability of DVFS as an en-

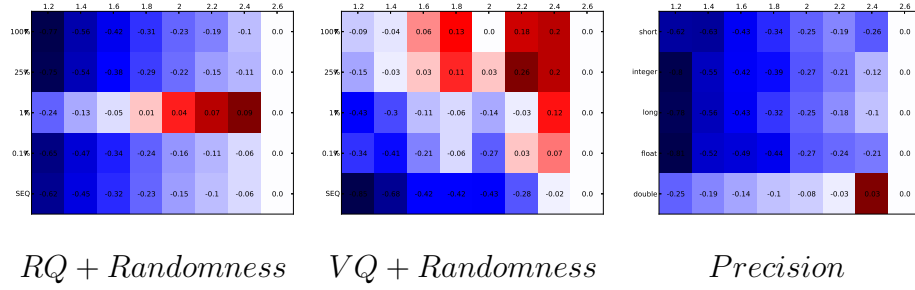


Figure 4.3: Selected Energy Results of DVFS Combined with Data Access, Data Representation, and Data Precision. (Labels on top are CPU frequencies, and labels to the left are random/sequential access patterns. All data are normalized energy consumption against the 2.6Ghz data of the same row. Red indicates savings, whereas Blue indicates loss. The darker the Red shade, the more “favorable” the configuration is, *i.e.*, greater energy savings. The darker the Blue shade, the more “unfavorable” the configuration is *i.e.*, greater energy loss.)

ergy management strategy: whereas downscaling can be effective in some scenarios, blind DVFS is likely to fall short in goals. This somewhat pessimistic conclusion does have a positive “coda” — thanks to the difference between micro-benchmarks and real-world applications — a discussion we will continue in Section 4.4.

Furthermore, observe that we have adopted a very narrow view to equate “being favorable” as being able to save energy. As an example beyond this view, running CPUs at the lowest frequency may reduce heat dissipation, and improve the reliability of program execution.

Overall, our results can serve as a “lookup” chart to guide energy-aware programmers to desirable combinations of application-level energy management and hardware-level energy management. For example, if a programmer wishes to randomly access an array and query the value held by the array element object (*VQ+Randomness*) with a fixed energy budget, she can look up the results from Figure 4.3, and run the program either at 2GHz or at 2.6Ghz. The former may reduce heat dissipation, whereas the latter may produce results faster.

Specific Findings. In Figure 4.3, observe that for *VQ+Randomness*, 100% random access or 25% random access at frequencies of 2.4GHz, 2.2GHz, 2GHz, and 1.8GHz can all yield energy savings. There is a performance loss in these configurations, but the loss is also

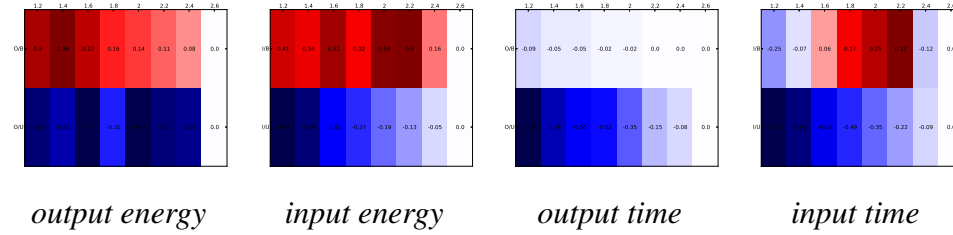


Figure 4.4: DVFS and Data I/O (0: Output, 1: Input, B: Buffered, U: Unbuffered)

smaller than their more sequential counterparts. These configurations may be useful for energy management since they represent a possible trade-off between energy saving and performance loss. The more random access patterns react to DVFS more gracefully because random access leads to more cache misses and instruction pipeline stalls. As a result, the CPU more frequently “waits for” data fetch. When the CPU frequencies are lowered, the relative impact on performance is smaller.

The most encouraging results come from Figure 4.4. Here, especially in the buffered I/Os, lowering CPU frequency can often yield energy savings. This is dramatic for cases such as buffered input (I/B), where the energy consumption for 2.2GHz is less than half of that of 2.6GHz, whereas the execution time at 2.2GHz turns out being shorter than that of 2.6GHz. This is a “sweet spot” in energy management: the program is not only more energy-efficient, but also runs faster. The cause behind this behavior is that CPUs running such I/O-intensive benchmarks are mostly idle, so lowering the CPU frequency has little impact on performance, but can significantly save energy. The improved performance may come as a mild surprise to some; we believe this demonstrates the execution time is not bound by CPU, but the storage system. The operations of the latter are often less deterministic, causing delays at unpredictable times.

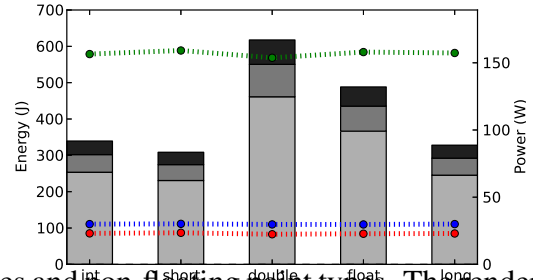
RQ2 Summary: *Blindly downscaling CPU frequency often leads to increased energy consumption and performance loss. Downscaling can play a prominent role in the energy optimization of I/O-intensive benchmarks.*

4.4 Case Study

In this section we apply our findings to two real-world benchmarks, SUNFLOW and XALAN, from the well-known DaCapo suite benchmark².

SUNFLOW renders a set of images using ray tracing, a CPU-intensive benchmark. The original program represents rendering data in type `double`. We performed our experiments by varying the data types appearing in the rendering method from `double` to `short`, `int`, `float`, and `long`. The rest of the source code remained unchanged.

The results here confirm some patterns from micro-benchmarking: for instance, `short` still consumes less energy than `int`, and `float` is still cheaper than `double`. The figure here highlights the non-comparability between floating point types and non-floating point types. The rendering process of SUNFLOW involves complex floating point operations (such as division), leading to heavy overhead on FPU operations (such as rounding [36]). In other words, these heavy operations significantly outpace their `short`/`int`/`long` counterparts in execution time, and subsequently energy consumption.



Another observation is that the difference in energy consumption of `short`, `int` and `long` is not as drastic as the one in micro-benchmarking. The same also holds for the difference between `float` and `double`. Real-world programs such as SUNFLOW are more likely to lead to instruction pipeline stalls (due to branching, synchronization, *etc*) than micro-benchmarks, and we speculate these additional stalls may help mask some of the difference.

Even though SUNFLOW is a complex application — it has more than 22,000 lines of Java code — we observed that a simple modification on the data types of a single method can have a considerable influence on the overall energy consumption of the application. In this example, the energy-aware programmer needs to balance the trade-off between energy

²<http://www.dacapobench.org>

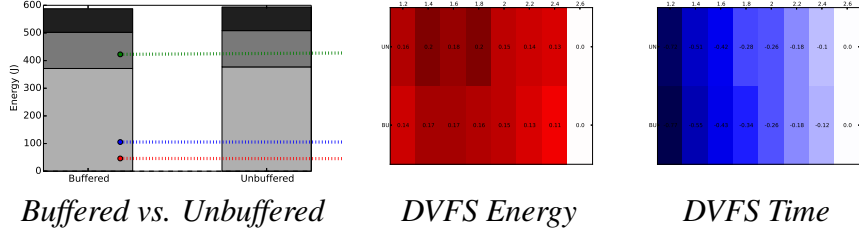


Figure 4.5: XALAN Results

efficiency and accuracy.

XALAN transforms XML documents into HTML. This benchmark performs reads and writes from input/output channels, and it has 170,572 lines of Java code. In its default version, the benchmark does not use a buffer. We add buffers to two program points in the XSLTBench class. With this modification, we observed an energy saving of 4.29%. Execution time kept roughly the same. The first figure in Figure 4.5 shows the results. On one hand, the savings here are not as “dramatic” as what micro-benchmarking showed. On the other hand, real-world applications often consume more energy, so a small percentage of savings can still make a difference (4.29% for XALAN implies more than 20J). The insights from micro-benchmarking guide us to identify and perform this optimization.

We also studied the impact of DVFS on XALAN, with results shown in the same figure. In all configurations, executing XALAN can lead to energy savings than running it at 2.6Ghz. This is consistent with our findings in the micro-benchmarking, because XALAN does perform significant I/O operations on files. DVFS may be useful for XALAN when one is willing to trade performance for energy savings.

The power consumptions of SUNFLOW and XALAN also deserve attention. Different applications operate on very different power levels: the CPU power for SUNFLOW nearly doubles that for XALAN. Our power analysis is consistent with the established fact that SUNFLOW is a CPU-intensive benchmark.

Finally, the gap between CPU power consumption and Uncore/DRAM power consumption is much larger than those in micro-benchmarks. This is good news for CPU-centric energy management strategies such as DVFS: they may sometimes be ineffective for micro-benchmarks because Uncore/DRAM power consumption has a large proportion to offset

the savings from CPUs, the proportional offset is smaller when we apply these strategies to real-world benchmarks. To validate this, we conducted the data precision experiment of SUNFLOW over different CPU frequencies and produced a counterpart of the *Precision* heat map of Fig. 4.3. As it turns out, unlike all cells are blue in the *Precision* heat map of Fig. 4.3, most cells are red for SUNFLOW. In other words, 2.6GHz is not the most energy-saving frequency for data precision choices. Readers can find the detailed data of this result in our online repository.

4.5 Threats to Validity

Internal factors: First, accessing MSRs also consumes energy (see discussions in Section 4.1.1). This overhead cannot be ignored if MSR accesses are too frequent, *e.g.*, at microsecond intervals. We mitigate this problem by using the RAPL interface only at the beginning and at the end of the benchmark execution. Second, the readings from the RAPL interface are hardware (CPU core or socket)-based. It cannot isolate the energy consumption of OS execution, VM execution, and application execution. As our experiments are mostly set up to be *comparative* — such as demonstrating the difference in energy consumption between sequential vs. random access — and our OS/VM settings remain unchanged throughout experiments, the root cause of relative difference in energy consumption for different experiments is likely to be the (direct and indirect) effect of the application, not OS or VM. Third, analyzing code with a short execution time may disproportionally amplify the noise from hardware and OS. We mitigate this problem by increasing the execution length of our benchmarks (such as via designing the benchmark to operate on a large amount of data) and averaging the results of multiple executions.

External factors: First, our results are limited by our selection of benchmarks. Second, there are other possible data manipulations beyond the scope of this chapter. With our tool, we expect similar analysis can be conducted in the future when other aspects of data-related application features become relevant. Third, our results are reported with the assumption that JIT is enabled. This stems from our observation that later runs of JIT-enabled executions do stabilize in terms of energy consumption and performance. We experienced

differences in standard deviation of over 30% when comparing the warmup run (first 2 executions) and later runs, but less than 5% when comparing the last 4 runs.

4.6 Chapter Summary

In this chapter, we take a data-centric view to empirically study the optimization space of application-level energy management. Our investigation is distinctive for several reasons: (1) it focuses on application-level features, instead of hardware performance counters, CPU instructions, or VM bytecode; (2) it is carried out from the data-oriented perspective, charting an optimization space often known to be too “application-specific” to quantify and generalize; (3) it offers the first clues on the impact of unifying application-level energy management and hardware-level energy management; (4) it provides an in-depth analysis from a whole-system perspective, considering energy consumption not only resulting from CPU cores, but also from caches and DRAM.

The focus of this chapter lies upon “charting” the optimization space. In the future, we are interested in applying the findings in this chapter — together with the library we developed — to application-level energy optimization. Two directions that appear to fit nicely with our study are (1) energy co-optimization through program refactoring and deployment-site configuration; (2) energy optimization through search-based software engineering, such as applying the data-oriented characterizations described in the paper as the dimensions of search space, and jRAPL as a tool, for software energy optimization.

A full set of the experimental results, the source code of jRAPL, the benchmarks, and all raw data, can be found online at <http://kliu20.github.io/jRAPL/>.

Chapter 5

A Comprehensive Study on the Energy Efficiency of Java Thread-Safe Collections

5.1 Introduction

A question that often arises in software development forums is: “since Java has so many collection implementations, which one is more suitable to my problem?”¹. Answers to this question come in different flavors: these collections serve for different purposes and have different characteristics in terms of performance, scalability and thread-safety. Developers should consider these characteristics in order to make judicious design decisions about which implementation best fits their problems. In this study, we consider one additional attribute: *energy efficiency*.

Traditionally addressed by hardware-level (e.g. [21, 27]) and system-level approaches (e.g. [75, 10]), energy optimization is gaining momentum in recent years through application-level software engineering techniques (e.g. [25, 49, 77]). The overarching premise of this crescent direction is that the high-level knowledge from software engineers on application design and implementation can make significant impact on energy consumption, as confirmed by recent empirical studies [52, 72]. The space for application-level energy optimization, however, is diverse. Developers sometimes rely on conventional wisdom, consult software development forums and blogs, or simply search online for “tips and tricks.” Many of these guidelines are often anecdotal or even incorrect [70].

In this chapter, we elucidate one important area of the application-level optimization space: the energy consumption of different Java thread-safe collections running on parallel

¹<http://stackoverflow.com/search?q=which+data+structure+use+java+is:question>

architectures. This is a critical direction at the junction of data-intensive computing and parallel computing, which deserves more investigation due to at least three reasons:

- Collections are one of the most important building blocks of computer programming. Multiplicity, a collection may hold many pieces of data items, is the norm of their use, and it often contributes to significant memory pressure, and performance problems in general, of modern applications where data are often intensive [90, 14].
- Not only high-end servers but also desktop machines, smartphones and tablets need concurrent programs to make best use of their multi-core hardware. A CPU with more cores (say 32) often dissipates more power than one with fewer cores (say 1 or 2) [54].
- Mainstream programming languages often provide a number of implementations for the same collection and these implementations have potentially different characteristics in terms of energy efficiency [40].

The current work is an broader extension of a preliminary study [69]. It is aimed at evaluating the performance and energy consumption characteristics of 16 Java collection implementations (13 thread-safe, 3 non-thread-safe) grouped by 3 well-known interfaces: List, Set, and Map. Through extensive experiments conducted in a multi-core environment, we correlate energy behaviors of different thread-safe implementations of Java collections and their knobs. Our research is motivated by the following questions:

- RQ1.** Do different implementations of the same collection have different impacts on energy consumption?
- RQ2.** Do different operations in the same implementation of a collection consume energy differently?
- RQ3.** Do collections scale, from an energy consumption perspective, with an increasing number of concurrent threads?
- RQ4.** Do different collection configurations and usages have different impacts on energy consumption?

In order to answer **RQ1** and **RQ2**, we select and analyze the behaviors of three common operations — traversal, insertion and removal — for each collection implementation. To answer **RQ3**, we analyze how different implementations scale in the presence of multiple threads. In this experiment, we cover the spectrum including both under-provisioning (the number of threads exceeds the number of CPU cores) and over-provisioning (the number of CPU cores exceeds the number of threads). In **RQ4**, we analyze how different configurations — such as the load factor and the initial capacity of the collection — impact energy consumption.

We analyze energy-performance trade-offs in diverse settings that may influence the high-level programming decisions of energy-aware programmers. We cross-validate the main findings into two well-known benchmarks (XALAN and TOMCAT). To gain confidence in our results in the presence of platform variations and measurement environments, we employ two machines with different architectures (a 32-core AMD vs. a 16-core Intel). We further use two distinct energy measurement strategies, relying on an external energy meter, and internal Machine-Specific Registers (MSRs), respectively.

Our study produces a list of interesting findings, some of which are not obvious. To highlight one of them, our experiments show that simple small changes have the potential of improving the energy consumption by 2x, in our micro-benchmarks, and by 10%, in our real-world benchmarks.

5.2 Study Setup

In this section we describe the benchmarks that we analyzed, the infrastructure and the methodology that we used to perform the experiments.

5.2.1 Benchmarks

The benchmarks used in this study consist of 16 commonly used collections (13 thread-safe, 3 non-thread-safe) available in the Java programming language. Our focus is on the thread-safe implementations of the collection. Hence, for each collection, we selected a single non-thread-safe implementation to serve as a baseline. For each implementation, we

analyzed insertion, removal and traversal operations. We grouped these implementations by the logical collection they represent, into three categories:

Lists (`java.util.List`): Lists are ordered collections that allow duplicate elements. Using this collection, programmers can have precise control over where an element is inserted in the list. The programmer can access an element using its index, or traverse the elements using an `Iterator`. Several implementations of this collection are available in the Java language. We used `ArrayList`, which is not thread-safe, as our baseline. We studied the following thread-safe `List` implementations: `Vector`, `Collections.synchronizedList()`, and `CopyOnWriteArrayList`. The main difference between `Vector` and `Collections.synchronizedList()` is their usage pattern in programming. With `Collections.synchronizedList()`, the programmer creates a wrapper around the current `List` implementation, and the data stored in the original `List` object does not need to be copied into the wrapper object. It is appropriate in cases where the programmer intends to hold data in a non-thread-safe `List` object, but wishes to add synchronization support. With `Vector`, on the other hand, the data container and the synchronization support are unified so it is not possible to keep an underlying structure (such as `LinkedList`) separate from the object managing the synchronization.

`CopyOnWriteArrayList` creates a copy of the underlying `ArrayList` whenever a mutation operation (e.g. using the `add` or `set` methods) is invoked.

Maps (`java.util.Map`): Maps are objects that map keys to values. Logically, the keys of a map cannot be duplicated. Each key is uniquely associated with a value. An insertion of a (key, value) pair where the key is already associated with a value in the map results in the old value being replaced by the new one. Our baseline thread-unsafe choice is `LinkedHashMap`, instead of the more commonly used `HashMap`. This is because the latter sometimes caused non-termination during our experiments². Our choice of thread-safe `Map` implementations includes `Hashtable`, `Collections.synchronizedMap()`, `ConcurrentSkipListMap`, `ConcurrentHashMap`, and `ConcurrentHashMapV8`. The dif-

²A possible explanation can be found here: <http://mailinator.blogspot.com/2009/06/beautiful-race-condition.html>

ference between `ConcurrentHashMap` and `ConcurrentHashMapV8` is that the latter is an optimized version released in Java 1.8, while the former is the version present in the JDK until Java 1.7. While all Map implementations share similar functionalities and operate on a common interface, they are particularly known to differ in the order of element access at iteration time. For instance, while `LinkedHashMap` iterates in the order in which the elements were inserted into the map, a `Hashtable` makes no guarantees about the iteration order.

Sets (`java.util.Set`): Sets model the mathematical set abstraction. Unlike Lists, Sets do not count duplicate elements, and are not ordered. Thus, the elements of a set cannot be accessed by their indices, and traversals are only possible using an `Iterator`. Among the available implementations, we used `LinkedHashSet`, which is not thread-safe, as our baseline. Our selection of thread-safe Set implementations includes `Collections.synchronizedSet()`, `ConcurrentSkipListSet`, `ConcurrentHashSet`, `CopyOnWriteArraySet`, and `ConcurrentHashSetV8`. It should be noted that both `ConcurrentHashSet` and `ConcurrentHashSetV8` are not top-level classes readily available in the JDK library. Instead, they are supported through the returned object from `Collections.newSetFromMap(new ConcurrentHashMap<String,String>())` or the analogous implementation `Collections.newSetFromMap(new ConcurrentHashMapV8<String,String>())` respectively. The returned Set object observes the same ordering as the underlying map.

5.2.2 Experimental Environment

To gain confidence in our results in the presence of platform variations, we run each experiment on two significantly different platforms:

- **System#1:** A 2×16 -core AMD Opteron 6378 processor (Piledriver microarchitecture), 2.4GHz, with 64GB of DDR3 1600 memory. It has three cache levels (L1, L2, L3): L1 with 32KB per core, L2 with 256KB per core, and L3 20480 (Smart cache). It is running Debian 3.2.46-1 x86-64 Linux (kernel 3.2.0-4-amd64), and Oracle HotSpot 64-Bit Server VM (build 21) JDK version 1.7.0_11.

- System#2: A 2×8 -core (32-cores when hyper-threading is enabled) Intel(R) Xeon(R) E5-2670 processor, 2.60GHz, with 64GB of DDR3 1600 memory. It has three cache levels (L1, L2, L3): L1 with 48KB per core, L2 with 1024KB per core, and L3 20480 (Smart cache). It is running Debian 6 (kernel 3.0.0-1-amd64) and Oracle HotSpot 64-Bit Server VM (build 14), JDK version 1.7.0_71.

When we performed the experiments with Sets and Maps, we employed the jsr166e library³, which contains the ConcurrentHashMapV8 implementation. Thus, these experiments do not need to be executed under Java 1.8.

We also used two different energy consumption measurement approaches. For System#1, energy consumption is measured through current meters over power supply lines to the CPU module. Data is converted through an NI DAQ and collected by NI LabVIEW SignalExpress with 100 samples per second and the unit of the current sample is *deca-ampere* (10 ampere). Since the supply voltage is stable at 12V, energy consumption is computed as the sum of current samples multiplied by $12 \times 0.01 \times 10$. We measured the “base” power consumption of the OS when there is no JVM (or other application) running. The reported results are the measured results *modulo* the “base” energy consumption.

For System#2, we used jRAPL [56], a framework that contains a set of APIs for profiling Java programs running on CPUs with Running Average Power Limit (RAPL) [27] support. Originally designed by Intel for enabling chip-level power management, RAPL is widely supported in today’s Intel architectures, including Xeon server-level CPUs and the popular i5 and i7 processors. RAPL-enabled architectures monitor the energy consumption information and store it in Machine-Specific Registers (MSRs). Due to architecture design, the RAPL support for System#2 can access CPU core, CPU uncore data (*i.e.*, caches and interconnects), and in addition DRAM energy consumption data. RAPL-based energy measurement has appeared in recent literature (e.g. [46, 85]); its precision and reliability have been extensively studied [38].

As we shall see in the experiments, DRAM power consumption is nearly constant. In other words, even though our meter-based measurement strategy only considers the CPU

³Available at: <http://gee.cs.oswego.edu/cgi-bin/viewcvs.cgi/jsr166/src/jsr166e/>

energy consumption, it is still indicative of the relative energy consumptions of different collection implementations. It should be noted that the stability of DRAM power consumption through RAPL-based experiments does not contradict the established fact that the energy consumption of memory systems is highly dynamic [11]. In that context, memory systems subsume the entire memory hierarchy, and most of the variations are caused by caches [63] — part of the “CPU uncore data” in our experiments.

All experiments were performed with no other load on the OS. We conform to the default settings of both the OS and the JVM. Several default settings are relevant to this context: (1) the power management of Linux is the default *ondemand* governor, which dynamically adjusts CPU core frequencies based on system workloads. (2) For the JVM, the parallel garbage collector is used, and just-in-time (JIT) compilation is enabled. The initial heap size and maximum heap size are set to be 1GB and 16GB respectively. We run each benchmark 10 times within the same JVM; this is implemented by a top-level 10-iteration loop over each benchmark. The reported data is the average of the last 3 runs. We chose the last three runs because, according to a recent study, JIT execution tends to stabilize in the latter runs [72]. Hyper-threading is enabled and turbo Boost feature is disabled on System#2.

5.3 Study Results

In this section, we report the results of our experiments. Results for **RQ1** and **RQ2** are presented in Section 5.3.1, describing the impact of different implementations and operations on energy consumption. In Section 5.3.2 we answer **RQ3** by investigating the impact of accessing data collections with different numbers of threads. Finally, in Section 5.3.3 we answer **RQ4** by exploring different “tuning knobs” of data collections.

5.3.1 Energy Behaviors of Different Collection Implementations and Operations

For **RQ1** and **RQ2**, we set the number of threads to 32 and, for each group of collections, we performed and measured insertion, traversal and removal operations.

- For the insertion operation, we start with an empty data collection, and have each

thread insert 100,000 elements. Hence, at the end of the insertion operation, the total number of elements inside the collection is 3,200,000. To avoid duplicate elements, each insertion operation adds a `String` object with value *thread-id* + “-” + *current-index*.

- For the traversal operation, each thread traverses the entire collection generated by the insertion operation, *i.e.*, over 3,200,000 elements. On `Sets` and `Maps`, we first get the list of keys inserted, and then we iterate over these keys in order to get their values. On `Lists`, the traversal operation is performed using a top-level loop over the collection, accessing each element by its index using the `E get(int i)` method of each collection class, where `E` is the generic type (instantiated to `String` in our experiments).
- For the removal operation, we start with the collection with 3,200,000 elements, and remove the elements one by one. For `Maps` and `Sets`, the removals are based on keys, and we remove until the collection becomes empty. On `Lists`, however, the removal operation is based on indexes, and occurs *in-place* — that is, we do not traverse the collection to look up for a particular element before removal.

Here, according to the `List` documentation, the `E remove(int i)` method “*removes the element at the specified position in this list (optional operation). Shifts any subsequent elements to the left (subtracts one from their indices). Returns the element that was removed from the list.*”⁴. As we shall see, removal operations on `Lists` are excessively expensive. In order to make it feasible to perform all experiments, we chose to remove only half of the elements.

Lists. Figure 5.1 shows the energy consumption (bars) and power consumption (lines) results of our `List` experiments. Each bar represents one `List` implementation. The three graphs at top of the figure are collected from `System#1`, whereas the three graphs in the bottom are from `System#2`. We do not show the figures for `CopyOnWriteArrayList`

⁴Documentation available at [http://docs.oracle.com/javase/7/docs/api/java/util/List.html#remove\(int\)](http://docs.oracle.com/javase/7/docs/api/java/util/List.html#remove(int))

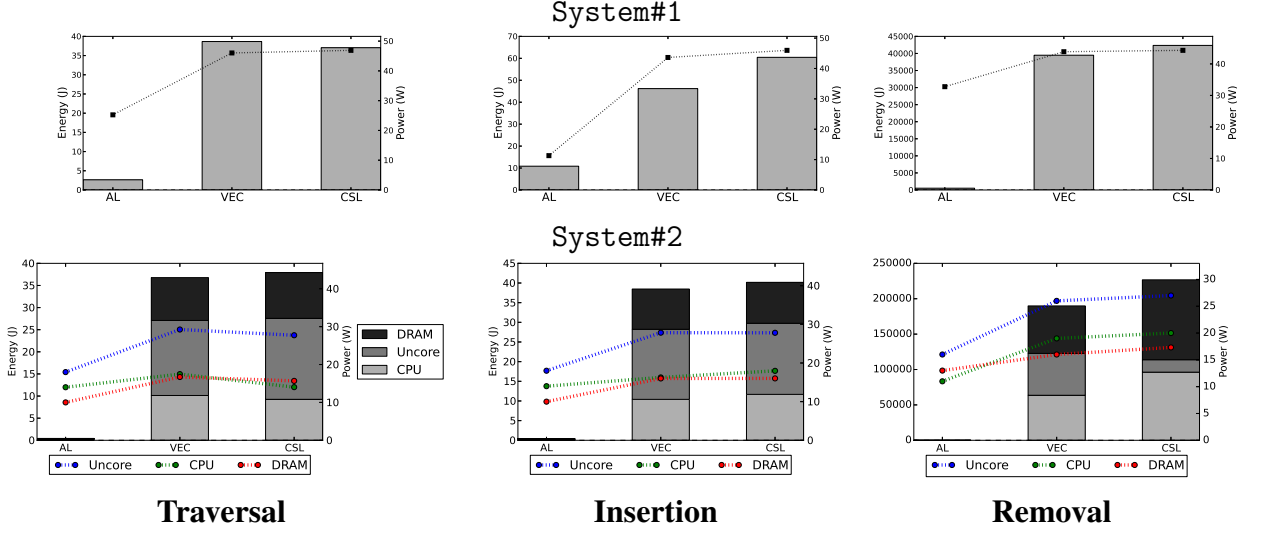


Figure 5.1: Energy and power results for traversal, insertion and removal operations for different List implementations. Bars denote energy consumption and lines denote power consumption. AL means ArrayList, VEC means Vector, and CSL means `Collections.synchronizedList()`.

because the results for insertion and removal are an outlier and would otherwise skew the proportion of the figures.

First, we can observe that synchronization does play an important role here. As we can see, ArrayList, the non-thread-safe implementation, consumes much less energy than the other ones, thanks to its lack of synchronization. Vector and `Collection.synchronizedList()` are similar in energy behaviors. The greatest difference is seen on insertion, on System#1, in which the former consumed about 24.21% less energy than the former. Vector and `Collection.synchronizedList()` are strongly correlated in their implementations, with some differences. While both of them are thread-safe on insertion and removal operations, `Collection.synchronizedList()` is not thread-safe on traversals, when performing through an Iterator, whereas Vector is thread-safe on the Iterator. `CopyOnWriteArrayList`, in contrast, is thread-safe in all operations. However, it does not need synchronization on traversal operations, which makes this implementation more efficient than the thread-safe ones (it consumes 46.38x less energy than Vector on traversal).

Furthermore, different operations can have different impacts. As we can see

on traversal, the Vector implementation presents the worst result among the benchmarks: it consumes 14.58x more energy and 7.9x more time than the baseline on System#1(84.65x and 57.99x on System#2, respectively). This is due both Vector and `Collection.synchronizedList()` implementations need to synchronize in traversal operations. As mentioned contrast, the `CopyOnWriteArrayList` implementation is more efficient than the thread-safe implementation.

For insertion operations, `ArrayList` consumes the least energy for both System#1 and System#2. When comparing the thread-safe implementations, `Collections.synchronizedList()` consumes 1.30x more energy than Vector (1.24x for execution time) on System#1. On System#2, however, they consume barely the same amount of energy (`Collections.synchronizedList()` consumes 1.01x more energy than Vector). On the other hand, `CopyOnWriteArrayList` consumes a total of 6,843.21 J, about 152x more energy than Vector on System#1. This happens because, for each new element added to the list, the `CopyOnWriteArrayList` implementation needs to synchronize and create a fresh copy of the underlying array using the `System.arraycopy()` method. As discussed elsewhere [72, 28], even though the `System.arraycopy()` behavior can be observed in sequential applications, it is more evident in highly parallel applications, when several processors are busy making copies of the collection, preventing them from doing important work. Although this behavior makes this implementation thread-safe, it is ordinarily too costly to maintain the collection in a highly concurrent environment where insertions are not very rare events.

Moreover, removals usually consumes much more energy than the other operations. For instance, removal on Vector consumes about 778.88x more energy than insertion on System#1. Execution time increases similarly, for instance, it took about 92 seconds to complete a removal operation on Vector. By way of contrast, insertions on a Vector takes about 1.2 seconds. We believe that several reasons can explain this behavior. First, the removal operations need to compute the size of the collection in each iteration of the for loop and, as we shall see in Section 5.3.4, such naive modification can greatly impact both performance and energy consumption. The second reason is that each call to the

`List.remove()` method leads to a call to the `System.arraycopy()` method in order to resize the `List`, since all these implementations of `List` are built upon arrays. In comparison, insertion operations only lead to a `System.arraycopy()` call when the maximum number of elements is reached.

Power consumption also deserves attention. Since `System.arraycopy()` is a memory intensive operation, power consumption decreases, and thus, execution time increase. Moreover, for most cases, power consumption follows the same shape of energy. Since energy consumption is the product of power consumption and time, when power consumption decreases and energy increase, execution time tends to increase. This is what happens on removal on `System#2`. The excessive memory operations on removals, also observed on DRAM energy consumption (the black top-most part of the bar), prevents the CPU to do useful work, which increases the execution time.

We also observed that the baseline benchmark on `System#2` consumes the least energy when compared to the baseline on `System#1`. We attribute that to our energy measurement approaches. While RAPL-based measurement can be efficient in retrieving only the necessary information (for instance, package energy consumption), our hardware-based measurement gathers energy consumption information pertaining to everything that happens in the CPU. Such noise can be particularly substantial when the execution time is small.

For all aforementioned cases, we observed that energy follows the same shape as time. At the first impression, this finding might seem to be “boring”. However, recent studies have observed that energy and time are often not correlated [53, 72, 87], which is particularly true for concurrent applications. For this set of benchmarks, however, we believe that developers can safely use time as a proxy for energy, which can be a great help when refactoring an application to consume less energy.

Ultimately, although we have found some differences in the results, both `System#1` and `System#2` presented a compelling uniformity.

Maps. Figure 5.2 presents a different picture for the `Map` implementations. For the `LinkedHashMap`, `Hashtable`, and `Collections.synchronizedMap()` implementations, energy follows the same curve as time, for both traversal and insertion operations, on both

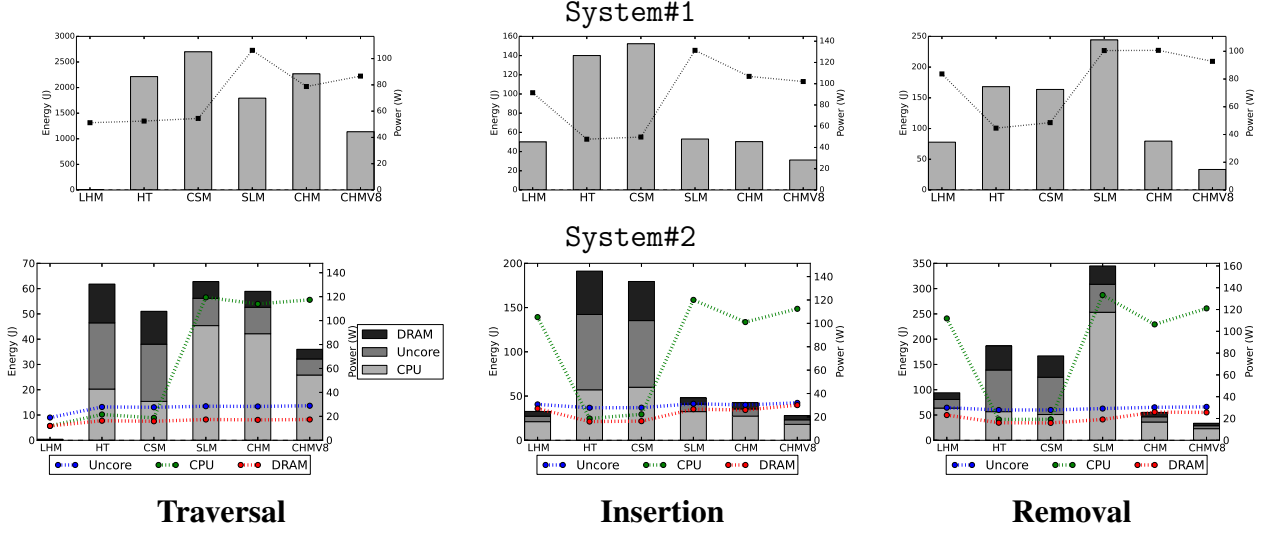


Figure 5.2: Energy and power results for traversal, insertion and removal operations for different Map implementations. Bars mean energy consumption and line means power consumption. LSM means LinkedHashMap, HT means Hashtable, CSM means `Collections.synchronizedMap()`, SLM means `ConcurrentSkipListMap`, CHM means `ConcurrentHashMap`, and CHMV8 means `ConcurrentHashMapV8`.

System#1 and System#2. Surprisingly, however, the same cannot be said for the removal operations. Removal operations on `Hashtable` and `Collections.synchronizedMap()` exhibited energy consumption that is proportionally smaller than their execution time for both systems. Such behavior is due to a drop on power consumption. Since such collections are single-lock based, for each removal operation, the other threads need to wait until the underlying structure is rebuilt. This synchronization prevents the collection to speed-up, and also decreases power usage.

On the other hand, for the `ConcurrentSkipListMap`, `ConcurrentHashMap` and `ConcurrentHashMapV8` implementations, more power is being consumed behind the scenes. As we mentioned that energy consumption is the product of power consumption and time, if the benchmark receives a 1.5x speed-up but, at the same time, yields a threefold increase in power consumption, energy consumption will increase twofold. This scenario is roughly what happens in traversal operations, when transitioning from `Hashtable` to `ConcurrentHashMap`. Even though `ConcurrentHashMap` produces a speedup of 1.46x over the `Hashtable` implementation on System#1, it achieves that by consuming 1.51x more power. As a result, `ConcurrentHashMap` con-

sumed slightly more energy than `Hashtable` (2.38%). On System#2, energy consumption for `Hashtable` and `ConcurrentHashMap` are roughly the same. This result is relevant mainly because several textbooks [65], research papers [29] and internet blog posts [35] suggest `ConcurrentHashMap` as the *de facto* replacement for the old associative `Hashtable` implementation. Our result suggests that the decision on whether or not to use `ConcurrentHashMap` should be made with care, in particular, in scenarios where the energy consumption is more important than performance. However, the newest `ConcurrentHashMapV8` implementation, released in the version 1.8 of the Java programming language, handles large maps or maps that have many keys with colliding hash codes more gracefully. On System#1, `ConcurrentHashMapV8` provides performance savings of 2.19x when compared to `ConcurrentHashMap`, and energy savings of 1.99x in traversal operations (these savings are, respectively, 1.57x and 1.61x in insertion operations, and 2.19x and 2.38x in removal operations). In addition, for insertions and removals operations on both systems, `ConcurrentHashMapV8` has performance similar or even better than the not thread-safe implementation.

`ConcurrentHashMapV8` is a completely rewritten version of its predecessor. The primary design goal of this implementation is to maintain concurrent readability (typically on the `get()` method, but also on `Iterators`) while minimizing update contention. This map acts as a binned hash table. Internally, it uses tree-map-like structures to maintain bins containing more nodes than would be expected under ideal random key distributions over ideal numbers of bins. This tree also requires an additional locking mechanism. While list traversal is always possible by readers even during updates, tree traversal is not, mainly because of tree-rotations that may change the root node and its links. Insertion of the first node in an empty bin is performed with a Compare-And-Set operation. Other update operations (insertional, removal, and replace) require locks. Locking support for these locks relies on builtin “synchronized” monitors.

Sets. Figure 5.3 shows the results of our experiments with `Set`. We did not present the results for `CopyOnWriteHashSet` in this figure because it exhibited a much higher energy consumption, which made the figure difficult to read. First, for all of the implementations

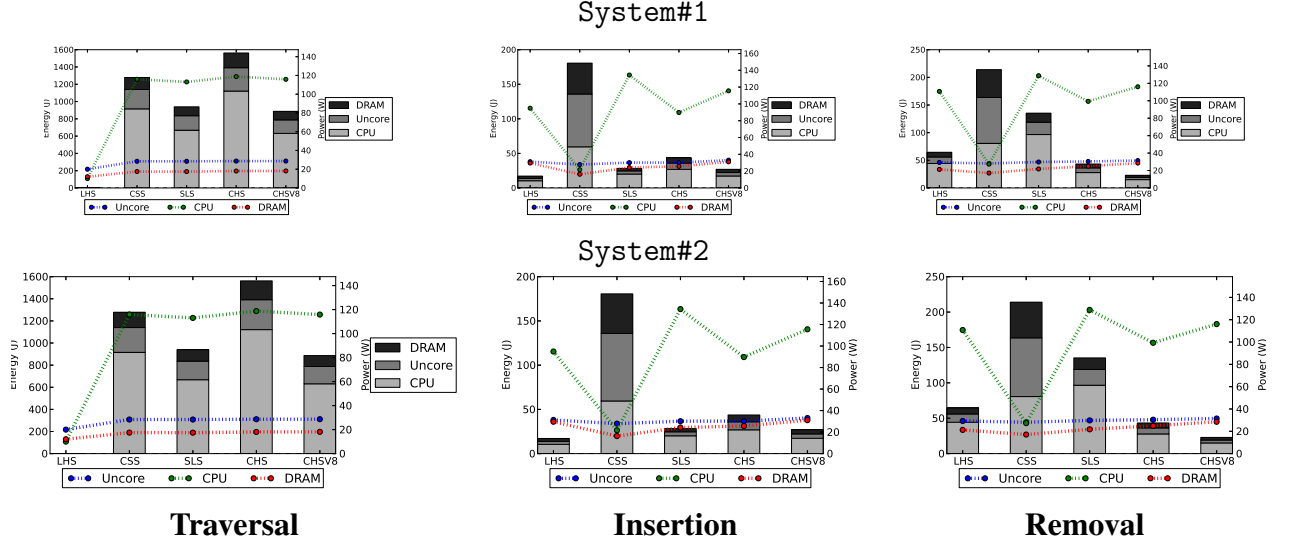


Figure 5.3: Energy and power results for traversal, insertion and removal operations for different Set implementations. Bars mean energy consumption and lines mean power consumption. LSH means `LinkedHashSet`, CSS means `Collections.synchronizedSet()`, SLS means `ConcurrentSkipListSet`, CHS means `ConcurrentHashSet`, and CHSV8 means `ConcurrentHashSetV8`.

of Set, we can observe that energy consumption follows the same behavior of power on traversal operations for both System#1 and System#2. However, for insertion and removal operations, they are not always proportional.

Notwithstanding, an interesting trade-off can be observed when performing traversal operations. As expected, the non-thread-safe implementation, `LinkedHashSet`, achieved the least energy consumption and execution time results, followed by the `CopyOnWriteArraySet` implementation. We believe that the same recommendation for `CopyOnWriteArrayList` fits here: this collection should only be used in scenarios where reads are much more frequent than insertions. For all other implementations, the `ConcurrentHashSetV8` presents the best results among the thread-safe ones. Interestingly, for traversals, `ConcurrentHashSet` presented the worst results, consuming 1.23x more energy and 1.14x more time than `Collections.synchronizedSet()` on System#1 (1.31x more energy and 1.19x more time on System#2).

Another interesting result is observed with `ConcurrentSkipListSet`, which consumes only 1.31x less energy than a `Collections.synchronizedSet()` on removal operations on System#1, although it saves 4.25x in execution time. Such energy consumption over-

head is also observed on System#2. Internally, `ConcurrentSkipListSet` relies on a `ConcurrentSkipListMap`, which is non-blocking, linearizable, and based on the compare-and-swap (CAS) operation. During traversal, this collection marks the “next” pointer to keep track of triples (predecessor, node, successor) in order to detect when and how to unlink deleted nodes. Also, because of the asynchronous nature of these maps, determining the current number of elements (used in the `Iterator`) requires a traversal of all elements.

These behaviors are susceptible to create the energy consumption overhead observed in Figure 5.3.

5.3.2 Energy Behaviors with Different Number of Threads

In this group of experiments, we aim to answer **RQ3**. For this experiment, we chose Map implementations only, due to presence of both single-lock and high-performatic implementations. We vary the number of threads (1, 2, 4, 8, 16, 32, 64, 128, and 256 concurrent threads) and study how such variations impact energy consumption. An increment in the number of threads also increments the total number of elements inside the collection. Since each thread inserts 100,000 elements, when performing with one thread, the total number of elements is also 100,000. When performing with 2 threads, the final number of elements is 200,000, and so on. To give an impression on how Map implementations scale in the presence of multiple threads, Figure 5.4 demonstrates the effect of different thread accesses on benchmarks.

In this figure, each data point is normalized by the number of threads, so it represents the energy consumption per thread, per configuration. Generally speaking, `Hashtable` and `Collections.synchronizedMap()` scale up well. For instance, we observed a great increment of energy consumption when using `Collections.synchronizedMap()` when we move from 32 to 64 threads performing traversals, but this trend can also be observed for insertions and removals. Still on traversals, all Map implementations greatly increase the energy consumed as we add more threads. Also, all thread-safe implementations have their own “15 minutes of fame”. Despite the highly complex landscape, some patterns do seem to recur. For instance, even though `ConcurrentHashMapV8` provides the best scalability

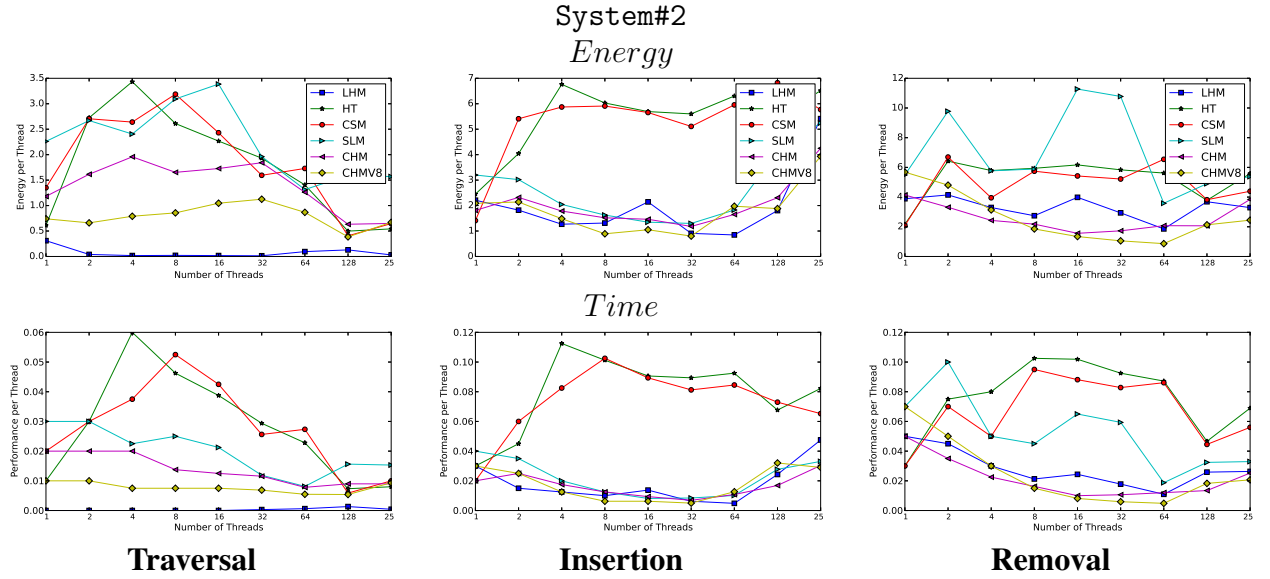


Figure 5.4: Energy consumption and execution time in the presence of concurrent threads (X axis: the number of threads, Y axis: energy consumption normalized against the number of element accesses, in joules per 100,000 elements)

among the thread-safe collection implementations, it still consumes about 11.6x more energy than the non-thread-safe implementation. However, the most interesting fact is the peak of ConcurrentSkipListMap, when performing with 128 and 256 threads. As discussed earlier, during traversal, ConcurrentSkipListMap marks or unlinks a node with null value from its predecessor (the map uses the nullness of value fields to indicate deletion). Such mark is a compare-and-set operation, and happens every time it finds a null node. When this operation fails, it forces a re-traversal from caller.

For insertions, we observed a great disparity; while Hashtable and Collections.synchronizedMap() scale up well, ConcurrentSkipListMap, ConcurrentHashMap and ConcurrentHashMapV8 scale up very well. One particular characteristic about ConcurrentHashMapV8 is that the insertion of the first element in an empty map employs compare-and-set operations. Other update operations (insert, delete, and replace) require locks. Locking support for these locks relies on builtin “synchronized” monitors. When performing using from 1 to 32 threads, they have energy and performance behaviors similar to the non-thread-safe implementation. Such behavior was previously discussed in Figure 5.2.

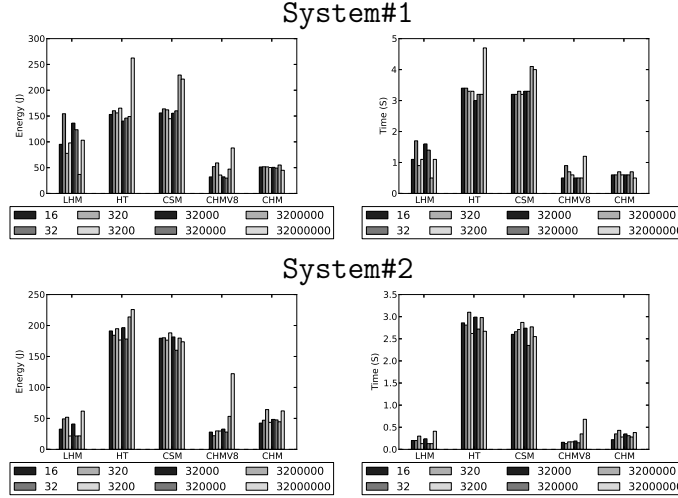


Figure 5.5: Energy and performance variations with different initial capacities.

For removals, interestingly, both `ConcurrentHashMap` and `ConcurrentHashMapV8` scale better than all other implementations, even the non-thread-safe implementation, `LinkedHashMap`. `ConcurrentSkipListMap`, on the other hand, presents the worst scenario, in particular with 16, 32 and 128 threads, even when compared to the single-lock implementations, such as `Hashtable` and `Collections.synchronizedMap()`.

5.3.3 Collection configurations and usages

We now focus on **RQ4**, studying the impact of different collection configurations and usage patterns on program energy behaviors. The Map implementations have two important “tuning knobs”: the *initial capacity* and *load factor*. The capacity is the total number of elements inside a Map and the initial capacity is the capacity at the time the Map is created. The default initial capacity of the Map implementations is only 16 locations. We report a set of experiments where we configured the initial capacity to be 32, 320, 3,200, 32,000, 320,000, and 3,200,000 elements — the last one is the total number of elements that we insert in a collection. Figure 5.5 shows how energy consumption behaves using these different initial capacity configurations.

As we can observe from this figure, the results can vary greatly when using different initial capacities, in terms of both energy consumption and execution time. The most evident cases are when performing with a high initial capacity in `Hashtable` and

ConcurrentHashMap. ConcurrentHashMapV8, on the other hand, presents the least variation on energy consumption.

The other tuning knob is the load factor. It is a measure of how full the hash table is allowed to get before its capacity is automatically increased. When the number of elements inside a Map exceeds the product of the load factor and the current capacity, the hash table is rehashed; that is, its internal structure is rebuilt. The default load factor value in most Map implementation is 0.75. It means that, using initial capacity as 16, and the load factor as 0.75, the product of capacity is 12 ($16 * 0.75 = 12$). Thus, after inserting the 12th key, the new map capacity after rehashing will be 32. If the initial capacity is greater than the maximum number of entries divided by the load factor, no rehash operations will ever occur. Figure 5.6 shows how energy consumption behaves using different load factors configurations. We perform these experiments only with insertion operations⁵.

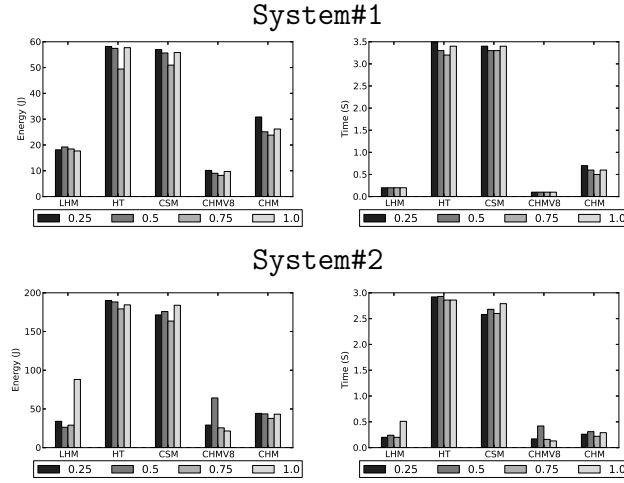


Figure 5.6: Energy and performance variations with different load factors.

From this figure we can observe that, albeit small, the load factor also influences both energy consumption and time. For instance, when using a load factor of 0.25, we observed the most energy inefficient results on System#1, except in one case (the energy consumption of LinkedHashMap). On System#2, the 0.25 configuration was the worst in three out of 5 of the benchmarks. We believe they are due to the successive rehashing operations that

⁵We did not performed experiments with ConcurrentSkipListMap because it does not provide access to initial capacity and load factor variables.

must occur. Generally speaking, the default load factor (.75) offers a good tradeoff between performance, energy, and space costs. Higher values decrease the space overhead but increase the time cost to look up an entry, which can reflect in most of the Map operations, including `get()` and `put()`). It is possible to observe this cost when using a load factor of 1.0, which means that the map will be only rehashed when the number of current elements reaches the current maximum size. The maximum variation was found when performing operations on a `Hastable` on `System#1`, in the default load factor, achieving 1.17x better energy consumption over the 0.25 configuration, and 1.09x in execution time.

5.3.4 The Devil is in the Details

In this section we further analyze some implementation details that can greatly increase energy consumption.

Upper bound limit. We also observed that, on traversal and insertion operations, when the upper bound limit needs to be computed in each iteration, for instance, when using

```
for(int i=0; i<list.size(); i++) { ... }
```

the `Vector` implementation consumed about twice as much as it consumed when this limit is computed only once on (1.98x more energy and 1.96x more time), for instance, when using

```
int size = list.size();  
for(int i=0; i < size; i++) { ... }
```

When this limit is computed beforehand, energy consumption and time drop by half. Such behavior is observed on both `System#1` and `System#2`. We believe it happens mainly because for each loop iteration, the current thread needs to fetch the `list.size()` variable from memory, which would incur in some cache misses. When initializing a `size` variable close to the loop statement, we believe that such variable will be stored in a near memory location, and thus, can be fetched all together with the remaining data. Using this finding, well-known IDEs, such as Eclipse and IntelliJ, can take advantage of it and implement

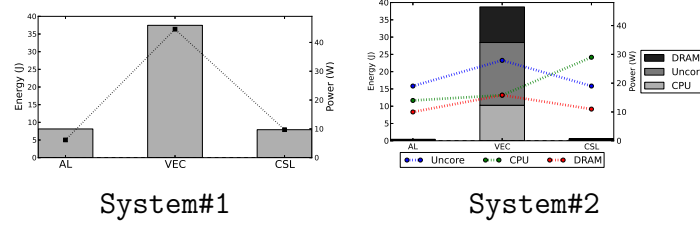


Figure 5.7: Traversal operations using the `get()` method. We use the same abbreviations of Figure 5.1.

refactoring suggestions for developers. Currently, the Eclipse IDE does not provide such feature. Also, recent studies have shown that programmers are more likely to follow IDE tips [62]. One concern, however, is related to removal operations. Since removal on Lists shift any subsequent elements to the left, if the limit is computed beforehand, the `i++` operation will skip one element.

Enhanced for loop. We also analyzed traversal operations when the programmer iterates using an *enhanced for loop*, for instance, when using

```
for (String e: list) { ... }
```

which is translated to an Iterator at compile time. Figure 5.7 shows the results. In this configuration, Vector need to synchronize in two different moments: during the creation of the Iterator object, and in every call of the `next()` method. By contrast, the `Collections.synchronizedList()` does not synchronize on the Iterator, and thus has similar performance and energy usage when compared to our baseline, `ArrayList`. On System#1, energy decreased from 37.07J to 2.65J, whereas time decreased from 0.81 to 0.10. According to the `Collections.synchronizedList()` documentation, the programmer must ensure external synchronization when using Iterator.

Removal on objects. When using Lists, instead of perform removals based on the indexes, one can perform removals based on object instances, for instance, when using

```
for (int i = 0; i < threads; i++) {
    for (int j = 0; j < list.size(); j++) {
```

```
        boolean b = list.remove(i + "-" + j);  
    } }
```

we observed an increment on energy consumption of 39.21% on System#1 (32.28% on execution time). This additional overhead is due to the traversal needed for this operations. Since the collection does not know in which position the given object is placed, it needs to traversal and compare each element until it finds the object – or until the collection ends.

5.4 Case Study

In this section we apply our findings into real-world benchmarks. We select benchmarks that made several use of Hashtables. We chose the Hashtable implementation because it presents one of the greatest different in terms of energy consumption, when compared to its newest version, ConcurrentHashMap (see Figure 5.2). The first selected benchmark is XALAN, from the well-known DaCapo suite [12]. This benchmark transforms XML documents into HTML. It performs reads and writes from input/output channels, and it has 170,572 lines of Java code. We chose this benchmark because it employs more than 300 Hashtables.

Since the DaCapo framework is not under active development, we used the BOA infrastructure [31] to select *active*, *i.e.*, have at least one commit in the last 12 months, *non-trivial*, *i.e.*, have at least 500 commits in the whole software history, benchmarks that use at least 50 Hashtables. We found a surprisingly number of 151 projects that fit on this criteria. Among the projects, we selected TOMCAT, which is an open-source web server. In the selected version 8.5, which is one of the latest one, it has 188,645 lines of Java code. Also, one of its previous version (6.0) is also part of the DaCapo framework. In this study we analyzed the most recent one.

For each benchmark, we performed our experiments by changing the Hashtable instance to ConcurrentHashMap and ConcurrentHashMapV8. The rest of the source code remained unchanged. We ran the benchmarks on System#1, with 32 concurrent threads. Figure 5.8 shows the results.

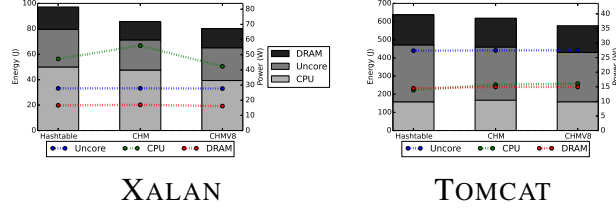


Figure 5.8: Energy and performance variations with different initial capacities.

The results here confirm some patterns from micro-benchmarking. Both XALAN and SUNFLOW present an improvement in energy consumption when migrating from Hashtable to ConcurrentHashMap. XALAN, in particular, presented an improvement of 12.21% when varying from Hashtable to ConcurrentHashMap, and 17.82% when varying from Hashtable to ConcurrentHashMapV8. This is particularly due to its CPU intensive nature, which is also observed with the green line. SUNFLOW, on the other hand, spends most of its computational time with logging and network operations — which are intrinsically IO operations. Despite of it, it is still capable of yielding a 9.32% energy saving when moving from Hashtable to ConcurrentHashMapV8.

These results suggests that even small changes have the potential of improving the energy consumption of a non-trivial software system. It is important to observe that the degree of energy saving is related to the degree of use of an inefficient collection (e.g. Hashtable). Therefore, benchmarks that make heavily use of single lock based collections are more likely to have high energy gains.

Finally, although both Hashtable and ConcurrentHashMap share the same interface, it is not always straightforward to perform this transformation, due to at least three reasons:

1. Hashtable and ConcurrentHashMap do not obey the same hierarchy. For instance, Hashtable inherits from Dictionary and implements Cloenable, while ConcurrentHashMap does not. It means that operations such as `hash.clone()` raises a compile error when changing the instance of the hash variable.
2. Third party libraries often require implementations instead of interfaces. If a method is expecting a Hashtable instead of, say, a Map, a ConcurrentHashMap needs to be converted to Hashtable, decreasing its effectiveness.

3. Programmers often use methods that are present only in the concrete implementation, not in the interface (e.g. `rehash`). This creates a strong tie between the client code with the concrete implementation, hampering the transition from `Hashtable` to `ConcurrentHashMap`.

5.5 Threat to Validity

Internal factors. First, the elements which we used are not randomly generated. We chose to not use random number generators because they can greatly impact the performance and energy consumption of our benchmarks. We observed standard deviation of over 70% between two executions when using the random number generators. We mitigate this problem by combining the index of the for loop plus the thread id that inserted the element. This approach also prevents compiler optimizations that may happen when using only the index of the for loop as the element to be inserted in the collection.

External factors. First, our results are limited by our selection of benchmarks. Nonetheless, our corpus spans a wide spectrum of collections, ranging from lists, sets, and maps. Second, there are other possible collections implementations beyond the scope of this chapter. With our methodology, we expect similar analysis can be conducted by others. Third, our results are reported with the assumption that JIT is enabled. This stems from our observation that later runs of JIT-enabled executions do stabilize in terms of energy consumption and performance [72]. We experienced differences in standard deviation of over 30% when comparing the warmup run (first 3 executions) and later runs, but less than 5% when comparing the last 3 runs.

5.6 Chapter Conclusions

In this chapter, we presented an empirical study that investigates the impacts of using different collections on energy usage. As subjects for the study, we analyzed the main methods of 16 types of commonly used collection (13 thread-safe, 3 non-thread-safe) in the Java language. Some of the findings of this study include: (1) Different operations of the same implementation also have different energy footprints. For example, a removal operation

in a `ConcurrentSkipListMap` can consume more than 4 times of energy than an insertion to the same collection. Also, for `CopyOnWriteArraySet`, an insertion consumes three order of magnitude more than a read. (2) Small changes have the potential of improving the energy consumption by 2x, in our micro-benchmarks, and by 10%, in our real-world benchmarks.

Chapter 6

Vincent: Energy-Efficient Hot Methods for Java Applications

6.1 Introduction

The carbon footprint of data centers has recently received significant scrutiny [61]. With this backdrop, developing energy-efficient and sustainable computing infrastructure is of critical importance within and beyond computing. This cross-sectioned design goal can be addressed at many layers of the computing stack. Among them, a relatively less explored approach is to study the impact of *application runtime* design on energy consumption. Outnumbered by approaches from other layers, existing runtime-level system designs [22, 18, 1, 44, 76] and empirical studies [89, 32, 79, 71, 68, 37, 73] nonetheless demonstrate the critical role of this layer on energy optimization. Relative to lower-layer techniques on hardware design (e.g., [20]) and OS design (e.g., [91]), a runtime-level approach has the benefit of guiding energy optimization with runtime-specific information unavailable to the underlying systems. Relative to higher-layer techniques such as energy-aware programming models [83, 8, 78, 42, 24, 9, 47, 41, 59, 94, 16], a runtime-level approach can work with legacy code written in existing programming models and languages, arguably easier for adoption. In a nutshell, the runtime — strategically positioned in between the lower layers and the higher layers — can often combine the benefits of both sides of its neighbors on the computing stack.

At their essence, all runtime-based approaches are motivated by the same question: what information uniquely available in the runtime can be harvested to guide energy optimization? As examples, existing efforts have relied on thread and synchronization states

(e.g., [1]), Just-In-Time (JIT) compilation strategies (e.g., [89]), and garbage collector (GC) designs (e.g., [44]) to inform energy optimization.

6.1.1 VINCENT

VINCENT is a novel runtime-based energy optimizer in a JVM. Rather than drawing insight from JVM-specific services like existing work, VINCENT relies on two rather “mundane” pieces of information available in the JVM: (i) the JVM is aware of the boundary of programming abstractions such as methods; (ii) the JVM is aware of how often a method is used.

The premise of VINCENT is that each method as a logical unit of the program behavior can serve as an ideal granularity for energy optimization. For example, the method `Matrix4.transformP` in a ray-tracing benchmark `sunflow` may carve out the boundary of a CPU-intensive computation, and the method `PSSStream.write` in a file processing benchmark `fop` may carve out the boundary of an I/O-intensive computation. Well known in classic energy optimization techniques such as Dynamic Voltage and Frequency Scaling (DVFS) [43, 15], understanding *phased behaviors* [81, 82, 45] — an application may go through phases of different levels of CPU intensity — is vital for energy optimization. For example, running an I/O-intensive program fragment (i.e., not CPU-intensive) at a lower CPU frequency can often save energy without hampering performance.

Phase identification in the state of the art predominately relies on monitoring low-level system information, such as hardware performance counters (e.g., cache misses). A classic example of this approach is the ONDEMAND governor, the default power manager in Linux. This governor continuously predicts the level of CPU intensity demanded by the application and dynamically adjusts the CPU frequency to meet the demand. This approach is unaware of the logical structure of the running application, and fundamentally reactive: it uses the level of CPU intensity at the *current* time interval to set the CPU frequency for the *next* time interval.

VINCENT features *method-grained energy optimization*, which aligns the boundary of energy phases with the boundary of methods for optimization. Operationally, it relies on

profiling to assign desirable CPU frequencies to the most energy-consuming methods, and dynamically adjust CPU frequencies accordingly in production runs.

A large number of methods typically exist in a Java application. Subjecting every method to DVFS, i.e., identifying the best frequency to run every method in the runtime, is impractical: DVFS comes with a small but non-negligible overhead. In VINCENT, only *hot methods* deemed by the JVM are candidates for energy optimization. This design decision is aligned with the fact that hot methods are frequently executed, and any improvement to their energy behavior may have an amplified effect. Practically, focusing on hot methods also allows VINCENT to piggyback on existing JIT design, where information on hot methods is readily available.

6.1.2 Contributions

VINCENT a novel multi-pass feedback-directed energy optimizer with a focus on applying DVFS to hot methods. To the best of our knowledge, it is the only runtime-level solution that performs DVFS at the granularity of methods. This chapter makes the following contributions:

- the novel philosophy of method-grained energy optimization at the level of application runtimes;
- the specification of the multi-pass energy optimization through instrumentation inside the JVM;
- the implementation and evaluation of method-grained DVFS on top of JikesRVM [3, 2], which demonstrates its effectiveness in improving the energy efficiency of Java applications.

VINCENT is an open-source project. Its source code and all experimental data reported in this chapter can be found at a website that will become available after the anonymous review period is over.

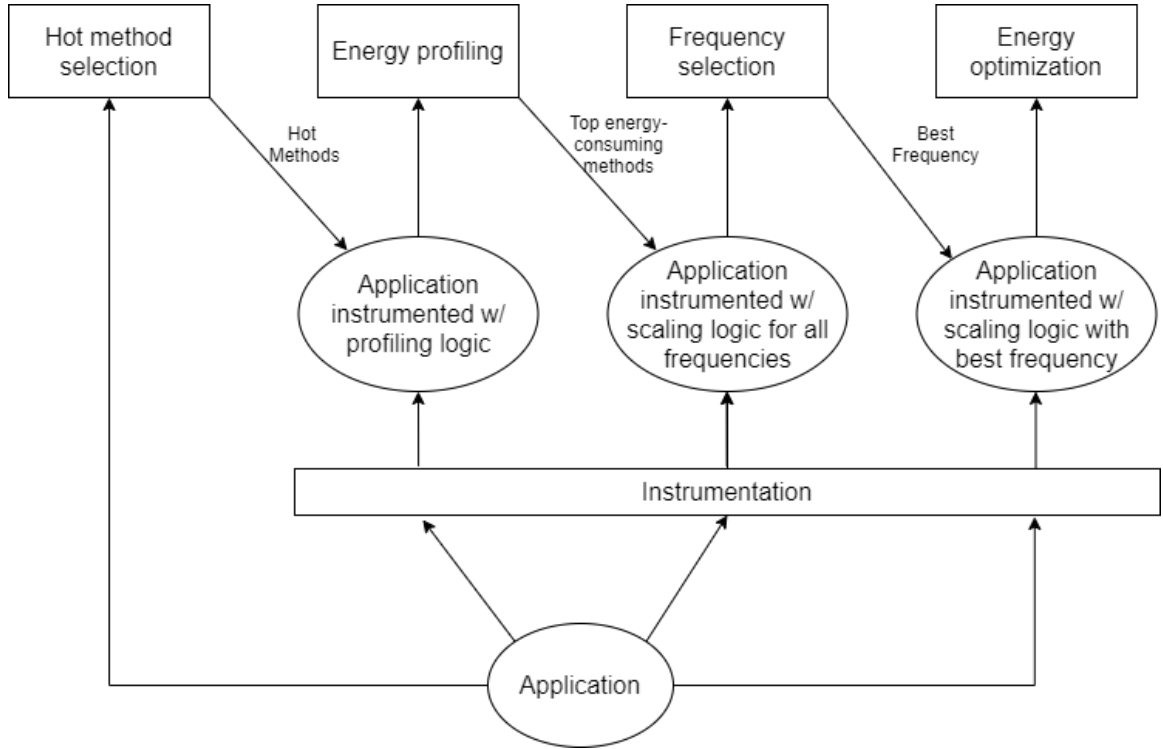


Figure 6.1: VINCENT Design and Workflow

6.2 VINCENT Design

In this section, we describe the design of VINCENT, with a high-level description in § 6.2.1, followed by an algorithm specification in § 6.2.2.

6.2.1 VINCENT Design

The system components and the workflow of VINCENT are shown in Fig. 6.1. On the high level, VINCENT is a feedback-directed optimizer that conceptually consists of 4 passes:

- **Hot Method Selection:** VINCENT first obtains a list of *hot methods*.
- **Energy Profiling:** VINCENT profiles the energy consumption of hot methods under the default ONDEMAND governor. It ranks their energy consumption, and reports a list of *top energy-consuming methods* as the output of this pass.
- **Frequency Selection:** For each top energy-consuming method, VINCENT observes the energy consumption of the application when the execution of this method is

scaled to each CPU frequency, which we call a *configuration*. VINCENT determines the best CPU frequency for each top energy-consuming method by ranking the energy efficiency of different configurations.

- **Energy Optimization:** VINCENT runs the application when the execution of each top energy-consuming method is scaled to its best CPU frequency.

The workflow described here is conceptual. For instance, the VINCENT system combines hot method selection and energy profiling in one single run, with the former achieved by reusing the results identified by JIT. The core design elements are the algorithms for energy profiling (used by pass 2) and method-based scaling (used by passes 3 and 4). These details will be provided in § 6.2.2.

The key observation over this workflow is that VINCENT places the spotlight on *methods*: in each of the workflow tasks, the unit of processing — be it selection, profiling, or optimization — is *at the granularity of methods*. For this reason, despite that the workflow itself may not look surprising as a multi-pass feedback-directed optimizer, it represents a significant departure from the state of the art of optimizing the energy consumption of applications.

6.2.2 VINCENT Specification

We now specify the algorithm implemented by VINCENT. We first describe the top-level thread bookkeeping in § 6.2.2. For the key system components described in the previous section, hot method selection is largely achieved by building on top of existing JIT infrastructure, a topic we will defer as an implementation detail (§ 6.3). The rest of the system components are enabled by instrumentation, which we describe in this section as the profiling algorithm (§ 6.2.2) and the scaling algorithm (§ 6.2.2).

Thread Bookkeeping

Algorithm 1 overviews the bookkeeping in a multi-threading environment. Here, all threads visible to the JVM (other than the timer thread itself) are maintained in a global structure

Algorithm 1 Thread Bookkeeping and Timer Thread Loop

```
1: typedef T {  
2:   vtimer: int // VINCENT timer  
3:   skipCount: int // # of invocations to skip  
4:   sampleCount: int // # of samples to collect  
5:   edata: EDATA // energy profiling data  
6:   gov: GOVERNOR // saved governor  
7:   freq: FREQ // saved CPU frequency  
8: }  
9: const SKIPNUM // skipped samples between collections  
10: const SAMPLENUM // collected samples per timer interval  
1: ts: T[THREADNUM] // running threads  
2: procedure TIMER  
3:   while TRUE do  
4:     SLEEP(EPOCH)  
5:     for each t ∈ ts do  
6:       t.vtimer++  
7:     end for  
8:   end while  
9: end procedure
```

ts, a collection of threads of type T. Each thread contains thread-local bookkeeping information; in particular, note that *vtimer* manages the sampling rate for profiling and scaling. As profiling and scaling belong to different passes of VINCENT and do not share the same runtime, *vtimer* is used for both runs. The thread-local fields used only for profiling and those only for scaling are illustrated with GREEN box and RED box respectively. The specific meanings of the constants and the fields in T other than *vtimer* will be detailed in the rest of this section.

The timer thread is defined as an infinite loop. When the JVM timer interrupt happens at the rate of EPOCH, the *vtimer* associated with each thread is incremented.

Profiling Instrumentation

Recall that the goal of profiling is to identify the top energy-consuming methods. The raw energy consumption maintained by the underlying hardware (see § 6.3) is *accumulative*, i.e., reported as monotonically increasing values. To determine the energy consumption of a method, we conceptually need to “diff” the raw energy reading obtained at the beginning of the method execution, and one obtained at the end of the method execution.

Algorithm 2 Profiling Algorithm

```
1: typedef LOG {
2:   mn: MNAME // method name
3:   edata: EDATA // data
4: }
5: typedef CVAL enum { TAKE, SKIP, LAST }
6: const PN // profiling timer factor (relative to EPOCH)
7: l: LOG[LOGNUM]
8: procedure PROLOGUEPROFILE()
9:   t  $\leftarrow$  CURRENTTHREAD()
10:  if COUNTER(t, PN) == TAKE then
11:    t.edata  $\leftarrow$  READENERGY()
12:  end if
13:  if COUNTER(t, PN) == LAST then
14:    t.edata  $\leftarrow$   $\perp$ 
15:  end if
16: end procedure
17: procedure EPILOGUEPROFILE()
18:   t  $\leftarrow$  CURRENTTHREAD()
19:   if COUNTER(t, PN) == TAKE or LAST then
20:     energy  $\leftarrow$  READENERGY()
21:     if t.edata  $\neq$   $\perp$  then
22:       l  $\stackrel{+}{\leftarrow}$  LOG(THISM, DIFF(energy, t.edata))
23:     else
24:       t.edata  $\leftarrow$  energy
25:     end if
26:   end if
27:   if COUNTER(t, PN) == LAST then
28:     t.edata  $\leftarrow$   $\perp$ 
29:   end if
30: end procedure
31: function COUNTER(t: T, factor: int): CVAL
32:  if t.vtimer  $\geq$  factor then
33:    t.skipCount  $\leftarrow$  t.skipCount - 1
34:    if t.skipCount == 0 then
35:      t.skipCount  $\leftarrow$  SKIPNUM
36:      t.sampleCount  $\leftarrow$  t.sampleCount - 1
37:      if t.sampleCount == 0 then
38:        t.vtimer  $\leftarrow$  0
39:        t.sampleCount  $\leftarrow$  SAMPLENUM
40:      return LAST
41:    end if
42:    return TAKE
43:  end if
44:  end if
45:  return SKIP
46: end function
```

Algorithm 3 Scaling Algorithm

```
1: enum GOVERNOR {USERSPACE, ONDEMAND}
2: const SN // scaling timer factor (relative to EPOCH)
3: procedure PROLOGUESCALE( $f$  : FREQ)
4:    $t \leftarrow \text{CURRENTTHREAD}()$ 
5:   if COUNTER( $t$ , SN) == TAKE then
6:      $t.gov \leftarrow \text{GETGOVERNOR}()$ 
7:     if  $t.gov$  == USERSPACE then
8:        $t.freq \leftarrow \text{GETFREQ}()$ 
9:     else
10:      SETGOVERNOR(USERSPACE)
11:    end if
12:    SETFREQ( $f$ )
13:  end if
14:  if COUNTER( $t$ , SN) == LAST then
15:    SETGOVERNOR(ONDEMAND)
16:  end if
17: end procedure
18: procedure EPILOGUESCALE()
19:    $t \leftarrow \text{CURRENTTHREAD}()$ 
20:   if COUNTER( $t$ , SN) == TAKE then
21:     if  $t.gov \neq \perp$  then
22:       SETGOVERNOR( $t.gov$ )
23:       if  $t.gov$  == USERSPACE then
24:         SETFREQ( $t.freq$ )
25:       end if
26:     end if
27:   end if
28:   if COUNTER( $t$ , SN) == LAST then
29:     SETGOVERNOR(ONDEMAND)
30:   end if
31: end procedure
```

Challenges and Strawman Solutions A root hurdle against energy profiling is that obtaining a raw energy reading from the underlying hardware incurs a non-trivial overhead, often taking tens of microseconds to complete. As a result, standard solutions known to be effective for execution time profiling may not be ideal for energy profiling.

A strawman solution is to instrument the begin (i.e., prologue) and the end (i.e., epilogue) of every hot method, where a raw energy reading is taken each time the prologue and epilogue is encountered. The energy consumption of a method can thus be the difference between the two readings.

Unfortunately, thanks to the non-trivial overhead with raw energy readings, this approach may incur prohibitively high overhead (10x-200x in our experience), severely altering the program behavior. In other words, the instrumented run may produce the result no longer representative of the original benchmark’s energy behavior. Even instrumenting each hot method “one at a time” following this approach does not solve the problem. The hot methods are “hot” for a reason: they are frequently called, and the per-call overhead may rapidly accumulate.

A second strawman solution is to perform sampling at fixed time intervals. For example, assume the JVM has just taken an energy sample of $90J$ at the beginning of its 100th time interval. After one time interval elapses, it takes another energy sample of $90.25J$, and the epilogue of a method is encountered. The approach can thus attribute $0.25J$ to that method.

This approach however may lead to over-attribution: $0.25J$ is attributed to one method encountered at the end of the time interval, but many other methods may have contributed to the energy consumption during the interval. This sampling approach is widely used for execution time sampling, because precision can be improved by shortening the time interval. For energy profiling however, the room for shortening the time interval is limited due to the overhead of raw energy readings.

Delimited Sampling with VINCENT The energy profiler of VINCENT is a hybrid of the two strawman solutions above, which we call *delimited sampling*. Similar to the first strawman approach, VINCENT takes energy readings when the method prologue and the method epilogue are encountered, and computes the difference of the two. VINCENT however does

not take energy readings at every encounter of method prologues and epilogues. Instead, the number of energy readings at the method prologue/epilogue are bounded for each time interval, similar to the second strawman approach.

As seen in Algorithm 2, each hot method is instrumented with a pair of methods, with `PROLOGUEPROFILE` inserted before the entry point of the method body, and `EPILOGUEPROFILE` inserted after each exit point of the method body. Auxiliary function `READENERGY` obtains a raw energy sample from the underlying hardware (a value of `EDATA` type). Binary function `DIFF` computes the difference of two raw energy samples, and function `CURRENTTHREAD` returns the current thread of the execution, of type `T`. Constant `THISM` is the name of the instrumented method, an implementation detail we clarify in § 6.3. Sampling happens within the function of `COUNTER`, which we describe shortly.

An observable reader may notice that we do not match the method name between the prologue and the epilogue. This is intentional: in a sampling-based approach, the method encountered during the prologue and one encountered during the epilogue may not match. The key insight here is that we are not attempting to replicate the first strawman approach, but to avoid the overattribution problem in the second strawman approach. The philosophy here is *refutation*: if a prologue (of any method) is encountered before the epilogue of the method m of our interest, we know the energy consumption incurred before the prologue encounter must not be due to m , thanks to how call stacks are structured.

Counter-based Sampling Our description so far can be *conceptually* viewed as taking two energy readings — one at the prologue and the other at the epilogue — for each time interval. `VINCENT` extends from this conceptual view by adopting counter-based sampling [4], allowing multiple (but still bounded) pairs of energy readings to be collected within a time interval. The benefit of counter-based sampling in improving the accuracy of sampling is well documented, especially for complex call graphs where methods are of variant lengths. Specific to energy optimization, this means that `VINCENT` cares about both longer but less frequently invoked methods and shorter but more frequently invoked methods, as long as they incur high energy consumption.

As shown in Fig. 6.2, this approach alternates between taking samples and skipping

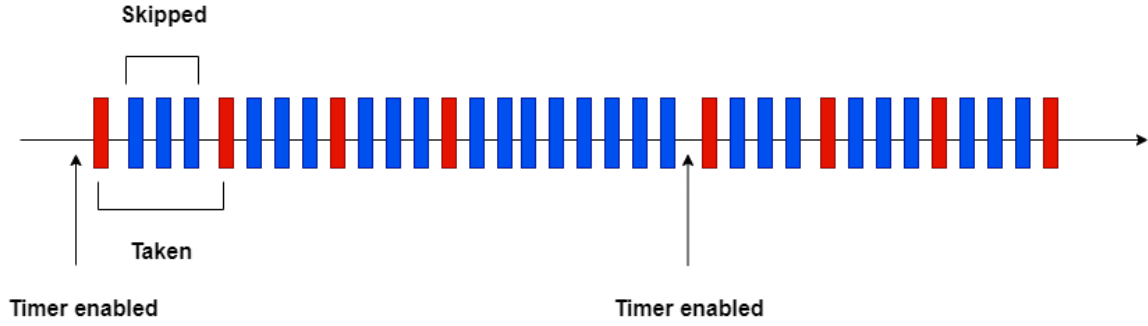


Figure 6.2: Counter-based Sampling where $SKIPNUM = 3$ and $SAMPLENUM = 4$

samples within each time interval. This is achieved through maintaining two counters: the number of samples to take (`sampleCount` in our algorithm) and the number of samples to skip between two samples (`skippedCount` in our algorithm).

In Algorithm 2, counter-based sampling is captured by function `COUNTER`, at Lines 31-46. Here, the profiling time interval is set as $PN \times EPOCH$; recall that `vtimer` is incremented at each VM `EPOCH`, so PN is the “slowdown” factor of profiling relative to the top-level timer loop. Constants `SAMPLENUM` and `SKIPNUM` represent the number of samples to take and skip, respectively, within each profiling time interval.

The `COUNTER` function may return one of the 3 values: `TAKE` (indicating a sample should be taken), `SKIP` (indicating a sample should not be taken), and `LAST` (indicating one last sample should be taken for each time interval). The `LAST` value plays a role of re-initializing the environment for the next time interval. For profiling, this means to reset the `edata` field.

Scaling Instrumentation

Algorithm 3 defines the instrumentation-based algorithm for CPU scaling. Convenience function `GETGOVERNOR` retrieves the current governor (power manager) from the underlying system, which can either be `USERSPACE` (i.e., with frequencies manually set by the user) or `ONDEMAND`. Function `SETGOVERNOR` sets the governor to its argument value. Function `GETFREQ` retrieves the current CPU frequency, whereas `SETFREQ` sets the CPU frequency to its argument value.

Benchmark	Time (ms)	Energy (J)
sunflow	2539 ± 50	62.817554 ± 1.813304
pmd	2140 ± 115	42.107129 ± 3.230344
avroa	5459 ± 55	75.340426 ± 23.990996
jython	2740 ± 204	46.315670 ± 4.523543
fop	939 ± 108	19.521309 ± 2.953879
antlr	1029 ± 84	18.449691 ± 2.391040
bloat	3657 ± 145	62.353593 ± 5.164790
luindex	887 ± 45	14.486979 ± 1.384693

Table 6.1: Benchmark Statistics (Time and energy numbers are collected from runs with the default ONDEMAND governor.

Recall that the scaling instrumentation is used for VINCENT’s passes of frequency selection or energy optimization. The instrumentation is only applied to the hot top-energy consuming methods. When the application is bootstrapped, VINCENT sets the governor to ONDEMAND. When a top energy-consuming method is encountered at its PROLOGUESCALE, the governor and the CPU frequency are set according to the need of frequency selection or energy optimization. VINCENT in addition preserves the governor/frequency context, i.e., the settings of governor/frequency before the PROLOGUESCALE is encountered. The EPILOGUESCALE recovers the preserved context.

Just as profiling, counter-based sampling is also at work during scaling. Note that profiling and scaling do not have to follow the same rate. Constant SN adjusts the rate for scaling. In addition, note that when we reach the LAST sample in each time interval, the governor is reset to ONDEMAND.

6.3 Implementation and Experimental Settings

Hardware/OS/VM Setup We evaluated VINCENT on a dual socket Intel E5-2630 v4 2.20 GHz CPU server, with 10 cores in each socket and 64 DDR4 RAM. Hyperthreading is enabled. The machine runs Debian 4.9 OS, Linux kernel 4.9. For profiling based on individual CPU frequencies and the DVFS-based optimization, we explored all CPU frequencies that can be stably supported by our hardware, ranging from 1.2GHz to 2.2GHz, with the incremental of 0.1GHz. For the rest of the paper, we use F1 to refer to 2.2Ghz, F2

Benchmark	Time (ms)	Energy (J)
sunflow	3838 +- 49	67.627734 +- 0.743458
pmd	4594 +- 65	43.812830 +- 2.369663
avrora	7156 +- 47	76.442363 +- 15.361707
jython	6159 +- 178	61.028495 +- 3.886373
fop	2043 +- 47	19.531982 +- 1.683151
antlr	2166 +- 94	22.675000 +- 1.179513
bloat	8157 +- 105	80.016667 +- 3.608112
luindex	1710 +- 29	16.125000 +- 1.057710

Table 6.2: Benchmark Statistics (Time and energy numbers are collected from runs with the default Powersave governor.)

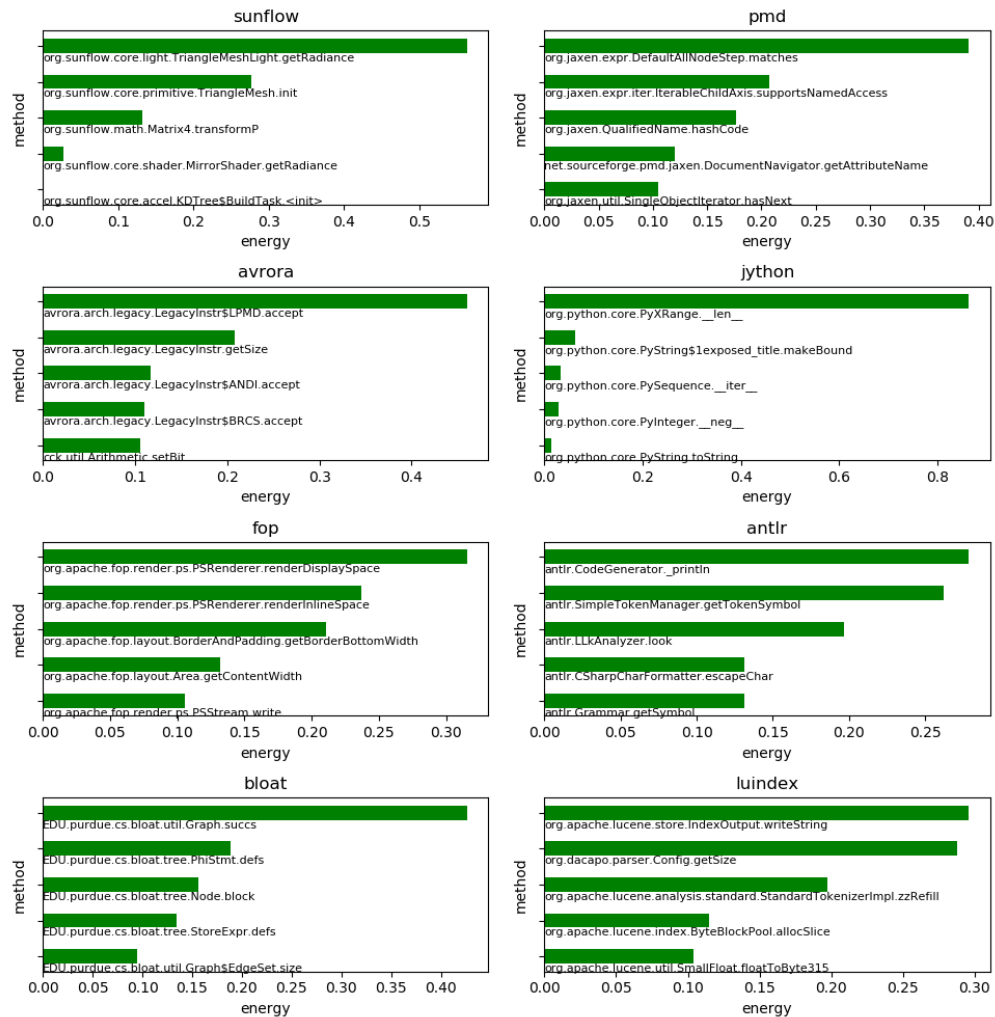


Figure 6.3: Top Energy-Consuming Methods According to VINCENT Energy Profiling (For each benchmark, the top-5 energy consuming methods are shown. The length of each bar represents its normalized energy consumption relative to the overall energy consumption. The name below each bar is the name of the top consuming method.)

for 2.1Ghz, F3 for 2.0Ghz, . . . , F11 for 1.2Ghz.

We rely on RAPL [?] and a Java-based tool jRAPL [57] to obtain raw energy readings. The energy consumption reported by RAPL is accumulative. Each energy sample – as shown of the EDATA type in the algorithm specification — is the sum of energy readings from all sockets; and each socket-wise reading consists of energy consumption for the CPU cores, the uncore (cache, TLB, etc), and the DRAM. Specific to our environment, this means we collect $2 \times 3 = 6$ raw readings for each energy sample.

We implemented VINCENT on JikesRVM version 3.1.4. The hot method selection is built on top of the Adaptive Optimization System (AOS) [5] of JikesRVM.

Hot Method Selection We rely on the JIT component of JikesRVM for hot method selection, where the runtime compiler is set as the optimizing compiler. The hot method selection process in JikesRVM is adaptive, so is the process of profiling based on them. Whenever a new method is identified as hot, VINCENT’s profiler will instrument it dynamically and start its profiling.

One design consideration was whether we should exclude very short methods such as getters and setters from the hot methods. Intuitively, if such methods were subjected to scaling, the scaling overhead might well offset the benefit of setting the method to the desirable frequency. Fortunately, the top energy-consuming methods identified by VINCENT’s energy profiler appear to rarely include them. In other words, these very short methods, even though hot from the perspective of invocation counts, rarely accumulate enough energy consumption to become top energy-consuming methods. As a result, we choose to keep our design simple, and do not alter the hot method selection logic in JikesRVM.

Algorithm Implementation The prologue and epilogue program fragments for profiling and optimization we specified in the previous section are inserted as IR instrumentation through `hir2lir`. Recall that we need to obtain the “this method” information (THISM in Algorithm 2). This is implemented through the optimizing compiler. As the method signature is carried with the IR, VINCENT stores the method information when instrumentation is added.

In the top-level timer loop, the interval EPOCH is identical to the default time interval of AOS, 4ms. Unless otherwise noted, we set the time interval for both profiling and scaling at 8ms, i.e., $PN = 2$ and $SN = 2$. Within each time interval, counter-based sampling is at work for both profiling and scaling. Unless otherwise noted, parameter SAMPLENUM is set at 16. In both scenarios, SKIPNUM = 7. The fact the skipped number of samples should be an odd number is well known in counter-based sampling [4].

All energy readings are stored as a C array and printed after the experiments end for posterior analysis.

Benchmarking and Experimental Setup We evaluate VINCENT with benchmarks in the Dacapo suite [13]. Our benchmarks by default come from the last version of Dacapo known to work with JikesRVM, Dacapo MR2. Dacapo has a more recent release, Dacapo 9.12-bach, and we successfully ported some benchmarks in this version — sunflow, luindex, and avrora specifically — to work with JikesRVM. The rest of porting was unsuccessful because JikesRVM cannot support some advanced Java features that appeared in the later versions of benchmarks. The execution time and energy consumption of each benchmark while running with the ONDEMAND and POWERSAVE governors can be found in Table 6.2.

Throughout this chapter, all experiment results are collected by running each benchmark 20 times in a hot run, and reporting the average of the last 15 runs.

6.4 Chapter Conclusion

VINCENT is a method-grained energy optimizer residing inside the JVM. It identifies the top energy-consuming methods in the Java runtime, and performs feedback-directed optimization guided by DVFS. Our experiments show VINCENT can reduce the energy consumption and improve the energy efficiency of Java applications. Broadly, VINCENT belongs to a small number of energy optimization approaches that take advantage of the information available to the application runtime. It requires no modification to the underlying OS/hardware, and no programmer effort.

Chapter 7

Conclusions and Future Directions

Energy optimization is an active direction in many computer science areas including hardware level, system level and programming model. However, energy optimization in application runtime is less considered in this area. With the knowledge of energy consumption behaviors, application runtime has the advantage of the ability of accessing the method-grained program behavior that other compute stack doesn't have.

7.1 Summary of Contributions

We implemented a software-based energy profiling library jRAPL. Different with the traditional meter-based energy profiling, jRAPL is able to allow developers customize the synchronization of the energy profiling scope. It greatly improves the flexibility of energy optimization in application level.

For the data-oriented characterization of application, We first explored How data management features could impact the energy consumption from 5 perspective: (i) Data access pattern (ii) Data representation (iii) Data organization (iv) Data precision (v) Data I/O strategies. We further explore how application-level energy management interact with hardware-level energy management from both micro-benchmarks and real-world application benchmark perspectives.

We also studied the energy efficiency of Java thread-safe collections and explored the energy optimization possibilities in the real world application. We investigated 13 thread-safe and 3 non thread-safe Java collections and chart the energy optimization possibilities. The small changes have the potential of optimizing the energy consumption from both

micro-benchmarks and real-world benchmarks.

We proposed Vincent, an JVM-based energy optimizing runtime system. Vincent is a novel runtime-based energy optimizer for method-grained energy profiling and optimization. Vincent has unique advantages compared with other layers of energy optimization. Relative to lower-level techniques such as hardware design and OS design, Vincent has ability to access the application runtime specific information which is unavailable to underlying systems. Relative to higher layer energy optimization techniques such as energy-aware programming models, Vincent have an advantage of backward compatibility with legacy code.

7.2 Future Directions

Some challenges of Vincent need to be addressed.

Performance Improvement of Vincent: The biggest challenge of the application runtime system like Vincent is to limit the overhead of the instrumentation for both profiling and optimization. Since any profiling or optimization code added to the JVM could result in hundreds of thousands of invocations. Without careful design, it could impact the original program behaviors which make the energy profiling meaningless. Furthermore, in energy optimization stage, instrumentation overhead would reduce energy optimization gains through formula $E = P * t$. So minimizing the overhead in optimization is critical to improve the energy optimization directly.

Compare Against Powersave Governor: Ondemand governor was replaced by Powersave governor as the default governor in the recent Linux kernel version. Vincent is currently using the Ondemand governor as the baseline to calculate the cost and benefits. We will also work on more efforts to compete the baseline of Powersave governor in the future.

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