CS4575: Sustainable SE - Project
Energy Profiling of Static Analysis Tools

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Abstract

With increasing interest in software security, more automated tools for vulnerability detection and enforcing secure coding standards, also known as static analysis tools, are being utilized. On the other hand, with sustainability becoming a critical non-functional requirement, effectiveness is no longer the only parameter that needs to be considered. This research paper aims to provide developers with a tool that enables them to make informed decisions regarding energy consumption by analyzing how different configurations and rule sets of static analysis tools affect energy expenditure during development. It outlines a published pypi framework that captures and compares the energy usage of static analysis tools used in security audit definitions, namely Bandit and Semgrep. The framework was used on three Python repositories (Deepseek v3, requests, and vLLM), using a minimal and maximum rule set for each respective tool to investigate energy consumption patterns. Findings show that Bandit consistently consumed the least CPU energy due to its fast, lightweight design, while Semgrep scaled more efficiently on larger projects due to parallel multi-threading. Increasing rule set complexity led to higher energy usage and runtime for both Bandit and Semgrep, which scaled with project size.

CCS Concepts

• **Static analysis tools** → **Sustainable SE**.

Keywords

Energy Profiling, Static analysis tools

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1 Introduction

Software Engineering (SE) is a constantly developing field, and software applications are becoming increasingly complex by the day [11]. Academic studies show that there is a direct correlation between software complexity and security vulnerabilities [1]. This introduces additional demands within all phases of the software development life cycle (SDLC), especially in the context of software security practices.

Security concerns are considered to be an integral part of the SDLC [15]. The consequences of inadequate security within a software system could potentially be detrimental, especially due to the increasing reliance on software systems in various sensitive domains (such as banking, medicine, etc.) [13]. Hassan et al. (2024) emphasizes that security must be prioritized and practiced in every SDLC phase to mitigate security threats, and consequently, the negative effects that arise from insecure software systems [8].

A highly important software security practice is code reviewing for security [12]. This can be achieved through **static-analysis tools**, which are tools that allow for the identification of many common coding problems through automated means before a program is released [3]. This includes examining code for bugs, vulnerabilities, and other quality issues without executing the source code. Tools such as Bandit and Semgrep are commonly used within the security domain to detect insecure coding patterns to ensure better coding practices at scale.

While static analysis tools help improve code quality, and in turn, security, they also have the potential to consume computing resources. With the increasing need for secure code due to ubiquitous software systems, static analysis is more frequently integrated into CI/CD pipelines, often without consideration for its environmental cost. This could lead to significant and unnecessary energy usage, especially in larger code bases. While automated quality assurance processes are crucial for software reliability, their electricity consumption raises environmental concerns [16].

Sustainable software engineering (SSE) is an important goal to follow, to develop software systems that minimize environmental impact via energy optimization. As security-related static analysis tools become increasingly important, so does the need to assess their sustainability. This project aims to bridge that gap by profiling energy consumption across different tools and configurations, investigating the potential trade-off between differing configurations

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across different Open-source software (OSS) projects, and enabling developers to optimize their tool usage both from a security and sustainability standpoint.

This report has the objective to investigate energy consumption patterns in security-focused static analysis tools. To achieve this objective the following research questions were devised:

- **RQ1:** How do rule set complexity and configuration choices affect the energy efficiency of static analysis tools in different codebase contexts?
- **RQ2:** Can energy usage data be effectively used to guide configuration selection for secure static analysis tools without compromising detection accuracy?

To address these research objectives, we propose an energy profiling framework to:

- Measure energy usage during static analysis tool runs.
- Compare different rule sets and configurations within and across tools.
- Generate actionable reports to help developers reduce energy consumption.

2 Background and Related Work

Although efforts to quantify and mitigate energy dissipation attributed to software date back over a decade, the initial efforts were primarily directed towards the runtime efficiency of software systems and not much development tooling. One original approach was Hindle's Green Mining (2015) [9] which attempted to relate software revisions to power measurements with the hope of discovering how code modifications impact energy utilization. Such efforts set the stage to begin considering energy as a quantitative variable in software engineering research.

Later, there was energy-conscious software development that came into existence. Pang et al.'s work (2016) [14] reported on a survey given to programmers and noted an overall ignorance of the issues surrounding software energy dissipation and stressed the importance of education and tools in this domain. In response to this gap in awareness, researchers like Chowdhury et al. (2019) developed techniques to give developers feedback on energy usage. Chowdhury's GreenScaler project [4], for instance, trained models to estimate the energy consumption of code by using automatically generated tests. The underlying idea is that if developers are informed about which tests or code paths are energy-hungry, they can make more sustainable design choices.

Another venture of green software research has been to create tools and methodologies for energy profiling. For example, Di Nucci et al. (2017) introduced PETrA [6], a software-based tool to estimate the energy profile of Android applications. Although PETrA targets mobile apps, its existence reflects a growing toolkit for software energy analysis in general.

Recently, attention has turned toward the energy overhead of development infrastructure and processes. As described by Verdecchia et al. (2021) [7], automation of tools and developer workflows are part of the equation for greener IT. Zaidman (2024) [16] reported that the automated building and testing of software projects consume a significant portion of the projects' energy. In his case study, he found that the figures were remarkably different between the projects. Some of them, made only a couple of watt-hours during a build, whereas, others consumed energy over tens of kWh. Cruz and Abreu (2020) [5] also discovered that some mobile testing automation frameworks are more energy efficient than others, disproving the common assumption. Collectively, these works suggest that not all tools or practices are equal with respect to energy usage: the selection of frameworks, frequency of tests, and infrastructure used all affect electricity consumption to some extent.

Although green software engineering literature has initiated the investigation of other tools such as testing, build processes, and even runtime diagnostics, there is still a lack of coverage on the topic of security-focused static analysis tools. Most existing research either treats static analysis generically as part of overall CI energy costs or focuses on how static analysis can help reduce software energy use – not on the energy cost of running the analyzers themselves. For example, Zaidman's study mentions static analysis as one of several automated quality practices but concentrates on testing and integration. Likewise, studies such as Hindle's Green Mining or Cruz and Abreu's work on test frameworks did not examine static code scanners.

One recent study by Brosch [10] considered the influence of static code analysis (Pylint) on a game system algorithm's energy consumption, finding that certain static checks (e.g., for inefficient code) could lead to more energy-efficient codebases – but this was more type checking as compared to security static analysis testing.

To summarize, tools such as Bandit and Semgrep have not had their energy profiles estimated to date. It is likely that regularly executed security-focused static analyses (which are sometimes done for every build or pull request) accumulate over time and can draw power, especially if they are done on bigger codebases. This gap is filled by our work which provides the energy profile of Bandit and Semgrep. We focus on understanding how such security tools impact the environment and whether their design is sufficiently optimized for "green IT" by measuring energy consumption and duration of execution in real-life settings.

In this paper, we add to the emerging literature that sits at the boundary of software energy analysis and DevSecOps. This study illustrates the future of sustainable software engineering, in which decisions made, such as the selection of security scanning tools, consider effectiveness alongside sustainability. Gaining insights into the cost of energy for automated security checks will ultimately enable practitioners to mitigate the impacts of code security on environmentally friendly software development practices, thereby simultaneously improving quality and sustainability.

3 Methodology

3.1 Objective of the Study

In this research paper, we study the energy efficiency of static application security testing (SAST) tools with Python based codebases.

We investigate the functionalities and security aspects of two popular SAST tools, `Bandit` and `Semgrep`, under varying configurations. We also quantify the energy consumed by each scan using a Python tool developed by us, called `sast-energy-monitor`[1], which incorporates `energibridge` for detailed energy consumption measurement.

3.2 Selection of Open Source Projects

To evaluate the energy consumption of static analysis tools in real-world scenarios, we selected a set of open-source Python projects. These projects vary in size, complexity, and popularity to ensure generalizable results.

Project Repository 1: Deepseek-v3[2]

- **Language:** Python
- **Lines of Python Code:** 1,202
- **Purpose:** Lightweight AI tools and utilities.
- **Popularity:** Moderate (growing adoption in ML communities)

Rationale for Selection:

- Compact codebase suitable for low-overhead static analysis.
- Includes AI-specific logic and processing utilities.
- Serves as a baseline for energy usage in smaller repositories.

Project Repository 2: Requests[3]

- **Language:** Python
- **Lines of Python Code:** 9,164
- **Purpose:** A simple, yet elegant HTTP library for Python
- **Popularity:** High (well-maintained, widely used in the Python ecosystem)

Rationale for Selection:

- Popular and mature Python library used in thousands of projects.
- Contains both application logic and input/output handling, offering a rich target for static security analysis.
- Its high usage in production environments makes it a practical candidate for sustainability evaluation.

Project Repository 3: vLLM[4]

- **Language:** Python
- **Lines of Python Code:** 286,537
- **Purpose:** High-throughput and memory-efficient LLM serving engine
- **Popularity:** High (widely adopted in large-scale LLM serving applications)

Rationale for Selection:

- Large codebase introduces challenges for static analysis tools.
- Includes multithreading, CUDA integration, and complex logic layers.
- Ideal for stress-testing the tools' scalability and energy profiles.

[1]https://pypi.org/project/sast-energy-monitor/
[2]https://github.com/deepseek-ai/DeepSeek-V3
[3]https://github.com/psf/requests
[4]https://github.com/vllm-project/vllm

Security Static Analysis Tools

`Bandit`[5] is a static analysis tool specialized in Python and scans source files by traversing their AST to discover known security vulnerabilities. In the case of security issues, a specific rule containing a code such as `B101` (which corresponds to misuse of `assert`) is predefined. `Semgrep`[6], on the other hand, is a powerful structural pattern matcher that combines knowledge of programming languages and scans the source code to extract structural code patterns. Its rule definitions permit generic context and context-sensitive checks thus providing a powerful customizable vulnerability scanner.

For a comprehensive evaluation, we employed both tools in two configurations, termed *loose* and *strict*. They both represent different degrees of security checks realized through custom configuration files.

Configuration Strategy

The energy monitoring tool, `sast-energy-monitor`, allows for either a 'strict' or 'loose' configuration level[7] and calls the appropriate scanner. For `Bandit`, the loose mode refers to a subset configuration (.bandit-basic) which only performs two simple checks: scanning for assert statements (B101) and dynamic exec usage (B102). This is a lightweight scan that is useful for rapid iteration.

`Bandit` `strict` mode uses the full `.bandit` configuration file which contains more than 60 rules.[8] These rules include scanning for assert statements and dangerous imports such as `pickle` and `subprocess`, weak cryptographic methods like MD5 with low-entropy keys, hardcoded secrets, XML parser bombs, insecure network connections, and others. This configuration follows industry standards by incorporating many CWE and OWASP rules that enable to perform production-level scans.

With `Semgrep`, the loose configuration has a simplistic YAML rule set targeting hardcoded JWT secret tokens, which in Python applications, represent a common but sensitive vulnerability. The strict mode uses the complete Semgrep Registry ruleset under the `p/bandit`[9] policy with 90 rules.

Energy Monitoring Tool

To allow for reusability of our code, we created the Python package `sast-energy-monitor`, which encapsulates the invocation of Bandit or Semgrep scans, with varying configurations using `energibridge`[10] in one package. `Energibridge` in turn was built by leveraging low-level tools such as Intel RAPL to access energy usage metrics at runtime.

By automating both the scanning and measurement processes, this methodology ensures consistency across experiments and allows

[5]https://pypi.org/project/bandit/
[6]http://pypi.org/project/semgrep/
[7]https://github.com/Ayushkuruvilla/Energy_consumption/tree/main/test_configs
[8]https://bandit.readthedocs.io/en/latest/plugins/index.html#complete-test-plugin-listing
[9]https://semgrep.dev/p/bandit
[10]https://github.com/tdurieux/energibridge

for comparative evaluation of different scanners and configurations in terms of their energy footprint and vulnerability detection depth.

3.3 Experiment Setup

To ensure reliable and reproducible measurements of both energy consumption and security findings, each experiment followed a controlled execution run. At the start of each run, a Fibonacci warmup function was executed for one minute. This step served to stabilize CPU performance and avoid energy spikes that might occur at the onset of computation, ensuring the baseline energy draw remained consistent across all iterations.

Each test condition defined by a specific combination of the static analysis tool and its corresponding rule set, was executed thirty times. The order of these conditions was randomized before each round of testing to mitigate systematic bias from thermal or power-related fluctuations. The library automates the execution of every scan through subprocess calls while working together with Energibridge to measure and register the total energy spent during the scan time. The results from each iteration was captured in CSV files for post analysis of tool results and energy measurements.

To avoid drift, a twenty-second resting time was implemented between iterations. This break assisted in normalizing system usage to minimize the chances of performance throttling and getting more precise energy consumption measures.

All experiments were conducted in ‘zen mode’. This involved disabling all non-essential background apps and services, removing external hardware peripherals, and setting screen brightness to a particular value. These steps helped ensure that every iteration captured the true nature of the scanning tools and the configurations instead of being impacted by other external noise or factors.

4 Results and Analysis

Static Analysis Mechanics: Bandit and Semgrep

Both Bandit and Semgrep were configured to scan for a comparable set of Python security vulnerabilities. Although the rule sets covered equivalent issues, the way each tool handles rule execution differs significantly and directly influences their energy behavior.

- **Bandit:** Bandit’s rules are implemented as Python code that inspects the abstract syntax tree (AST) of each file. Each rule is essentially a function that runs over relevant AST nodes (for example, a rule might trigger when it sees an `eval()` call or a hard-coded password in the code). Bandit runs in a single thread and iterates through each file’s AST, applying all relevant rules. More rules mean more checks per file, increasing runtime roughly linearly. However, Bandit’s checks are generally fairly simple (looking for specific function names, constants, or patterns), which keeps each check lightweight.
- **Semgrep:** Semgrep doesn’t have built-in rules in the same way; it uses an external ruleset. In this experiment, Semgrep was supplied with a ruleset equivalent to Bandit’s coverage (the Semgrep community provides rulesets like p/bandit that cover the same issues as Bandit). Thus, Semgrep was effectively looking for the same kinds of security patterns. Under the hood, Semgrep compiles these rules (written in a declarative pattern syntax) into its scanning engine. Many Semgrep rules correspond one-to-one with Bandit checks, though some may be implemented with multiple pattern clauses or regexes to cover variations. Semgrep’s engine will parse each source file and then apply all the pattern rules to that file’s parse tree. It can do this efficiently in C/OCaml, but it does incur some overhead to load and compile the rules (especially since the ruleset was fairly large, 90 rules). By default, Semgrep also utilizes multiple threads to process files in parallel.

Complexity Impact: In this comparison, both tools were configured with a comparable number of rules (covering similar checks), so the rule count was kept roughly constant between them. But, the nature of those rules can affect performance. Bandit’s Python-based rules might short-circuit quickly if a pattern isn’t found (for example, if a file has no import statements related to security, many Bandit rules do nothing on that file). Semgrep’s pattern matching might involve more work upfront (it may attempt matches even if ultimately none are found, which is some overhead). In a few cases, Semgrep’s rules could be more complex – for instance, a Bandit rule that checks for the use of a weak hash function might simply look for the string "md5" in the code, whereas a Semgrep rule might be written to pattern-match function calls using hashlib.md5 or openssl.md5 etc., covering more variants. This can make Semgrep’s analysis a bit heavier, but also more comprehensive.

Project Codebase Characteristics and Complexity

- **DeepSeek-V3:** The codebase is small and self-contained, with no heavy concurrency or large data processing. This low complexity meant static analysis had a light workload. Bandit and Semgrep only needed to parse and check a handful of files, so the runtime was very short. In such a scenario, the fixed overhead of the tool dominates—i.e., the time/energy the tool spends initializing and loading rules can outweigh the actual scanning of code. This is why Semgrep, which has a larger upfront cost, used more energy here, whereas Bandit’s simpler run had an advantage.
- **Requests:** Requests has a well-structured codebase with multiple modules (e.g., sessions, auth, adapters) but remains relatively straightforward. It primarily uses synchronous I/O and does not spawn threads internally. The moderate size means a few dozen source files. Static analysis had to process more code than DeepSeek-V3, but still at a manageable scale. Bandit’s sequential scan handled this efficiently, and its overhead remained low. Semgrep had more work to do than in DeepSeek, but still needed to expend effort setting up its engine. The result was that Bandit maintained a lower total CPU energy usage on Requests as well. The project’s architecture (being a typical Python library) did not present special challenges to either tool—the main factor was just code volume, where 9k LOC is still small enough that Bandit’s lack of parallelism wasn’t a problem.

- **vLLM:** This project is vastly more complex. It includes advanced features like request batching, asynchronous scheduling, and integration with GPU acceleration (optimized CUDA kernels are part of its design). The codebase spans hundreds of Python files and incorporates multithreading or asynchronous code to manage inference tasks. This sheer size and complexity posed a stress test for the static analysis tools. Scanning vLLM means parsing a huge number of files and checking many possible code patterns. Bandit, being single-threaded, had to process files one by one for the entire 286k LOC, which took a long time. Semgrep, on the other hand, could distribute the workload across CPU cores. The concurrency and architectural complexity of vLLM (while relevant at runtime) mostly affects the static analyzers by way of code quantity and possibly some complicated syntax. For instance, vLLM uses dynamic constructs or long chains of calls that each tool's rules need to examine. This increases the workload linearly with LOC (each additional function or class is another thing to check for vulnerabilities). The end result was that vLLM demanded far more processing, and here the ability to parallelize gave Semgrep a big edge in performance and energy. Bandit's pure Python implementation may also struggle with memory usage on such a large project (large ASTs, many objects), potentially causing slowdowns (e.g., garbage collection pauses) that add to its energy consumption.

Influence on energy use: In summary, small, simple projects (like DeepSeek-V3) don't fully utilize modern CPUs—the static analysis finishes so quickly that a tool with more overhead (Semgrep) doesn't get to amortize that cost, resulting in proportionally higher energy per LOC. Large, complex projects (like vLLM) keep the analyzer busy for much longer and can take advantage of optimizations like parallel threads. Thus, project size is a major factor: Bandit excels on smaller codebases where its lightweight, single-process approach means lower overhead, whereas on large codebases the lack of parallelism becomes a disadvantage. Meanwhile, Semgrep's design incurs a startup cost that is paid off when there's a lot of code to scan; its architecture works well in large, complex projects by leveraging concurrency and efficient parsing to handle scale.

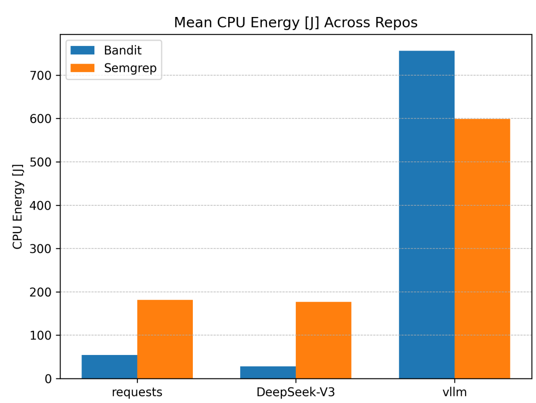

Figure 1: Energy difference between repositories

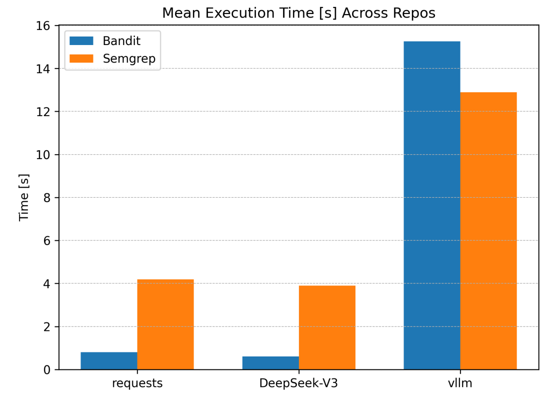

Figure 2: Time difference between repositories

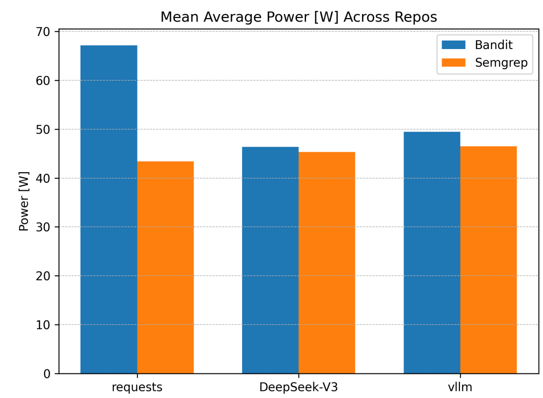

Figure 3: Power difference between repositories

Tool Configuration: Ruleset Size and Complexity

- **Bandit – Minimal vs Full Configuration:**
  Across all three projects (DeepSeek-V3, requests, and vllm), moving from Bandit's minimal (loose) configuration to the full (strict) ruleset (73 rules) consistently led to higher energy consumption and longer runtimes, with the impact increasing alongside project size. In the requests project, runtime rose by 33.8% and energy by 32.4%. In the larger vllm project, the increase was even more substantial—65% more energy and 64.7% longer execution time. On the small DeepSeek-V3 project, however, runtime remained unchanged (approximately 0.60s), and the only statistically significant change was a modest 3.4% increase in energy. These results, supported by a statistical significant p-value (see Table 1), suggest that Bandit's AST traversal is highly efficient on small projects, but becomes more resource-intensive as rule and code complexity grow.
- **Semgrep – Minimal vs Full Configuration:**
  Semgrep exhibited consistent and statistically significant increases in execution time and energy usage across all projects

when switching from a minimal configuration to a full ruleset (90 rules from the p/bandit registry). Time increased by 59–65% and energy usage by 29–47%, with all results showing strong statistical significance (see Table 1). Interestingly, CPU power draw decreased slightly (by 8–10%), suggesting that although more work was performed overall, the load was spread more evenly—likely due to Semgrep's rule-matching engine incurring more I/O and pattern compilation overhead rather than raw CPU-intensive computation.

CPU Power, Energy, Time, and Variability

Using EnergiBridge measurements, we compared CPU energy usage, power, and execution time for Bandit and Semgrep across three Python projects. Each tool was executed 30 times to assess consistency. The detailed results of these scans and their specific configurations can be seen in Appendix A.

- **DeepSeek-V3:** As we can see in Figure 3, Bandit used 47W on average and finished in 1s. Semgrep drew similar power (45W) but took 4s to complete. This longer runtime led Semgrep to consume significantly more energy. Despite near-identical power profiles, Bandit's quick execution ensured lower energy use.
- **Requests:** Bandit completed scans in under a second, drawing an average of 65–70W, while Semgrep, as we can see in Figure 2, took 4–5 seconds at 43W. Despite lower power, Semgrep consumed 3–4× more total CPU energy due to longer runtime.
- **vLLM :** Bandit consumed more energy and took longer than Semgrep. Here, Semgrep's multithreaded execution paid off, completing faster (13s vs. 15s) and using less energy (600J vs. 750J). Power draw was nearly the same (49–50W), but the shorter runtime made Semgrep more efficient on this large project.

Configuration	Energy t-test p-value	Power t-test p-value
Deepseek Bandit	1.24×10^{-5}	1.28×10^{-5}
Requests Bandit	8.15×10^{-30}	4.30×10^{-2}
VLLM Bandit	6.30×10^{-26}	8.12×10^{-1}
Deepseek Semgrep	2.83×10^{-26}	5.19×10^{-30}
Requests Semgrep	1.60×10^{-38}	2.09×10^{-14}
VLLM Semgrep	9.64×10^{-23}	2.87×10^{-15}

Table 1: t-test p-values for energy and power comparisons across configurations

Key Insights and Energy Implications

In conclusion, the results reveal important insights into the energy efficiency and performance of Bandit and Semgrep, depending on the size and complexity of the codebase. Bandit is more efficient for small and medium projects due to its fast, low-overhead execution. Its simplicity allows it to minimize energy consumption, making it an ideal choice for smaller repositories, such as requests and DeepSeek-V3.

On the other hand, Semgrep introduced overhead on small codebases but demonstrated a more scalable and efficient performance on large projects, such as vllm, thanks to its parallel processing capabilities. Although Semgrep consumed more energy for smaller projects, its ability to scale effectively with the size and complexity of larger codebases meant that it could potentially offset the higher initial energy consumption by completing scans faster.

Execution time was the primary driver of energy consumption across both tools, with Semgrep's longer execution times on small codebases leading to higher energy consumption, while its parallelism on larger projects allowed for faster execution despite the higher energy cost.

Rule configuration impacted both tools: more rules lead to higher energy and runtime, especially on large codebases. Bandit's performance degraded more with added rule complexity, while Semgrep handled it better due to its efficient rule engine and load distribution.

Both tools showed low variability over 30 runs, confirming the reliability of the measurements and ensuring that the results are consistent and dependable across repeated tests. Therefore, Bandit is the preferred choice for small and medium projects, where minimal overhead is crucial, while Semgrep is more suited for larger projects, where its parallelism offers significant advantages in both time and energy efficiency.

5 Limitations

There have been some limitations to the research. This includes the following:

- **Limited Toolset:** Our analysis was restricted to two Python-based SAST tools—Bandit and Semgrep. The inclusion of additional tools, especially those targeting other languages or domains (e.g., Java, C++, JavaScript), could broaden the applicability of our framework.
- **Python-Only Codebases:** All evaluated projects were Python-based. The energy profiles and tool behaviors may vary significantly across programming languages due to differences in parsing complexity, syntax richness, and rule availability.
- **CI/CD Pipeline Integration Not Evaluated:** Although many teams use static analysis tools in automated pipelines, this study focused on standalone tool runs. Evaluating energy usage in CI/CD environments could uncover additional insights into realistic usage scenarios, including impact from parallel builds and caching.
- **Energy Measurement Limitations:** While energy consumption was measured during static analysis runs, the setup does not fully account for external variables such as background system load or hardware variability.

6 Future Work

Future work includes addressing the above limitations and expanding the framework to other programming languages and static analysis tools. Exploring multi-language support would further enhance the framework's domain of analysis, alongside its applicability to polygot codebases.

In addition, a study by Benett et al. (2024) reports that combining multiple SAST tools significantly improves vulnerability detection rates compared to using individual tools [2]. Investigating the energy consumption implications of multi-tool configurations may lead to additional insights that reflect the real-world tradeoff between security vulnerability detection rates and energy consumption, alongside how to optimize energy expenditure through hybrid rule sets.

Furthermore, future work could investigate energy consumption in practical environments by incorporating CI/CD workflows. This includes evaluating energy usage under common practices such as parallel builds, cashing, incremental scans, and pipeline-triggered executions.

7 Conclusion

This study proposes a reproducible model for analyzing the energy consumption of static analysis tools, highlighting the aspect of sustainability in programming as an important secondary attribute. We demonstrate through the analysis of real-world Python projects that energy consumption stems not only from the tool's design but also from its multi-threading architecture, rule set complexity, and the type of codebase.

Given its straightforward serial design, Bandit was found to expend the least total CPU energy on small, mid-sized, and even some large projects. Its speed and low overhead makes it unrivaled among tools intended for repeated scanning. Semgrep, though more efficient per-seconds, suffers from greater overhead on small projects. Nevertheless, it also has the potential to perform competitively, and at times more efficiently on larger, intricate codebases due to its scalable parallel architecture and rich rule set.

Selection of tools based on energy efficiency for specific descriptive tasks should be calibrated to the size of the project and the objectives of the analysis. In contrast to Bandit, Semgrep is advantageous for high-level, deep-seated audits owing to its variety of configurations but excels as long as the frequency of the scan is lower and the scan is more detailed. This fosters the alignment of security with sustainability and ultimately bolsters efforts toward greener software engineering.

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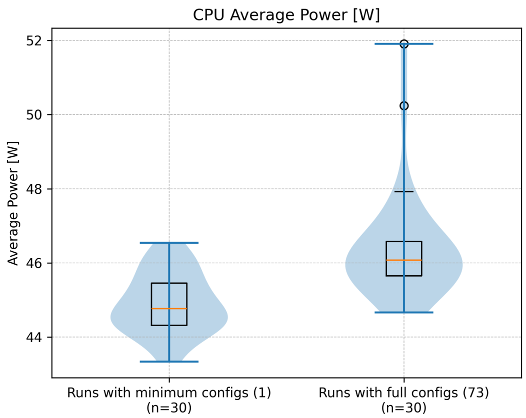
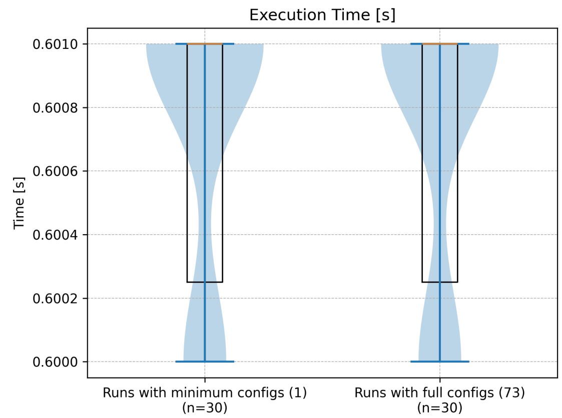
A Appendix

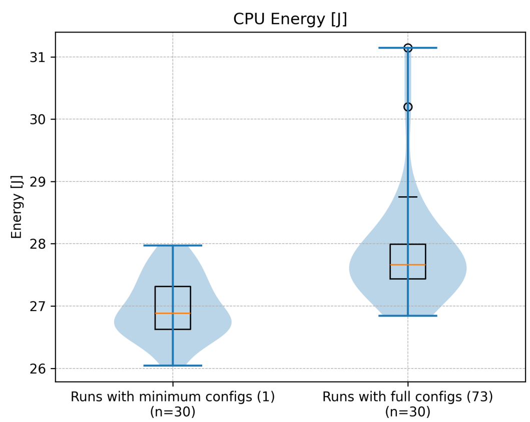
A.1 Performance Plots by Security Tool and Project



(a) Power

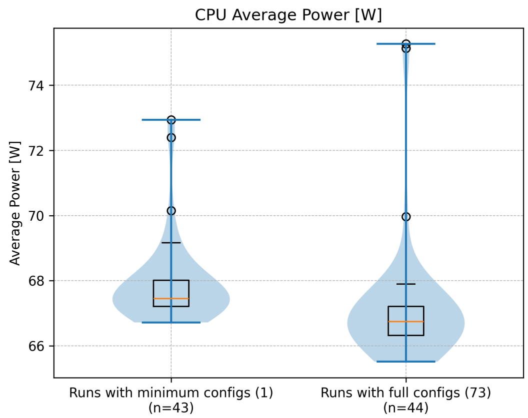


(b) Execution Time



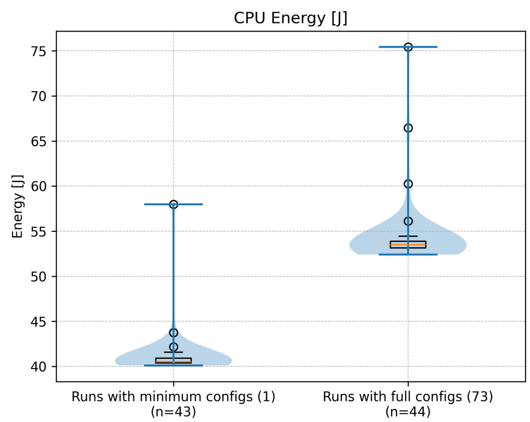
(c) Energy

Figure 4: Performance metrics for `bandit_DeepSeek-V3`.



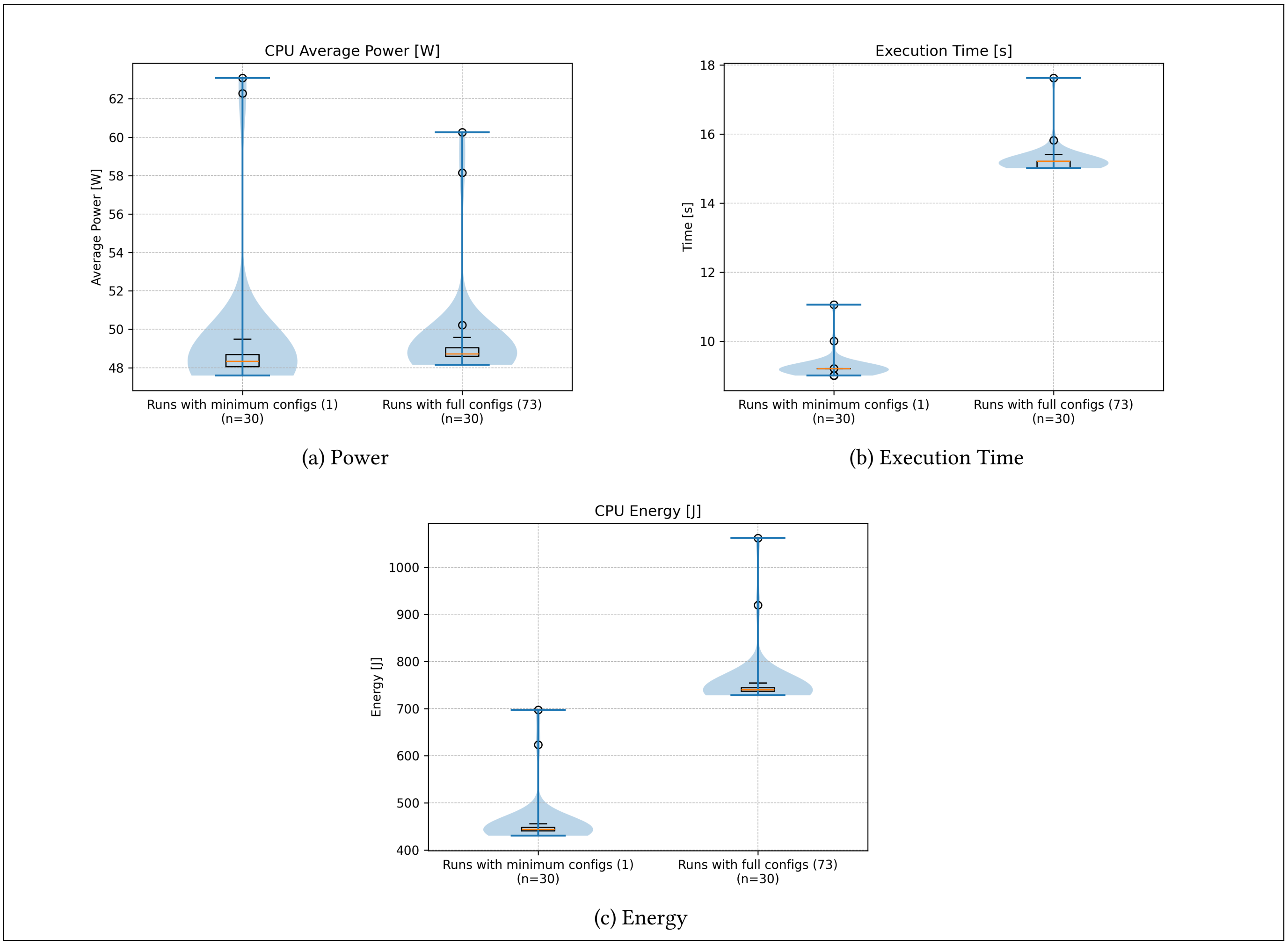
(a) Power

(b) Execution Time



(c) Energy

Figure 5: Performance metrics for `bandit_requests`.

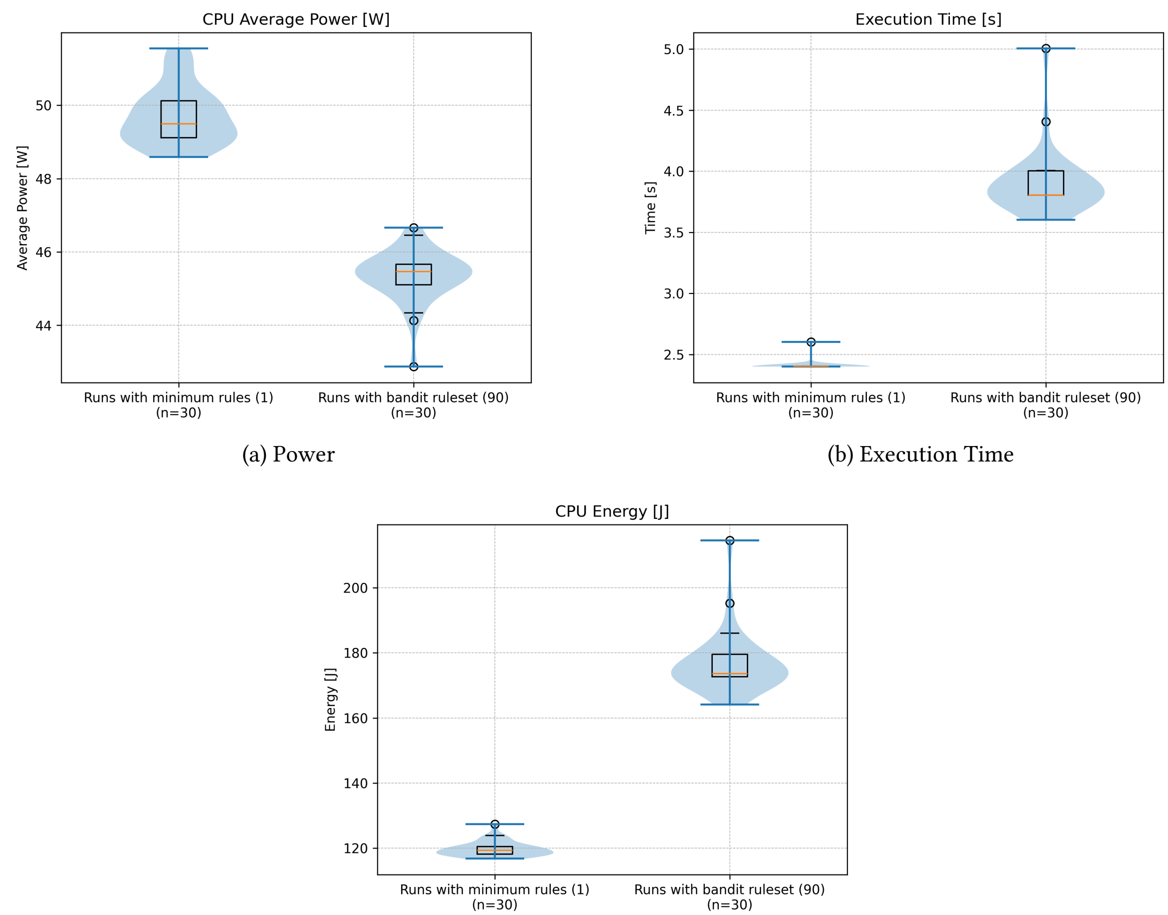


(a) Power

(b) Execution Time

(c) Energy

Figure 6: Performance metrics for `bandit_vllm`.

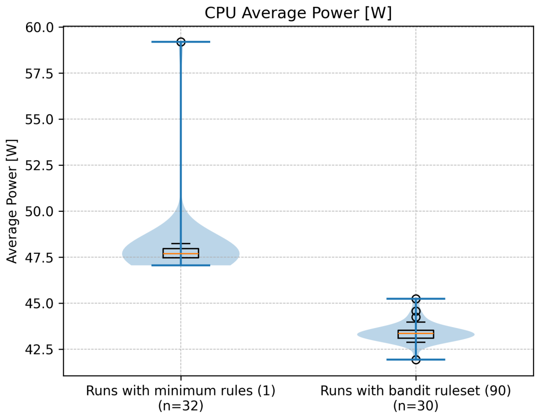


(a) Power

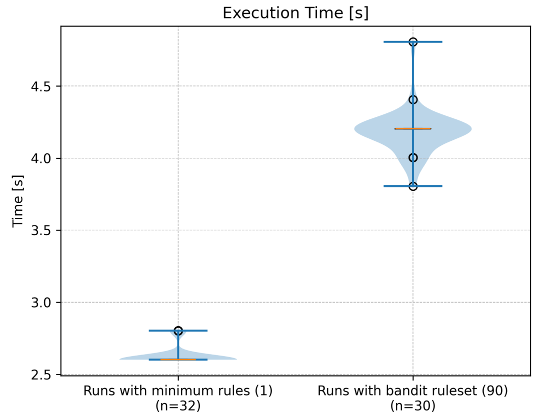
(b) Execution Time

(c) Energy

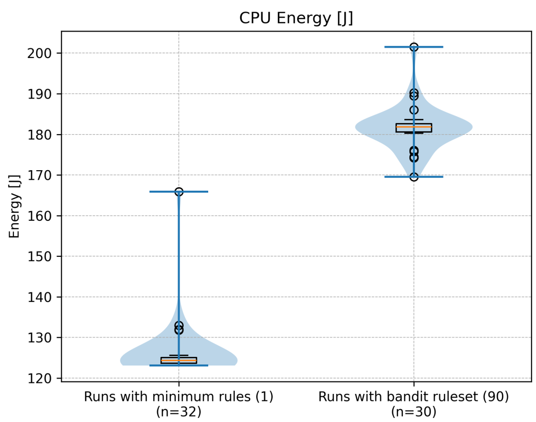
Figure 7: Performance metrics for `semgrep_DeepSeek-V3`.



(a) Power

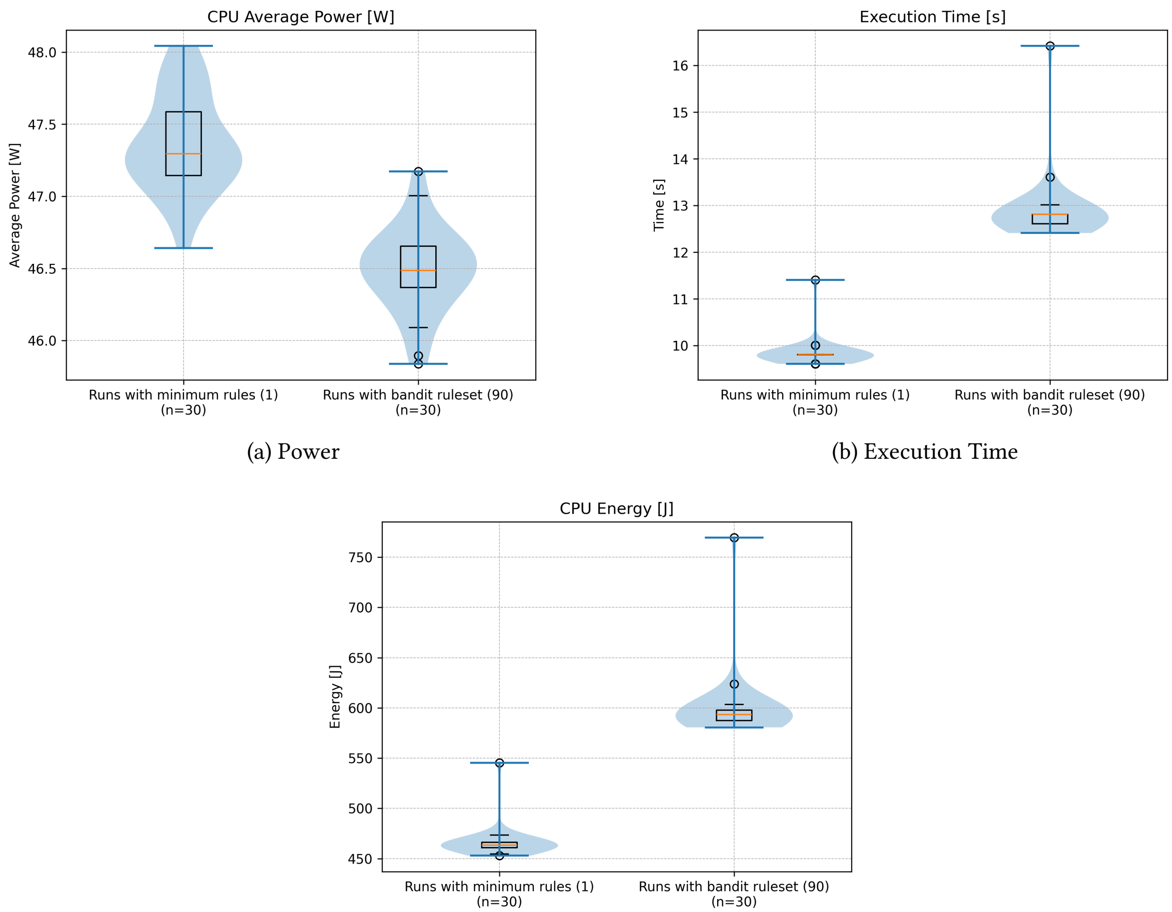


(b) Execution Time



(c) Energy

Figure 8: Performance metrics for `semgrep_requests`.



(a) Power

(b) Execution Time

(c) Energy

Figure 9: Performance metrics for `semgrep_vllm`.