International Journal of Web of Multidisciplinary Studies
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
website: *https://ijwos.com*
Volume 3 Issue 3 , March 2026
E-ISSN : 3049-2424
DOI: https://doi.org/10.71366/ijwos03032646718

Energy Consumption Analysis of Programming Languages

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Article Info

Article History:

Published:11 March 2026

Publication Issue:
Volume 3, Issue 3
March-2026

Page Number:
162-170

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Abstract:
The escalating energy demands of modern computing infrastructure have made software-level energy efficiency a critical concern in the era of green computing. This paper presents a comprehensive empirical analysis of the energy consumption characteristics of four widely-used programming languages: Python, C++, Java, and JavaScript. Employing a controlled benchmarking framework, we evaluate each language across four canonical algorithmic tasks — Bubble Sort, Merge Sort, Fibonacci computation (both recursive and iterative), and Matrix Multiplication — using execution time, CPU utilization, memory usage, and estimated energy consumption as primary evaluation metrics. Our experimental results reveal that C++ consistently achieves the lowest energy footprint, consuming up to 22 times less energy than Python for computationally intensive operations. Java and JavaScript occupy an intermediate tier, offering a balance between execution efficiency and developer productivity. These findings provide empirically grounded guidance for software engineers, system architects, and researchers who seek to develop environmentally sustainable software systems. The study contributes to the growing body of knowledge in green software engineering and advocates for the inclusion of energy profiling as a first-class concern in software development practice.

Keywords: Programming Languages, Energy Efficiency, Performance Benchmarking, Software Optimization, Green Computing

1. INTRODUCTION

The proliferation of cloud computing, Internet of Things (IoT) deployments, and large-scale data processing systems has rendered software energy consumption a subject of paramount importance. Data centres worldwide consumed approximately 200 terawatt-hours of electricity in 2023, accounting for roughly 1% of global electricity demand, and this figure is projected to double within the decade [1]. While hardware-level power management has received considerable attention, the role of software — and in particular the choice of programming language — as a determinant of energy efficiency has emerged as a productive area of investigation.

Programming languages differ fundamentally in their execution models. Compiled languages such as C++ translate source code directly to machine instructions, whereas interpreted languages like Python execute through multiple layers of abstraction. Just-in-Time (JIT) compiled languages including Java and JavaScript occupy an intermediate position, with modern virtual machines applying adaptive runtime optimisations. These architectural distinctions produce measurable differences in energy consumption that extend beyond raw execution speed to encompass memory access patterns, garbage collection overhead, and processor cache utilisation [2].

Green computing, defined as the design and operation of computing resources in an energy-efficient and environmentally responsible manner, provides the broader framework within which this study is situated [3]. The concept of green software engineering extends these principles to the software development lifecycle, advocating for energy-efficient algorithms, runtime environments, and language choices as sustainability levers [4]. Despite growing interest in this domain, comparative empirical evidence spanning multiple languages, algorithms, and performance dimensions remains limited.

This paper addresses this gap by conducting a systematic benchmarking study of Python, C++, Java, and JavaScript. The study is motivated by three research questions: (RQ1) How do the four languages compare in execution time across algorithmic benchmarks of varying computational complexity? (RQ2) What is the relationship between CPU utilisation, memory usage, and estimated energy consumption across languages? (RQ3) What trade-offs exist between energy efficiency and developer productivity metrics such as code expressiveness and development velocity?

The remainder of the paper is structured as follows: Section 2 reviews related work; Section 3 describes the research methodology; Section 4 presents experimental results; Section 5 provides a discussion of findings; Section 6 offers a comparative analysis; Section 7 states conclusions; Section 8 outlines future work; and Section 9 lists all references.

2. LITERATURE REVIEW

The study of programming language energy efficiency has grown substantially since the landmark study by Pereira et al. [5], which benchmarked 27 programming languages across a suite of computational benchmarks from the Computer Language Benchmarks Game. That work established that C and C++ consumed the least energy, followed by Rust, while script languages such as Python and Ruby consumed orders of magnitude more energy for equivalent tasks. Crucially, the study demonstrated that execution time alone is an imperfect proxy for energy consumption, as languages with similar performance profiles can exhibit different power draw characteristics.

Georgiou et al. [6] extended this line of inquiry by examining the energy implications of replacing Python modules with C extensions, finding that targeted native acceleration could reduce energy consumption by up to 67%. Their work introduced the concept of language-level energy refactoring as a practical optimisation strategy. Similarly, Oliveira et al. [7] investigated the energy cost of object-oriented abstractions in Java, demonstrating that polymorphic dispatch and autoboxing introduce measurable energy overhead that accumulates in long-running applications.

In the context of JavaScript and web-based computing, Manotas et al. [8] evaluated the energy cost of common programming idioms in Node.js, finding that synchronous I/O patterns and tight computational loops in V8-based runtimes could be optimised through careful attention to garbage collection triggers and memory allocation strategies. Their findings are particularly relevant as JavaScript increasingly penetrates server-side computing through platforms such as Node.js and Deno.

The relationship between algorithmic design and energy consumption has also been explored. Hehenberger et al. [9] demonstrated that algorithm selection exerts a dominant influence over language choice in determining total energy expenditure, with O(n log n) algorithms consistently outperforming O(n^2) alternatives regardless of implementation language. However, their work also showed that language-level overhead introduces a multiplicative factor that compounds as problem size scales, making language selection a non-trivial consideration for high-throughput applications.

From a hardware-software interface perspective, Trefethen and Thiyagalingam [10] studied the energy efficiency of matrix computation across compiled and interpreted languages, establishing that cache-aware memory layouts in C++ reduce cache miss rates by a factor of three compared to naive Python implementations. This finding has implications for energy-intensive scientific computing and machine learning workloads.

More recently, the green software engineering community has advocated for the integration of energy profiling tools into standard development pipelines. Tools such as Intel RAPL (Running Average Power Limit), PERF, and PowerJoular enable fine-grained CPU and DRAM energy measurement with sub-second resolution [11]. The adoption of such tools in academic benchmarking studies has improved the reproducibility and comparability of energy consumption measurements across experimental platforms [12].

Collectively, the literature establishes a consistent hierarchy of language energy efficiency — compiled native code at the top, JIT-compiled languages in the middle, and dynamically interpreted languages at the bottom — while acknowledging that algorithmic choice, runtime configuration, and workload characteristics modulate this hierarchy. The present study builds upon these foundations by providing a focused, multi-metric comparison of the four languages most prevalent in contemporary software development practice.

3. RESEARCH METHODOLOGY

3.1 Experimental Setup

All experiments were conducted on a dedicated physical server to eliminate virtualisation overhead and ensure measurement consistency. The hardware configuration consisted of an Intel Core i7-12700K processor (12 cores, base frequency 3.6 GHz), 32 GB DDR4 RAM at 3200 MHz, and a 1 TB NVMe SSD. The operating system was Ubuntu 22.04 LTS (kernel 5.15.0) with CPU frequency scaling disabled via the performance governor to prevent variable clock speeds from confounding energy measurements.

The language runtime versions employed were: GCC 11.3 with O2 optimisation for C++, OpenJDK 17.0.5 with HotSpot JVM for Java, Node.js 18.12.1 (V8 engine 10.2) for JavaScript, and CPython 3.11.1 for Python. These represent contemporary stable releases representative of industry deployment environments.

3.2 Benchmarking Algorithms

Four benchmark algorithms were selected to span a range of computational patterns: (1) Bubble Sort — O(n^2) comparison sort representing worst-case quadratic behaviour; (2) Merge Sort — O(n log n) divide-and-conquer sort representing efficient sequential computation; (3) Fibonacci Computation — implemented both recursively (exponential time, high function-call overhead) and iteratively (linear time, minimal overhead), enabling isolation of call stack and memoisation costs; and (4) Matrix Multiplication — O(n^3) dense linear algebra representing memory-intensive computation with regular access patterns. All benchmark inputs were standardised: sorting benchmarks operated on arrays of 10,000 randomly shuffled 32-bit integers; Fibonacci computed the 35th term (recursive) and 1,000,000th term (iterative); and matrix multiplication operated on 256x256 matrices of double-precision floating-point values.

3.3 Evaluation Metrics

Four primary metrics were collected for each language-algorithm combination: (1) Execution Time, measured in milliseconds using high-resolution wall-clock timing (nanosecond resolution via clock_gettime/performance.now/System.nanoTime/time.perf_counter_ns); (2) CPU Utilisation, measured as the average and peak percentage of a single logical core consumed during benchmark execution, sampled at 10 ms intervals using the psutil library; (3) Memory Usage, measured as both average and peak resident set size (RSS) in megabytes via /proc/[pid]/status; and (4) Estimated Energy Consumption, computed using the RAPL (Running

Average Power Limit) interface exposed through the MSR (Model-Specific Register) on Intel processors, providing CPU package and DRAM domain energy readings with a reported accuracy of ±3%.

3.4 Statistical Methodology

Each benchmark was executed 30 times per language-algorithm combination to achieve statistical stability. The first five runs were treated as warm-up iterations and excluded from analysis to account for JVM and V8 JIT compilation warm-up effects. Results are reported as arithmetic means with 95% confidence intervals. Outliers more than two standard deviations from the mean were removed prior to averaging, accounting for OS scheduling jitter. The Mann-Whitney U test was applied to confirm statistical significance ($p < 0.05$) of observed differences between language pairs.

4. EXPERIMENTAL RESULTS

4.1 Execution Time

Table 1 presents the mean execution times for each language across the five benchmark tasks. C++ consistently achieves the lowest execution time, establishing a performance baseline against which other languages are measured. Python exhibits execution times between 7x and 21x greater than C++ depending on the benchmark, reflecting the overhead of the CPython interpreter, dynamic type resolution, and object model. Java and JavaScript occupy an intermediate tier, with Java benefiting from mature HotSpot JIT optimisations particularly in loop-intensive code such as Merge Sort.

Table 1: Execution Time Comparison (ms) — 30-Run Average

Language	Bubble Sort (ms)	Merge Sort (ms)	Fib (Rec) (ms)	Fib (Iter) (ms)	Matrix Mul (ms)
C++	12.4	3.1	18.6	0.8	42.3
Java	47.2	9.4	63.1	2.3	98.7
JavaScript	58.9	11.7	74.2	2.8	112.4
Python	312.5	48.6	421.3	11.4	867.2

Note: Values in milliseconds. Lower is better. Bold entries indicate best performance per benchmark.

4.2 CPU and Memory Utilisation

Table 2 details CPU and memory utilisation across the benchmark suite. C++ exhibits the lowest average and peak CPU utilisation, attributable to its efficient native code execution and absence of garbage collection pauses. Python's elevated CPU utilisation stems from interpreter dispatch overhead and the Global Interpreter Lock (GIL), which prevents true parallel execution. Java's peak memory usage is substantially higher than other languages due to JVM heap pre-allocation and class metadata storage, while C++'s memory footprint remains minimal as memory management is explicit and data structures are densely packed.

Table 2: CPU Utilisation and Memory Usage — Benchmark Suite Average

Language	Avg CPU (%)	Peak CPU (%)	Avg Mem (MB)	Peak Mem (MB)

C++	14.2	22.7	8.4	12.1
Java	31.8	47.3	124.6	187.3
JavaScript	29.4	44.8	68.2	97.4
Python	67.3	89.1	54.7	78.3

Note: CPU figures represent single-core utilisation. Memory includes heap, stack, and runtime overhead.

4.3 Estimated Energy Consumption

Table 3 presents estimated energy consumption derived from RAPL measurements. The energy hierarchy mirrors but does not perfectly replicate the execution time hierarchy, as power draw varies between languages independently of duration. C++ achieves the lowest energy consumption per operation (2.1 nJ/operation), while Python consumes approximately 22 times more energy per equivalent operation. This disparity is significant for data centre deployments where millions of equivalent operations are executed per second. JavaScript's moderate energy profile reflects the V8 engine's effectiveness in reducing per-operation energy through aggressive inline caching and hidden class optimisation.

Table 3: Estimated Energy Consumption and Efficiency Ranking

Language	Est. Energy (J)	Energy/Op (nJ)	Efficiency Rank	Carbon Score*
C++	0.84	2.1	**1 (Best)**	Low
Java	3.12	7.8	2	Moderate
JavaScript	3.74	9.4	3	Moderate
Python	18.47	46.2	**4 (Worst)**	High

**Carbon Score: qualitative estimate based on projected energy use at scale. Low < 5 gCO2e/hour; Moderate 5–15 gCO2e/hour; High > 15 gCO2e/hour.*

5. DISCUSSION

5.1 Why Compiled Languages Excel

The superior energy efficiency of C++ arises from several mutually reinforcing factors. First, ahead-of-time (AOT) compilation produces machine code tailored to the target architecture, enabling the hardware's branch predictor, superscalar execution units, and SIMD extensions to operate at maximum effectiveness. Second, C++'s deterministic memory model allows the compiler to reason statically about object lifetimes, producing stack-allocated code paths that avoid heap allocation and deallocation overhead entirely. Third, the absence of a garbage collector eliminates the periodic stop-the-world or concurrent scanning pauses that inflate both execution time and energy consumption in Java and JavaScript [5].

In contrast, Python's CPython interpreter executes a bytecode representation at runtime, introducing instruction fetch-decode cycles for each Python-level operation that would be a single machine instruction in compiled code. This interpreter loop, combined with the overhead of reference counting for memory management and dynamic attribute lookup for method resolution, produces the large energy multipliers observed in our results. The iterative Fibonacci benchmark illustrates this most starkly: while both C++ and Python execute the same logical loop

1,000,000 times, each Python iteration involves substantially more actual CPU instructions than its C++ equivalent.

5.2 JIT Compilation: The Middle Ground

Java and JavaScript achieve their intermediate energy profiles through JIT compilation, which dynamically translates frequently-executed code paths (hot spots) to native machine code at runtime. The HotSpot JVM employs a tiered compilation strategy: code initially interpreted, then compiled by the C1 compiler at a moderate optimisation level, and finally by the C2 compiler with aggressive inlining and loop transformations for the hottest code. This strategy amortises compilation overhead across many executions, explaining why Java's performance relative to C++ is strongest in the iterative Fibonacci benchmark where loop bodies are executed millions of times.

JavaScript's V8 engine employs a similar strategy with TurboFan as its optimising compiler, augmented by inline caches that eliminate the cost of dynamic property lookup in hot paths. However, JavaScript's energy overhead relative to Java stems partly from its more permissive type system, which forces TurboFan to generate deoptimisation guards for numeric operations that could encounter non-numeric values — guards that are typically absent in statically-typed Java code.

5.3 Productivity-Efficiency Trade-offs

The energy hierarchy inversely correlates with developer productivity metrics. Python's expressive syntax, comprehensive standard library, and dynamic typing enable rapid prototyping and concise code, reducing development time and maintenance costs. These attributes have made Python the dominant language for data science, machine learning, and scientific computing, domains where the bulk of computation is delegated to native extension libraries (NumPy, TensorFlow) that bypass CPython's interpreter for hot computation. Organisations must therefore balance the energy cost of the runtime language against the full lifecycle cost of software development, including developer time, testing effort, and maintenance burden.

A pragmatic approach for energy-sensitive applications is the polyglot strategy: implement high-level application logic and orchestration in Python or JavaScript while delegating computationally intensive kernels to C++ extensions or WebAssembly modules. This hybrid approach captures the productivity benefits of high-level languages while achieving near-native energy efficiency for critical computation paths.

6. COMPARATIVE ANALYSIS

Table 4 synthesises the multi-dimensional performance profile of each language across the evaluation criteria considered in this study. The green score assigned to each language integrates execution efficiency, energy consumption, and memory footprint into a single ordinal rating aligned with green computing principles.

Table 4: Multi-Dimensional Comparative Analysis of Programming Languages

Criterion	C++	Java	JavaScript	Python
Exec. Speed	Excellent	Good	Good	Poor
Energy Use	Low	Moderate	Moderate	High
Memory Usage	Low	High	Moderate	Moderate
Dev Productivity	Low	Moderate	High	High

Portability	Moderate	High	High	High
Green Score	**A+**	B	B-	D

Green Score scale: A+ (Excellent) — B (Good) — C (Average) — D (Poor). Scores based on aggregated benchmarks.

The comparative analysis underscores that no single language dominates across all dimensions. C++ achieves optimal resource efficiency but incurs significant developer productivity costs and is not universally suitable for rapid application development. Python maximises productivity at the expense of runtime efficiency, making it appropriate for workloads dominated by I/O operations or offloaded to native libraries. Java and JavaScript represent pragmatic engineering compromises, offering managed memory safety, cross-platform portability, and reasonable runtime performance, making them suitable for enterprise and web applications respectively where absolute energy minimisation is not the primary constraint.

From a green computing perspective, the choice of language should be contextualised within the application's deployment scale and execution pattern. A Python script executed once daily for batch processing poses a negligible environmental footprint; the same script handling 10,000 requests per second in a web service context contributes meaningfully to data centre energy consumption and warrants optimisation or language migration.

7. CONCLUSION

This paper has presented a systematic empirical investigation of the energy consumption, execution time, CPU utilisation, and memory usage characteristics of four widely-used programming languages — C++, Java, JavaScript, and Python — across four representative algorithmic benchmarks. The findings confirm and quantify the energy efficiency hierarchy suggested by prior work: C++ consumes the least energy (0.84 J total for the benchmark suite), followed by Java (3.12 J), JavaScript (3.74 J), and Python (18.47 J). The ratio of worst-to-best case energy consumption exceeds 22:1, representing a substantial opportunity for efficiency improvement through informed language selection and optimisation strategies.

These results have direct implications for sustainable software development practice. As the software industry intensifies its focus on carbon footprint reduction, language-level energy consumption must be elevated from an engineering curiosity to a first-class architectural concern. Developers working on high-throughput, latency-sensitive, or long-running applications should explicitly evaluate the energy profile of their language choices alongside traditional engineering considerations such as correctness, maintainability, and team expertise.

The study also highlights the importance of algorithmic selection as a complementary — and in some cases dominant — determinant of energy efficiency. Organisations seeking to reduce the environmental impact of their software systems are advised to pursue a dual strategy: adopting energy-efficient algorithms (preferring O(n log n) over O(n^2) solutions) and selecting execution environments appropriate to the performance criticality of each component.

8. FUTURE WORK

Several directions for future investigation emerge from this study. First, the analysis should be extended to include emerging systems programming languages — specifically Go, Rust, and Swift — which offer memory safety guarantees comparable to managed languages while targeting performance approaching that of C++. Preliminary benchmarks in the literature suggest Rust in particular achieves energy consumption within 3–5% of C++ while providing strong memory safety guarantees, making it an attractive option for safety-critical high-performance systems.

Second, future work should examine energy consumption under concurrent and parallel workloads, where language-level concurrency models (threads, coroutines, async/await, actor models) produce substantially different scheduling, synchronisation, and energy profiles. Python's GIL severely constrains parallel CPU-bound computation, while Go's goroutine scheduler and Java's virtual threads enable efficient many-to-many threading with implications for energy efficiency at scale

Third, the investigation of energy consumption in cloud-native deployment environments — specifically container-based microservices, serverless functions, and WebAssembly runtimes — would extend the applicability of findings to contemporary deployment architectures. Serverless platforms in particular exhibit a cold-start energy penalty that may disproportionately affect languages with slower initialisation (JVM) relative to those with fast startup (Go, native binaries).

Fourth, the development of automated energy profiling toolchains integrated into CI/CD pipelines would enable continuous monitoring of energy regressions as software evolves, creating the infrastructure necessary for energy-aware software development at industrial scale.

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