# It's Not Easy Being Green: On the Energy Efficiency of Programming Languages

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Does the choice of programming language affect energy consumption? Previous highly visible studies have established associations between certain programming languages and energy consumption. A causal misinterpretation of this work has led academics and industry leaders to use or support certain languages based on their claimed impact on energy consumption. This paper tackles this causal question directly. It first corrects and improves the measurement methodology used by prior work. It then develops a detailed causal model capturing the complex relationship between programming language choice and energy consumption. This model identifies and incorporates several critical but previously overlooked factors that affect energy usage. These factors, such as distinguishing programming languages from their implementations, the impact of the application implementations themselves, the number of active cores, and memory activity, can significantly skew energy consumption measurements if not accounted for. We show—via empirical experiments, improved methodology, and careful examination of anomalies—that when these factors are controlled for, notable discrepancies in prior work vanish. Our analysis suggests that the choice of programming language implementation has no significant impact on energy consumption beyond execution time.

CCS Concepts: • Software and its engineering  $\rightarrow$  General programming languages; Software performance; • Social and professional topics  $\rightarrow$  Sustainability.

Additional Key Words and Phrases: Programming Languages, Performance, Sustainability

#### 1 Introduction

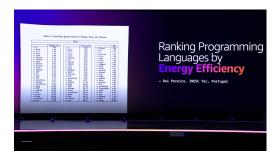
The acceleration of climate change due to use of fossil fuels has driven an increased focus on efforts to decrease both the energy consumption and carbon footprint of computer systems [9, 10, 32]. In 2018, an estimated 1% of total global energy consumption was attributed to datacenters alone [19]. Modern machine learning workloads—especially training—can generate hundreds of tons of  $CO_2$  emissions [34]. For example, Meta reports that training the Llama2 large language model generated an estimated 539 tons of  $CO_2$  emissions [7].

According to an influential line of work, one potential way to reduce energy consumption is to choose a different programming language. This work analyzes a wide selection of programming languages and workloads, and concludes that different programming languages consume widely varying amounts of energy [5, 28, 29]. The centerpiece of these papers is a ranking of programming languages by energy efficiency (reproduced in part in Table 1).

These studies have received wide attention, both in academic and industrial circles. They have been collectively cited over 500 times per Google Scholar (as of September 2024). The results—especially the ranking of programming languages—have had an unusually visible impact in industry, and are routinely quoted on social networks and in blog posts. As Figure 1 illustrates, the rankings have been cited by executives and engineers from Amazon [20–22, 37], Intel [23], SAP [24], and

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(a) Keynote talk at AWS re:Invent 2023: "There is no reason why you should not be programming in Rust, if you are considering cost and sustainability to be high priorities".



(b) Keynote talk at KubeCon + CloudNativeCon Europe 2022: "Coding with Python over Rust for large scale applications can mean a difference of up to 75× in energy usage".

Fig. 1. Prior work presented in industry talks to advocate for Rust over other languages due to reduced energy consumption (§2.1).

other companies [35] to argue for business decisions and to advocate for a shift in programming languages with an eye towards sustainability. Often, these rankings have been harnessed to support the adoption of Rust, which ranks as one of the most energy-efficient languages while providing safety guarantees that languages like C and C++ lack.

Despite the fact that these studies are statistical and only establish associations, they have nonetheless been broadly interpreted as establishing a *causal* relationship, that the choice of programming language has a direct effect on a system's energy consumption. This misinterpretation stems in part from the work's presentation, not only in ranking of languages by efficiency, but also from the specific claim that "it is almost always possible to choose the best language" when considering execution time and energy consumption [29, §3.3].

The above analysis and approach suffer from numerous other methodological flaws (§2.2, §3, §4.2, §4.5). However, the primary focus of this paper is carefully addressing the question: *does the choice of programming language affect energy consumption?* We embrace this question by developing a rich causal model of the relationship between programming language and energy consumption. Figure 2 presents a causal diagram representing of our final model. Causal diagrams illustrate how different factors influence each other, with arrows showing the direction of these influences [27]. We build this model incrementally, incorporating the various factors at play and their relationships, and provide quantitative and/or qualitative evidence supporting each step.

Our model specifically identifies the number of active cores and memory activity as the key contributors to power draw and consequently energy consumption. It highlights the importance of both programming language and application implementations: language implementation decisions can add runtime cost in the form of garbage collection or just-in-time warmup, while application implementations dictate the level of parallelism and overall performance of the program. These varying language and application implementation characteristics are the primary drivers of the anomalies we identify in prior work.

Our experimental approach incorporates several methodological improvements, correcting technical errors in prior work that led to negative or otherwise incorrect energy readings. We present an improved methodology based on hardware performance counter data that makes it possible to accurately quantify average core usage and account for memory activity. After controlling for confounds like varying CPU utilization by forcing benchmarks to run on a single

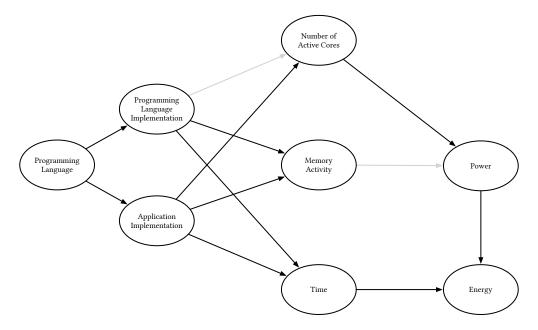


Fig. 2. The causal model (represented as a causal diagram) of the relationship between programming language and energy consumption presented in this paper (§4). Gray arrows represent comparatively weaker relationships, as Section 4 details: programming language implementation has only a minor effect on parallelism, and memory activity plays a minimal, less controllable role in energy consumption compared to CPU activity.

core, and by normalizing by time, we conclude that energy consumed is directly proportional to runtime, and independent of the choice of programming language. These results suggest that, to minimize energy consumption, programmers should focus primarily on optimizing performance.

The remainder of this paper is organized as follows: Section 2 introduces and presents a critical analysis of prior work. Section 3 describes the improved methodology we adopt in our experiments, detailing the measurement tool and the benchmarks used. Section 4 incrementally builds the causal model of the relationship between programming language and energy consumption, explaining and correcting anomalies found in prior work at each step. Section 5 concludes with a discussion of other related work.

#### 2 Prior Work

# 2.1 Overview

The line of work that is the point of departure for this paper explores the relationship between the choice of programming language and energy efficiency [5, 28, 29]. These papers rank programming languages based on energy consumption, runtime, and memory usage, and attempt to find associations between these metrics. In the remainder of this paper, we refer to these papers collectively as "Pereira et al.".

In essence, these studies compare the runtime, energy consumption and memory usage of benchmark implementations in 27 various programming languages. Table 1 presents some of the main results from Pereira et al., limited to the languages discussed in this paper, with anomalous results highlighted in boldface (Section 2.2 discusses this selection in detail). Their experiments

Table 1. **Partial results from Pereira et al. (§2.1)**, showing average runtime and energy consumption for the languages discussed in this paper, normalized to C. **Boldface** denotes anomalous results that Sections 2.2, 4.2, and 4.5 address.

| Language   | Execution Time | Energy Consumption |
|------------|----------------|--------------------|
| С          | 1.00           | 1.00               |
| Rust       | 1.04           | 1.03               |
| C++        | 1.56           | 1.34               |
| Java       | 1.89           | 1.98               |
| Go         | 2.83           | 3.23               |
| C#         | 3.14           | 3.14               |
| JavaScript | 6.52           | 4.45               |
| PHP        | 27.64          | 29.30              |
| TypeScript | 46.20          | 21.50              |
| Python     | 71.90          | 75.88              |
| Lua        | 82.91          | 45.98              |

leverage Intel's Running Average Power Limit (RAPL) interface to measure energy consumption, and GNU time or Python's memory\_profiler to measure peak or "total" memory usage, respectively.

The programs used for comparison are from the Computer Language Benchmark Game (CLBG) [8], a corpus of small benchmark implementations in various languages (22 to 287 lines of code). The most recent paper in the series [29] also incorporates 9 benchmarks from Rosetta Code, a repository of even smaller and simpler code snippets such as Fibonacci, Ackermann, or Sieve of Eratosthenes (typically under 50 lines of code). Because Rosetta Code benchmarks are strictly smaller in scope and size than the CLBG benchmarks, we exclude them from consideration in this paper.

These studies first identify a strong relationship between energy and time. Of course, energy is a linear function of time, hence a strong correlation is expected. They next investigate whether a fast language is always more energy efficient, and claim that this is not the case. They report no significant correlation between peak memory usage and energy consumption, but a strong correlation when considering total memory usage. Finally, they conclude by presenting a ranking of programming languages by energy efficiency, execution time, and memory usage, which programmers can use to select a language for their project.

# 2.2 Critique

As summarized here and discussed in the following sections, Pereira et al.'s studies suffer from several flaws, which this paper addresses and corrects.

- 2.2.1 Programming Language versus Implementation. Programming languages define the syntax and semantics, but it is their implementations that primarily influence performance. While some languages have only a single, widely-used implementation such as Rust or Go, others have multiple implementations, each with their own performance characteristics. For instance, Pereira et al. treat Ruby and JRuby as different languages, while they are in fact two separate implementations of the same Ruby language. The papers uses different benchmark implementations to compare these two Ruby implementations, confounding their comparison.
- 2.2.2 Quality of Benchmark Implementations. While benchmark implementations are claimed to employ the "exact same algorithm" across languages [29, §1], this is in fact not the case. Benchmark implementations have highly varied levels of parallelism and CPU usage, varying degrees of use of third-party libraries, and non-uniform use of vector instructions. These important differences are

not properties of the languages themselves, and their effect on performance and energy consumption must be accounted for.

- 2.2.3 Apparent Anomalies. Some results reported by Pereira et al. are counter-intuitive, and are presented without investigation or explanation. C++ is reported as being 34% less energy efficient and 56% slower than C. Since C++ is approximately a superset of C, and both share the same compiler, optimizations, and code generation backend, we would expect identical energy and runtime performance. Similarly, TypeScript is reported as being 4.8× less energy efficient and 7.1× slower than JavaScript. TypeScript is a strict superset of JavaScript: any valid JavaScript program is a valid TypeScript program. The same Node.js runtime is used for both languages. The compilation process for TypeScript may insert or modify code to support older JavaScript standards, but we do not expect this to result in any significant performance overhead. Java, C#, and Go are reported as 1.89×, 3.14×, and 2.83× slower than C, respectively. These numbers are unexpectedly high as these implementations are known to be highly optimized [18]. We expect low overhead from runtime garbage collection costs, plus initial just-in-time compilation overhead for Java and C#. Lua and TypeScript both stand out as exhibiting significantly lower normalized energy consumption than normalized execution time; this is explained by the fact that nearly all of the implementations of Lua and TypeScript benchmarks are sequential, while nearly all implementations in other languages are parallelized; Section 4.4.1 characterizes the impact of the number of active cores on energy consumption.
- 2.2.4 Memory Metrics. Peak memory usage and "total" memory usage are used to estimate memory activity. The tools used to gather both metrics are both based on resident set size (RSS), which is a poor proxy for memory usage and activity [2]. RSS includes memory that may not be actively used by the program, and crucially does not take cache activity into account. A well-optimized program can have a large RSS but excellent cache locality: if the cache can fulfill most memory requests, memory activity will be low. Benchmark implementation specifics heavily influence peak memory usage, which depends primarily on the choice of data structures used throughout the program. These differences should not be attributed to the languages themselves.

Finally, total memory usage is measured by summing each measurement of RSS taken using Python's memory\_profiler, which is sampled at a frequency of ten times per second. This metric is directly proportional and thus a proxy for the benchmark's execution time, which is itself directly proportional to energy consumption.

2.2.5 Language Implementation Specifics. Most language implementations have an initial cost to import and set up necessary in-memory data structures. Language implementations using a just-in-time compiler also require an initial warmup period [1,36]. These start-up costs are amplified by the benchmarks' short runtimes, which in some cases run for less than a fraction of a second. For example, measuring only the first iteration of a short-lived Java benchmark may not be indicative of Java's overall performance. Section 4.2.1 shows that this first iteration can be up to  $3\times$  slower than subsequent ones. Garbage collection also can have a significant impact on both runtime and memory usage [12], and can be fine-tuned to obtain better performance.

# 3 Methodology

#### 3.1 Setup

We conduct experiments in this paper using a server equipped with two Intel Xeon Gold 6430 processors totaling 128 logical cores and 128GB of memory, running Linux version 6.8.0-45-generic. Table 2 details specific compiler and runtime versions. Experiments in both this paper and Pereira et al.'s use a server architecture.

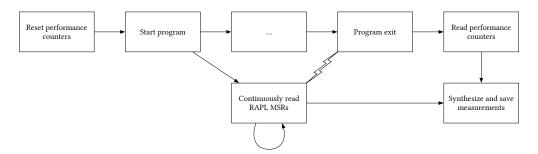


Fig. 3. Overview of the energy measurement tool we develop for this paper (§3.2). The tool reads performance counters at the beginning and end of each benchmark run, and samples energy consumption readings at regular intervals to avoid overflow. Once the program exits, it saves performance counter values and final energy consumption readings to a file. Periodic sampling and minor post-processing are necessary to ensure correct energy readings, as detailed in Section 3.2.1.

| Table 2. Version | s of compilers an | d runtimes used | (§3.1) | . All are most | t recent as of September 2024. |
|------------------|-------------------|-----------------|--------|----------------|--------------------------------|
|------------------|-------------------|-----------------|--------|----------------|--------------------------------|

| Language Implementation | Language(s)            | Version  |
|-------------------------|------------------------|----------|
| LLVM / Clang            | C, C++                 | 19       |
| Rust                    | Rust                   | 1.81.0   |
| OpenJDK                 | Java                   | 21.0.4+7 |
| Go                      | Go                     | 1.23.1   |
| C# / .NET               | C#                     | 8.0.8    |
| Node.js                 | JavaScript, TypeScript | 20.17.0  |
| PHP                     | PHP                    | 8.3.11   |
| tsc                     | TypeScript             | 5.6.2    |
| CPython                 | Python                 | 3.12.6   |
| РуРу                    | Python                 | 7.3.17   |
| Lua                     | Lua                    | 5.4.7    |
| LuaJIT                  | Lua                    | 87ae18a  |

Benchmark runs are isolated in Docker containers to ensure reproducibility. Docker introduces negligible performance overhead [6], which we confirm for the experiments detailed in this paper by obtaining equivalent results with and without Docker. Docker also provides easy access to control groups, which makes it possible to place restrictions on CPU usage or to pin programs to execute on specific cores. Section 4.3 details how we eliminate the effect of varying concurrency in different benchmark implementations by limiting benchmarks to execute on a single core.

#### 3.2 Measurement tool

Figure 3 provides an overview of the general structure of our energy measurement tool. Our tool takes energy samples once per second so as to minimize overhead.

- 3.2.1 RAPL. Since the Sandy Bridge microarchitecture (2011), most Intel processors provide a power management interface called Running Average Power Limit (RAPL). RAPL allows measurement of the energy consumption of various parts of the system [15]. The interface is exposed via Model Specific Registers (MSRs), of which the following measure energy consumption:
  - (1) MSR\_RAPL\_POWER\_UNIT contains information used to convert the raw energy status counter value to joules.

- (2) MSR\_PKG\_ENERGY\_STATUS contains the raw energy status counter for the entire processor package (denoted PKG in our graphs).
- (3) MSR\_DRAM\_ENERGY\_STATUS contains the raw energy status counter for the random access memory attached to that processor.

MSRs track energy consumption at the granularity of an entire package. There is no way to assign energy consumption to a specific thread or process, but only to the system as a whole. In particular, there is no way to eliminate overhead from the measurement tool and other background processes from the measurement. The measurement tool must therefore be as lightweight as possible. We disable all non-essential processes, keeping only those necessary for the machine to operate, and assume these processes remain constant across all experiments.

Further, RAPL samples include all cores, even if the program under test only uses a single core. If a benchmark is single-threaded or generally uses fewer cores than available, idle cores will be included in the energy consumption measurement. Therefore, using a varying level of parallelism across benchmark implementations can result in unfair comparison, as idle cores will add some constant energy consumption to each sample.

An inspection of Pereira et al.'s data files [4] reveals the presence of multiple negative energy readings. Of course, negative energy consumption is not physically possible. We expect that these values were removed by the outlier removal process described in their work and did not affect final results. To ensure correct energy readings, we developed a new measurement tool that corrects the following errors in the tool used by previous work:

- (1) The previous tool incorrectly includes the upper 32 bits of the energy status counters in their accounting. These upper bits are reserved and must be discarded; our tool tracks only the bottom 32 bits, which contain the actual count of consumed energy.
- (2) The previous tool only reads a start and end value of the energy status counter, but that counter overflows after "around 60 seconds when power consumption is high" [14]. To avoid overflow for long-running computations, our tool uses a separate thread that periodically (at 1Hz) reads the contents of this register.
- (3) The previous tool incorrectly subtracts counter readings after scaling and conversion to floating point numbers. This conversion will result in negative or otherwise incorrect results when overflow occurs. Our tool avoids this problem by converting results to floating point only after subtracting consecutive readings.
- 3.2.2 Performance counters. Hardware performance counters are a feature of modern processors that track various events, such as total cycles, cache misses, branch misses, and so on. They are often used to analyze program performance, notably when profiling. These counters are 64 bits in length and thus not susceptible to overflow, so it suffices to read them once at the beginning and once at the end of each experiment.

Memory activity. Section 4.4.2 highlights the impact of memory activity on energy consumption: a majority of memory energy consumption is dependent on the rate of read and write operations. We monitor the last level cache (LLC) using performance counters to estimate memory activity. Each LLC hit means that the cache already had a copy of the data, and therefore no further memory activity occurs. On the other hand, each LLC miss means that the system must fetch data from memory. Therefore, the number of LLC misses is a good proxy for memory activity.

Average CPU usage. There are multiple ways to measure average core usage while a program is running. For simplicity, we leverage performance counters provided by the operating system. The Linux kernel exposes the task-clock software event counter, which aggregates in nanoseconds

| Benchmark          | LoC    | Description   |
|--------------------|--------|---|
| binary-trees       | 36-98  | Allocates and frees binary trees of various specified depth.    |
| fannkuch-redux     | 40-158 | Computes the max number of flips to sort a permutation.         |
| fasta              | 84-287 | Generates random DNA sequences.                                 |
| k-nucleotide       | 57-202 | Counts frequencies of nucleotide sequences in a string.         |
| mandelbrot         | 32-140 | Plots the Mandelbrot set $[-1.5 - i, 0.5 + i]$ .                |
| n-body             | 78-157 | Models orbits of Jovian planets.                                |
| pidigits           | 41-149 | Generates digits of $\pi$ using arbitrary precision arithmetic. |
| regex-redux        | 22-111 | Uses simple regex patterns to manipulate DNA data.              |
| reverse-complement | 34-257 | Outputs complements of each nucleotide from sequence.           |
| spectral-norm      | 33-156 | Calculates the spectral norm of an infinite matrix.             |

Table 3. **Descriptions of benchmarks from the Computer Language Benchmark Game (§**3.3), along with the range of lines of code (LoC) across languages for each benchmark as reported by cloc.

the time spent on all processor cores. To obtain average core usage, we divide this counter's value by the total runtime of the program.

# 3.3 Computer Language Benchmark Game

The Computer Language Benchmark Game (CLBG) [8] is a collection of small programs implemented in many different programming languages (22 to 287 lines of code). We use the same benchmark implementations as Pereira et al. [4], which is in effect a snapshot of the fastest versions of the benchmarks as available on the CLBG repository at the time of the original work. Table 3 provides a brief description of each benchmark. We limit our analysis to eleven languages across thirteen implementations: C, C#, C++, Go, Java, JavaScript, Lua (Lua and LuaJIT), PHP, Python (CPython and PyPy), Rust, and TypeScript. These languages comprise 11 of the top 12 most popular general programming languages in the 2024 StackOverflow survey [26] (excluding Kotlin).

We attempt to compile and run all benchmark implementations with sources present in the repository, and omit those without source code or which fail with compilation or runtime errors. After these omissions, the analysis below spans 118 out of 130 possible language implementation / benchmark pairs. Some benchmarks make use of third-party libraries: we use the default package manager's version when available, or manually upgrade to the latest available version.

We stress that while the CLBG benchmarks themselves are not necessarily representative of real-world applications, the causal analysis this paper develops is largely independent of the details of the benchmark implementations. It instead highlights the impact of high-level *properties* of the benchmark implementations, such as their degree of parallelism and cache activity.

# 4 Causal Model for Energy Consumption in Programming Languages

This section builds piece by piece the causal model presented in its final form in Figure 2. Each subsection gradually adds nodes and edges to obtain a rich causal diagram that captures the essential factors in the relationship between the choice of programming language and energy consumption.

## 4.1 Starting Point

Our starting point, shown in Figure 4, is that the choice of programming language has a direct effect on energy consumption. The following sections will explore additional elements that come into play in this relationship, and build up a complex model exploring the impact of different factors on energy consumption.

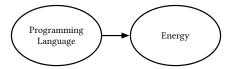


Fig. 4. The simple model used as a starting point in this paper (§4.1). This simple model captures the relationship implied in Pereira et al., namely that the choice of programming language has a direct impact on total energy consumption.



Fig. 5. **Programming languages may have multiple implementations (§4.2)**, and implementation decisions such as garbage collection or using just-in-time compilation have a more direct impact on performance. We are in fact comparing implementations of programming languages, not the languages themselves.

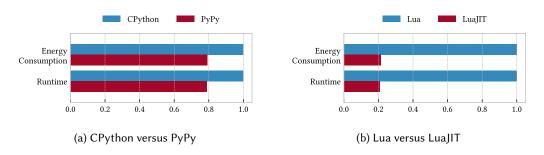


Fig. 6. **Programming Languages can exhibit different performance characteristics depending on the implementation used (§**4.2**).** Here, we compare interpreters (CPython, Lua) to their JIT equivalent (PyPy, LuaJIT) on the same benchmark sources. We normalize to the interpreter results. We find around 5× and 1.25× decreased runtime and energy consumption on average for LuaJIT over Lua and PyPy over CPython, respectively. These results demonstrate the impact of choice of programming language implementation versus the language itself.

## 4.2 Programming Languages and Implementations

Figure 5 introduces the important distinction between the programming languages themselves and their implementations. Some languages have a single well-known implementation, or a blurry line between language and implementation, such as Rust or Go. Others have multiple implementations, such as C/C++ with GCC, Clang, or MSVC, Java with various JVMs, Python with CPython and PyPy, or Lua with LuaJIT.

Of course, programming languages have an effect on implementation possibilities. They may dictate the general memory layout of objects, the need for a garbage collector, or the possibility of ahead-of-time compilation. For example, Java forces object dereferences to be indirect, and has no alternative for memory reclamation other than a garbage collector. Other dynamic features such as dynamic typing, reflection, or eval further limit the range of options available to implementers.

Figure 6 compares languages across multiple implementations on the same set of benchmarks, namely CPython/PyPy and Lua/Lua/IIT, and shows that the same language can have vastly different

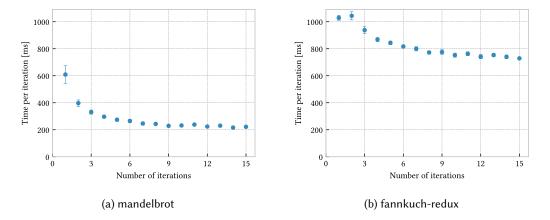


Fig. 7. Measuring just the first iteration is not indicative of Java's (OpenJDK) performance for long-lived applications (§4.2.1). We gradually increase the number of iterations, observing decreased per-iteration runtime on several benchmarks, including (a) mandelbrot and (b) fannkuch-redux shown above. This effect could be due to startup and cleanup time and/or a JIT warmup effect. The curve flattens as we average over more iterations.

performance characteristics, depending on the implementation used. On average for these benchmarks, PyPy is about  $1.25 \times$  faster than CPython, and LuaJIT is  $5 \times$  faster than the Lua interpreter.

Not only can programmers choose a specific implementation over another, implementation specific properties can cause significant differences in performance and energy consumption, and should be taken into account in a fair comparison. We discuss two of those properties below, just-in-time warmup and garbage collection.

4.2.1 Just-in-Time (JIT) Warmup. JIT program execution is typically split into a startup phase and a delayed steady state phase of peak performance. As a JIT program executes, it determines which code paths are frequently executed, and compiles them into machine code. As the program continues to revisit these hotspots, performance of further iterations improves. This system allows for a good startup time to peak performance tradeoff. However, existing research has already shown that a steady state of peak performance is not always reached [1, 36]. In fact, one of these studies [1] uses the same CLBG benchmark suite and demonstrates that for some benchmarks, a steady state is never reached.

Factors other than JIT warmup may also be affecting the very first iteration of those short-lived benchmarks, such as bytecode interpretation or memory and garbage collection initialization. To test this, we wrap each Java benchmark in a loop and gradually increase the number of in-process iterations. Figure 7 shows that for the mandelbrot and fannkuch-redux benchmarks, the first iteration's runtime is  $2.5\times$  and  $1.5\times$  slower respectively than when averaging over 15 iterations. Generally, we see that for these and other benchmarks, averaging over ten or more iterations amortizes the first iteration's impact. Applying this method over every benchmark, we observe 80% improved energy efficiency and runtime performance versus using only the first iteration.

4.2.2 Garbage Collection. An important property of higher-level languages and their implementations is garbage collection, which imposes significant performance overhead [12]. Out of the 13 language implementations discussed in this paper, 10 use a garbage collector at runtime. Garbage collectors can typically be configured and tuned for each application to offer maximal performance,

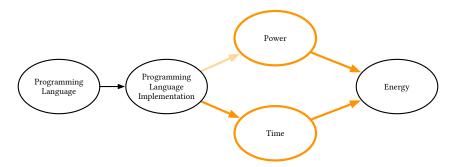


Fig. 8. **Energy consumption is the product of power and time (§**4.3**).** Splitting into these two components allows separate consideration of each factor. As Figure 9 shows, there is no significant difference in power draw between implementations when we keep external factors constant, hence the impact of programming language implementation on energy consumption beyond runtime is negligible.

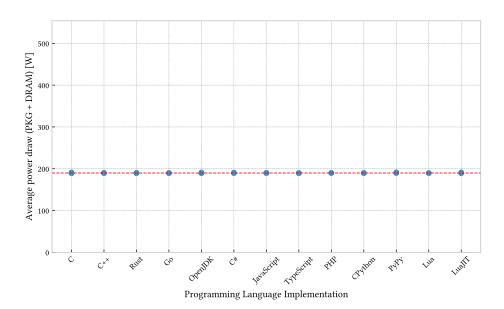


Fig. 9. Average power draw (package (PKG) + DRAM) does not differ significantly across programming language implementations (§4.3). Each point represents a single benchmark implementation (i.e., a single language implementation / benchmark pair). Points exhibit extremely low variance, and so are overlapped in the graph. After controlling for external factors such as varying number of active cores and runtime, average power draw is constant across benchmark and programming languages implementations. The red line indicates the mean power draw of  $189.8 \pm 0.5$  W.

which is standard practice in real-world applications to optimize for application throughput and/or latency. For example, Go's garbage collector can be disabled entirely with the GOGC environment variable. When doing so, we observe a 2.8× speedup on the allocation-intensive binary-trees benchmark.

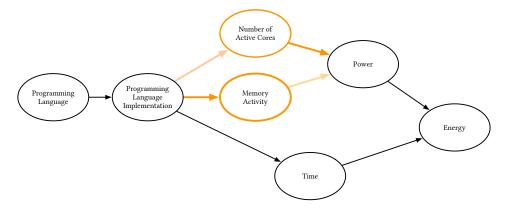


Fig. 10. Number of active cores is the primary factor in increased power draw (§4.4). Memory activity also increases power draw, but to a much lesser extent. Figure 11 quantifies this.

#### 4.3 Decomposing Energy into Power and Time

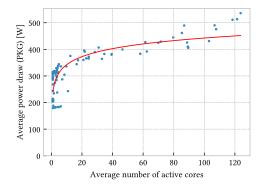
Fundamentally, energy consumption is the product of power and time. Figure 8 decomposes these two factors. To test if the choice of programming language implementation has an effect on power draw beyond runtime, we fix other factors that may affect power draw. We divide by execution time to normalize for runtime differences. We limit the program to a single core via Docker's --cpuset-cpus argument. To ensure frequency scaling and throttling do not increase power draw variance in our measurements, we pin CPUs to their minimum frequency with turbo mode disabled. Figure 9 shows that there is no significant difference in power draw between programming language implementations once these outside factors are controlled for.

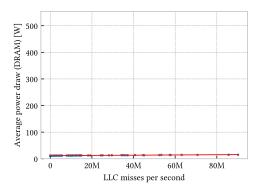
In theory, any language implementation with a runtime system running in parallel may affect energy consumption beyond the increased runtime, since increased core usage will increase power draw, as Section 4.4.1 details below. This hidden increased parallelism could occur with a parallel garbage collector or just-in-time compilation threads executing alongside the main program. In practice, compilation threads are primarily active only during startup, and both are rarely significant compared to the main program's execution and other general overhead costs. For this reason, we draw this edge in gray in our model.

#### 4.4 Contributors to Power Draw

Previous research has demonstrated that processor and memory energy usage are the main variable contributors to power draw [38]. We add these two factors to our model in Figure 10. For the studied programs on our experimental platform, the ratio of memory energy consumption to CPU energy consumption remains between 2 and 8%. This percentage is in line with the reported numbers in Pereira et al.

4.4.1 Number of Active Cores. Figure 11a shows the relationship between the number of active cores and power draw. Using multiple cores, energy usage grows up to around  $2\times$  the base power draw compared to using a single core. We fit a log curve to the data  $(R^2 = 0.70)$ , as the relationship does not appear linear, but results may vary across platforms. Denoting Power (x) as the average power draw using x cores, we find that, on our system, doubling the number of cores used increases





- (a) Average package (PKG) power draw by average number of active cores (§4.4.1). Log regression:  $y = 30 \log_2 x + 242 (R^2 = 0.70)$ .
- (b) Average DRAM power draw by memory activity (§4.4.2), approximated using LLC misses. Linear regression:  $y = 4.47 \cdot 10^{-8} x + 11.6 (R^2 = 0.94)$ .

Fig. 11. Power draw is much more significantly affected by the number of active cores than memory activity (§4.4). Each point on those graphs represents a single benchmark implementation (i.e., a single language implementation / benchmark pair).

average power draw by only roughly 30W:

Power 
$$(x) = 30 \log_2 x + 242$$
  
 $\Rightarrow \text{Power } (2x) = 30 \log_2 (2x) + 242$   
 $\Rightarrow \text{Power } (2x) = 30 \log_2 2 + 30 \log_2 x + 242$   
 $\Rightarrow \text{Power } (2x) = \text{Power } (x) + 30$ 

Further, on our machine, doubling the number of cores increases relative energy efficiency, provided throughput increases by at least 13%:

$$\frac{\text{Power }(2x)}{\text{Power }(x)} = \frac{30\log_2{(2x)} + 242}{30\log_2{x} + 242} \le 113\% \quad (1 \le x \le 128)$$

In other words, parallelization overhead up to 87% is acceptable. On our experimental platform, aggressively parallelizing programs is nearly always an energy-efficient choice.

4.4.2 Memory Activity. Previous research has shown that roughly 40% of dynamic random access memory (DRAM) energy consumption is constant and required to refresh memory cells to keep the system running properly, while the remaining 60% is related to read and write activity [33]. Section 3.2.2 introduces last level cache (LLC) misses as a better proxy for memory activity: any read or write request that cannot be fulfilled by the LLC will have to go to DRAM. Figure 11b shows a strong linear correlation between LLC misses and increased power draw ( $R^2 = 0.94$ ).

On the other hand, memory activity is not something that is easily controlled by the programmer. While certain algorithms or data structures maximize cache locality, there is eventually a limit stemming from the LLC's fixed, relatively small size. Programming languages or their implementations may impose additional overhead with a garbage collector, memory allocation overhead, or object memory layout. Because of the difficulty of controlling memory activity, as well as its comparatively smaller impact compared to CPU activity on power draw (2–8%), we draw this edge in gray in our model.

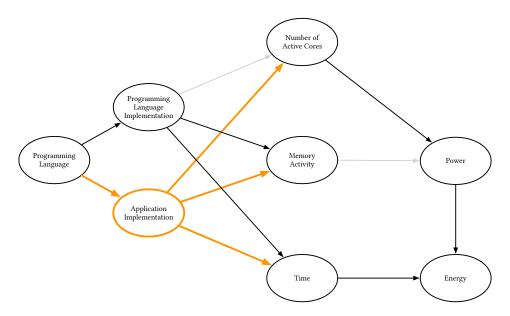


Fig. 12. **The final model incorporating application implementations (§**4.5**).** Application implementations notably dictate the number of cores used by the program and the use of third-party libraries. These implementation choices are not properties of the programming language itself.

# 4.5 Application Implementations

Finally, Figure 12 adds the application implementations themselves, which have the most direct impact on energy consumption. Implementations dictate the level of parallelism, the algorithms used, and the data structures employed. We discuss two factors, concurrency and third-party library usage, below.

4.5.1 Concurrency. Section 4.4.1 asserts that the number of cores used by an application is a major factor in energy consumption. Therefore, comparing benchmark implementations in different languages that use different numbers of cores is not a fair comparison. Level of parallelism imbalances are the main reason for the reported performance discrepancies between JavaScript and TypeScript. The TypeScript version of the mandelbrot benchmark takes 21× longer to run than its JavaScript implementation. Its execution is fully sequential, while the JavaScript version uses 28 cores on average.

Further, since TypeScript is a strict superset of JavaScript and we test them using the same runtime, there should be no differences in runtime or energy consumption. With some minor edits in four benchmarks, all JavaScript benchmark implementations pass the TypeScript compiler without any errors, and yield equal performance.

4.5.2 Third-Party Libraries. Choice of third-party libraries used has a significant impact on application performance. In fact, regular expression benchmarks are often poor candidates to make any comparison beyond the library used. This is the case for the CLBG regex-redux benchmark: it is 8.9× slower in its C++ implementation compared to the C version. This difference is entirely due to the choice of third-party library used: the C version uses the PCRE library, while the C++ version uses the Boost library. On this benchmark, Boost's library performs significantly worse than PCRE. This outlier alone accounts for the entire reported gap between C and C++.

Unlike TypeScript and JavaScript, C++ is not a strict superset of C. Nonetheless, all C benchmarks compile in C++ mode, only sometimes requiring the -fpermissive compiler flag or minor changes such as added types or casting. These programs then yield identical performance and energy consumption numbers.

Crossing Language Boundaries. Using third-party libraries also allows for easily crossing language boundaries, for instance to access lower-level system utilities or to obtain greater performance. In Python, using NumPy can yield up to 60,000× faster code when multiplying matrices [2, 16]. To some degree, this has even become the "correct" way of writing Python code, by using low-level languages for computation intensive tasks and wrapping those in Python functions. Even C++ may cross over to code originally written using C, Fortran, or direct Assembly for performance when using BLAS.

#### 4.6 Other Factors

There are many other factors that may affect energy consumption. CPU voltage and frequency scaling has a direct impact on power consumption, and there is active research focusing on reducing or increasing frequency based on memory activity or other factors to draw less power for a comparatively smaller performance penalty [39]. Specific processor model and architecture also have an impact on power draw, with newer processors generally being more energy-efficient. These factors are unrelated to choice of programming languages and are controlled for in our experiments.

#### 5 Related Work

Previous sections, notably Section 2, discuss the main line of research relating programming languages and energy consumption [5, 28, 29]. These studies discuss and rank programming languages based on runtime, energy consumption, and memory usage. Contrary to their results, we show in this paper that the interplay between these properties is complex and depends on many factors not taken into account in their work.

The processor's operating voltage and frequency also have an impact on energy consumption. This impact has been studied in the context of trading off speed for reduced energy consumption, where compiling for speed yields better energy efficiency in the general case [40]. For some specific applications, such as sparse matrix computations, compile-time techniques may decrease energy usage without impact to execution time by leveraging load imbalance [3]. Other work has shown that using characteristics of a program at runtime to reduce the processor's voltage or frequency can yield higher energy efficiency for a comparably smaller performance degradation [13]. For example, performance counter information can be used to scale the processor's frequency [39]. These approaches are orthogonal to the choice of programming language and could be applied in many programming environments.

Previous research also addresses the energy consumption of different data structures in certain languages, notably Java collections [11, 25, 30]. Data structures can be interesting candidates to study with an energy-focused lens as they can have a substantial impact on locality and memory activity, which are factors of energy consumption (as Section 4.4.2 describes). In many cases, however, programmers only have a limited choice of data structures that would be a good fit for their use case or algorithm.

Finally, past work has also investigated energy efficiency of concurrency related structures, such as Haskell's data sharing primitives [17] or Java's thread management constructs [31]. As Section 4.4.1 argues, these studies confirm that the power usage patterns of the processor and the machine as a whole are more complex when parallel execution is involved.

#### 6 Conclusion

This paper presents a detailed causal model exploring the complex relationship between choice of programming language and energy consumption. It shows some of the many factors at play, notably distinguishing implementation from programming language and establishing the number of active cores and memory activity as two important factors in power draw.

Using this causal model, we investigate and explain anomalies in previous research, finding that many factors such as parallelism level, benchmark implementation specifics, or language implementation properties must be taken into account for a fair comparison. Our results suggest that the choice of programming language has no significant impact on energy consumption beyond runtime. Programmers aiming to reduce energy consumption can do so even in "inefficient" programming languages like Python by using faster language implementations, employing faster algorithms, and using fast third-party (native) libraries.

### **Data-Availability Statement**

The software and benchmarks that support this paper's experiments are available on GitHub at github.com/nicovank/Energy-Languages.

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