Analyzing Programming Languages Energy Consumption: An Empirical Study

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ABSTRACT

Motivation: Shifted from traditional monolithic approaches to more cutting edge ones such as micro-services, where different services can be implemented and communicate in different programming languages, implies new challenges in terms of energy usage.
Goal: In this preliminary study, we aim to identify energy implications of small, independent tasks developed in different programming languages, compiled, semi-compiled, and interpreted ones.
Method: To achieve our purpose, we collected, refined, compared, and analyzed a number of available tasks from Rosetta Code, a publicly open repository for programming chrestomathy.
Results: Our analysis shows the programming languages such as C, C++, Java, and Rust offers the highest energy efficiency for all our tested tasks compared to C#, VB.NET, and Go among the compiled programming languages. In terms of interpreted programming language, Php and JavaScript exhibit the most energy savings compared to Swift, R, Perl, and Python.

CCS CONCEPTS

• **Hardware → Power estimation and optimization**; • **Software and its engineering →** *Software libraries and repositories*; *Software design tradeoffs*;

KEYWORDS

GreenIT, Energy Efficiency, Energy Optimization, Programming Languages

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1 INTRODUCTION

The increasing demands on services and computational applications from ICT-related products are major factors contributing to the increase energy consumption.[1] Recent research by Gelenbe and Caseau [9] and Van Heddeghem et al. [16] indicates a rising trend of the IT sector energy requirements, which are expected to reach 15% of the world's total energy consumption by 2020.

Traditionally, most of the studies, regarding energy efficiency, considered energy consumption at hardware level. However, there is much of evidence that software can also alter energy dissipation significantly [3, 7, 8]. Therefore, many conferences have identified the energy-efficiency at the software level as an emerging research challenge in order to reduce energy consumption of a software without compromising its run-time performance.

Nowadays, the development of a software has shifted from traditional monolithic architectures and follows a more agile, cutting-edge approach such as micro-services. The feature of this approach is the development of independent and reusable small services in a variety of programming languages. However, the energy impact of different tasks implemented in different programming languages is still new and unknown to researchers and developers.

In order to identify trends and possible gains in reduce energy consumption in software development, we conducted an empirical study aiming to elicit energy usage results starting from small tasks implemented in a variety of well-known and highly used programming languages. To this end, our aim in this research is to identify which programming languages offer more energy efficient implementations for different tasks.

The remainder of this paper is organized as follows. Section 2 describes in detail our experimental platform, the software and hardware tools we used, how we refined our dataset, and our methodology for retrieving our results. In Section 3, we present our preliminary results and in Section4 we discuss potential threats to validity. In Section 5, we discuss prior work done in the field and compare it with ours. Finally, we conclude in Section 6 and we discuss future work and possible directions for this research.

2 EXPERIMENT SETUP

In this Section, we describe the experimental approach for conducting our research and retrieving measurements. Initially, we provide information about the obtained dataset and the way we decided to select our tasks and refine it. Furthermore, we explain the setup up of our experimental platform, the additional hardware tools, and the software tools used to conduct this research.

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[1] Although in the physical sense energy cannot be consumed, we will use the terms energy "consumption", "requirement", and "usage" to refer to the conversion of electrical energy by ICT equipment into thermal energy dissipation to the environment. Correspondingly, we will use the term energy "savings", "reduction", "efficiency", and "optimization" to refer to reduced consumption

Table 1: Programming Languages, Compilers and Interpreters

	Programming Languages	Compilers and Interpreters version
Compiled	C, C++	gcc version 6.3.1 20161221-
	Go	go version go1.7.5
	Rust	rustc version 1.18.0
Semi-Compiled	VB.NET	mono version 4.4.2.0 (vbnc)[a]
	C#	mono version 4.4.2.0 (mics)[b]
	Java	javac version 1.8.0_131
Interpreted	JavaScript	node version 6.10.3
	Perl	perl version 5.24.1
	Php	php version 7.0.19
	Python	python version 2.7.13
	R	Rscript version 3.3.3
	Ruby	ruby version 2.3.3p222
	Swift	swift version 3.0.2[c]

[a] http://www.mono-project.com/docs/about-mono/languages/visualbasic/
[b] https://www.codetuts.tech/compile-c-sharp-command-line/
[c] https://github.com/FedoraSwift/fedora-swift2/releases/tag/v0.0.2

2.1 Dataset

In the context of this study, we used Rosetta Code,[2] a publicly available programming chrestomathy site that offers 851 tasks, 230 draft tasks, and a collection of 658 different programming languages. In general, not all tasks are implemented, and not all tasks are possible to implement in all languages. We found and downloaded a Github repository[3] which contains all the currently implemented tasks introduced in Rosetta Code website.

For selecting the highly used programming languages, we made use of tiobe,[4] a software quality company. Tiobe uses a search query for index rating of the most popular programming languages around the web on a monthly basis. This query is based on a formula[5] that uses the highest ranked search engines (according to Alexa)[6] and a number or requirements enlisted for programming languages. Initially, we decided to chose the top 15 programming languages as enlisted for June 2017. From the current list, we excluded programming languages such as Delphi (not available for Linux) and Assembly (since it is architecture dependent). In contrast, we included Rust in our dataset which is a memory safe programming language and is gaining vast popularity in the web. Therefore, we ended up with 14 programming languages as illustrated in Table 1.

In terms of selecting tasks, we developed a shell script (more details in Subsection 2.2.2) to identify which of the 851 tasks offer the most implementations for the programming languages of our selection. After launching our script, we obtained around 29 different tasks. For the context of our preliminary study, we chose only nine tasks implemented in the most of the programming languages of our selection. The selected tasks were *array-concatenation, classes* (creating an object and calling a method to print a variable's value), *url-encoding and decoding, bubble-, quick-, insertion-, merge-, and selection- sorting algorithms* Moreover, to further refine our dataset we used the following steps:

- Some of the tasks offered more than one implementation for the same programming language. Thus, we had to browse manually through each directory and remove them until we remained with only one that is consistent with the other implementation. For example, when most of the implemented tasks used iterative implementation we removed the ones using recursion.
- The Java file names were different from the public class names which results to compilation error if not changed accordingly.
- Some of the implementations did not have main classes, or the same data with other tasks. Therefore, we change the source code to offer consistency.
- For some programming languages which do not offer the class option such as C and Go, we used structs.
- Some of the tasks are relatively small and may finish faster than a second which makes it impossible for our power analyzer to capture those results. Therefore, we added all the selected tasks in an iteration loop of a million times.

After applying the above modification on our dataset, we categorized our programming languages in three main categories, namely, compiled, semi-compiled, and interpreted, as illustrated in Table 1. Moreover, for the programming languages which offer a compiled approach such as Java, VB.NET, and C#, we added them under the category of compiled languages. In addition, we compared the compiled and semi-compiled implementations while having scenarios with and without compiler optimizations.

2.2 Hardware and Software components

2.2.1 Hardware Components. The physical tools composed mainly from a portable personal computer (HP EliteBook 840 G3),[7] a real-time electricity usage monitoring tool, and an embedded device. The real-time power usage tools we used is the Watts Up Pro (WUP).[8]

In general, there are two venues for retrieving energy consumption from a computer-based system. On one hand, it is achievable by indirect energy measurements through estimation models or performance counters, core component of software monitoring tools. On the other hand, via direct measurement, hardware power analyzers and sensors. Each of these approaches has its own pitfalls. The direct approach , *i.e.,* hardware components, offers coarse-grained measurements for the whole systems' energy consumption and low sampling rate. The indirect approach , *i.e.,* software components, suffers from inaccuracy, lack of interoperability, and additional system overhead while using indirect measurements. In our research we decided to retrieve our energy consumption measurements using direct approach such as WUP since our tasks are relatively short in terms of source-code lines.

[2] http://rosettacode.org/wiki/Rosetta_Code
[3] https://github.com/acmeism/RosettaCodeData
[4] https://www.tiobe.com/tiobe-index/
[5] https://www.tiobe.com/tiobe-index/programming-languages-definition/
[6] http://www.alexa.com/
[7] http://www8.hp.com/us/en/products/laptops/product-detail.html?oid=7815294#!tab=specs
[8] https://www.wattsupmeters.com/secure/products.php?pn=0

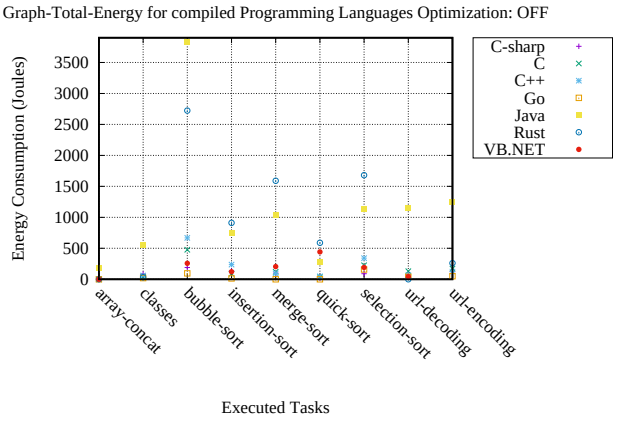

Figure 1: Energy Consumption for Compiled Programming Languages Optimization: OFF

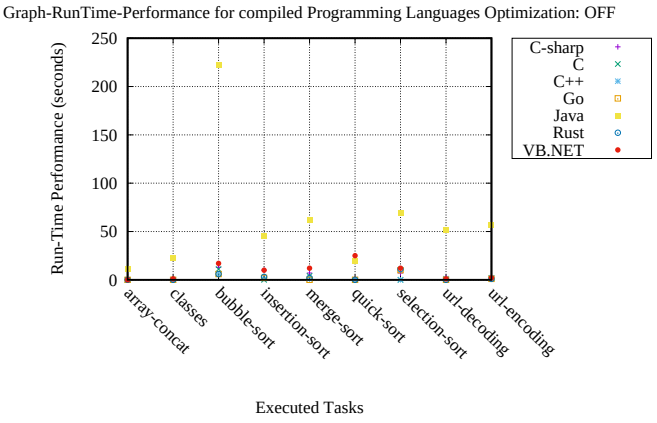

Figure 2: Run-time Performance for Compiled Programming Languages Optimization: OFF

In regards to WUP, it offers accuracy of ±1.5% and as minimum sampling rate of a second. In order to retrieve power-related measurements from the WUP we used a Linux-based interface utility available in a Git repository.[9] This software helped us retrieve measurements such as timestamps, watts, volts, amps, etc. through a mini USB interface after we integrated its code in our script that runs all the tasks. In order to avoid additional overhead in our measurements, we used a Raspberry Pi[10] to retrieve power consumption from our test-bed.

[9]https://github.com/pyrovski/watts-up
[10]https://www.raspberrypi.org/products/raspberry-pi-3-model-b/

2.2.2 Software Components. To extract data, manage, and use our Rosetta Code Repository, we developed a number of shell scripts as enlisted below, which are publicly available on our Git repository.[11]

- **script.cleanAll**, removes the current instance of tasks in the current working directory and copy the new one found from in the parent directory.
- **script.findCommonTasksInLanguages**, provides a list of tasks with the number of existing implementations in different languages.
- **script.createNewDataSet**, filters the Rosetta Code current dataset and removes programming languages and tasks not added as command line arguments.
- **script.fromUpperToLower**, changes the current instance of tasks directories and files from upper to lower case.
- **script.compileTasks**, compiles all tasks found under the tasks' directory and produces error reports if a task fails to compile.
- **script.executeTasksRemotely**, executes all the tasks' implementations found in under tasks directory. Moreover, it sends command to WUP, retrieves measurements and stores them on remote host, through *ssh*, in order to start retrieving measurements for each test case.
- **script.createPlottableData**, creates a single file that enlists all the executed tasks with the energy consumption for each implementation. In addition, we used NTP[12] to synchronize both system clocks which helped us to map our results of run-time performance and energy consumption.
- **script.plotGraphs**, after retrieving our data we use this script to plot our graphs. For plotting our graphs we used Gnuplot,[13] an open-source general purpose pipe-oriented plotting tool.

Note that most of the scripts offer the *–help* option that shows a list of available command line arguments and options. In addition, we provide a README.MD file, available in our repository, as a guideline for using our scripts and reproducing the obtained results. We tried to automate the execution procedure as much as possible in order to remove the burden from users who would like to use our scripts. Moreover, we suggest for the users not to change the directory's names or locations since it will alter the correct sequence of the execution.

2.3 Retrieving Energy Measurements

As an initial step for our experiment, we shut down background processes, as suggested by Hindle [10], found in modern OS (Operating System) such as disk defragmentation, virus scanning software, CRON jobs, automatic updates, disk indexing, document indexing, RSS feed updates, etc. to minimize possible noise interferences in our measurements. By making the following steps, we reduced our platform's idle power consumption from 8,6 to 5.8 watts on average.

We estimated when our OS is launched, it is necessary to wait for a short period to reach a *stable condition* which is close to five minutes [4]. After reaching *stable condition*, we launched our main

[11]https://github.com/stefanos1316/Rosetta-Code-Research
[12]http://www.ntp.org/
[13]http://www.gnuplot.info/

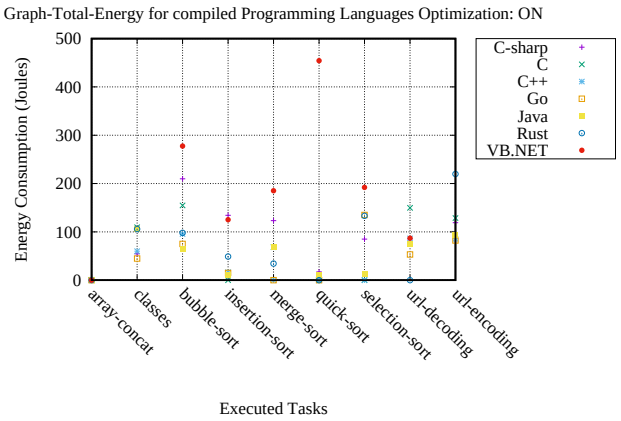

Figure 3: Energy Consumption for Compiled Programming Languages Optimization: On

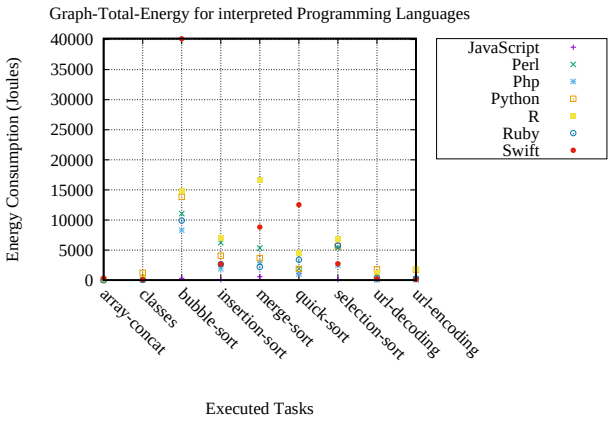

Figure 5: Energy Consumption for Interpreted Programming Languages

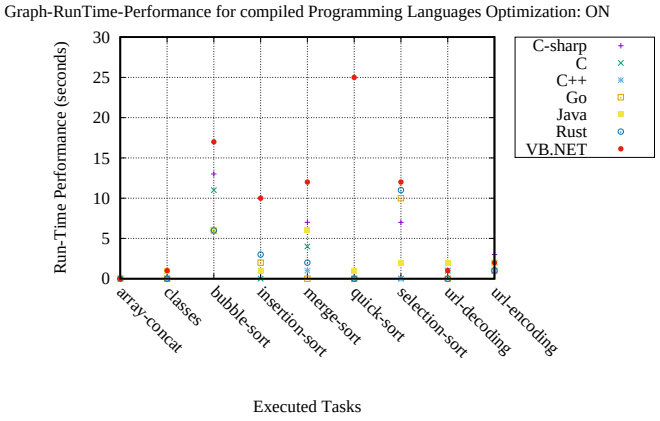

Figure 4: Run-time Performance for Compiled Programming Languages Optimization: On

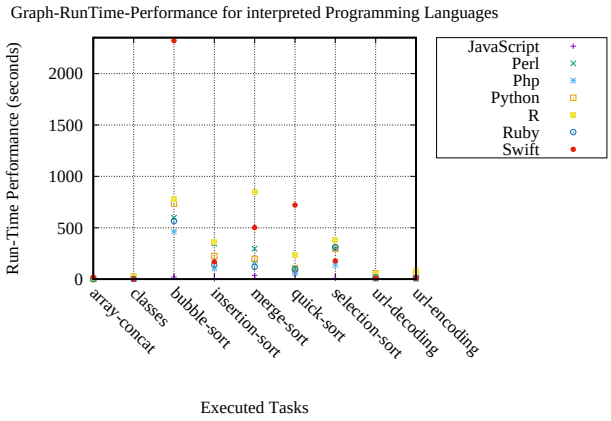

Figure 6: Run-time Performance for Compiled Programming Languages Optimization: On

script *i.e.,* **script.executeTasksRemotely**, that executes all the tasks implemented in different programming languages. Before executing a task, the execution script sends a command to the remote host ,*i.e.,* Raspberry Pi, through a password-less SSH connection to start collecting power consumption measurements from WUP for the currently executing task. In addition, the local host retrieves run-time performance measurements through command time[14] and stores them in timestamped directories which we analyze later. Between each execution of a task, we added a sleep[15] period of three minutes. The time gap exists to ensure that our experimental platform reached a *stable condition* and to avoid unnecessary noise in our measurements. For example, to ensure the platform's CPU is cooled down and the fan is no longer consuming more power.

[14]https://linux.die.net/man/1/time
[15]http://man7.org/linux/man-pages/man3/sleep.3.html

3 RESULTS AND DISCUSSION

For some tasks, the execution time is less than a second, a fact that justify the zeros shown in our graphs since it is impossible for WUP to collect measurements less than a second of time interval. Figure 1 illustrates the total energy required for each task implementation to execute. The results depict that Java and Rust have the highest energy consumption among the compiled programming languages while Go has the lowest when no compiler optimizations are used.

Table 2: Comparative Results show the percentage of increased energy usage while using the inefficient implementation in compare to the efficient

Tasks Name	Implementations		Comparative
	Efficient	Inefficient	Results
Array-Concat	Php, Ruby	Swift	8882.5%
Classes	Php	Python	1616.36%
Bubble	JavaScript	Swift	12694%
Insertion	JavaScript	Perl	9430.25%
Merge	JavaScript	R	2894.81%
Quick	Php	Swift	1212.23%
Selection	JavaScript	R	6657.71%
Url-Decode	Php	Python	2963.05%
Url-Encode	Php	R	3239.79%

Also, the results in Figure 2 show that energy consumption is directly affected by the run-time performance in all cases except from Rust. For Rust while the energy consumption is kept relatively high the run-time performance is not affected negatively like for Java.

Figure 3 shows the total energy dissipation from the beginning until the end of a task while making use of the compiler optimizations. The obtained results show the use of compiler optimizations reduces energy usage in most of the cases while it increases it in others. For C#, the energy usage of *quick-, insertion-, bubble- sort* and *url-decode* increased from 1% to 10% while for *merge-, selection-, classes- sort,* and *url-encode* reduced it from 3.8–36.6%. C's *gcc -O3* achieved energy reductions ranging from 43.36% to 99.6% for the majority of tasks apart from *url-decoding* where the energy increased to 14.7%. In the case of C++, the *g++ -O3* resulted in energy savings from 0.9% to 84.71% for all tasks except *url-decoding* that introduced increased energy usage of 33.33%. For Go most of sorting algorithms and *url-decoding* energy usage reduced from 14.39% to 31.35% while for *insertion-sort* and *url-encoding* increased from 15.38% to 62%. Java was the only programming language with energy reduction in all tasks ranging from 6% to 98.4%. In the case of Rust all the tasks energy requirements reduced in range of 15.8% to 97.7% apart from the *classes* task where the energy usage increase to 15.4%. In regard to VB.NET the compiler optimization had very small impact on energy consumption, less than 10%.

For the interpreted programming languages, we can see the energy consumption among them diverge significantly as depicted in Table 2. For the most inefficient case, Swift consumes 12694% more energy compares to JavaScript. In general, Php and JavaScript achieved the most energy efficiency compared to Swift, R, Perl, and Python which their implementations contributed to the highest energy consumption. In terms of run-time performance, Figure 6 results show the energy consumed by the interpreted tasks (Figure 2) have a correlation with the execution time.

4 THREATS TO VALIDITY

Internal: In order to avoid additional overhead on our experimental platform, we used a remote host to collect our results. Therefore, the need of wireless connection was necessary, which might incur in additional energy requirements by making use of the SSH to start and stop the WUP. Moreover, we cannot have full control of our OS workloads and background operations, therefore, is possible that some daemons might start running while test our experiment.
External: Our real-time power analyzer offers minimum sampling interval of a second. Therefore, in Figures 1, 3, and 5 the energy dissipation resulting to zero are interpreted as the tasks execution to be less than a seconds, which makes in impossible for WUP to capture such measurements.

5 RELATED WORK

Most empirical studies evaluate software projects from particular programming language families. Here, we count the energy consumption of programming tasks across more than ten programming languages. To the best of our knowledge, this is the first study that assess the energy consumption in different programming languages using the Rosetta Code. In the following, we present related work to our topic and compare our results with the results from previous studies.

5.1 Programming Languages

Studies regarding the strengths and weaknesses of different programming languages can help developers to decide *which* programming language they will use to perform specific programming tasks. For instance, if programmers aim at the scalability and performance of their systems, they use functional programming most of the times. On the other hand, when they want to develop programs with high modularity, they use object-oriented programming languages.

Closest to our paper is the empirical study that Nanz and Furia conducted on the Rosetta Code repository to compare the efficiency of eight popular programming languages, including C, Go, C#, Java, F#, Haskell, Python, and Ruby [13]. Contrary to this work, we used a power analyzer to run programming tasks on different programming languages in order to compare the energy consumption at runtime.

In addition, Meyerovich and Rabkin conducted an empirical study by analyzing 200,000 SourceForge projects and asking almost 13,000 programmers to identify characteristics that lead the latter to select appropriate programming languages in business level [12]. However, this study is a survey on the adoption of programming languages in the industry. Our goal here is different. We compare the energy consumption of programming tasks performed in several programming languages.

5.2 Energy Consumption and Performance

Several researchers have investigated the energy efficiency and run-time performance impact over programming languages. Also, a significant amount of works have compared the execution environment where the programs can run efficiently.

In particular, Abdulsalam et al. conducted experiments on workstations [1], whereas Rashid et al. used an embedded system [14] and Chen and Zong used smart-phones [5]. Abdulsalam et al. evaluated the energy effect of four memory allocation choices (`malloc`, `new`, `array`, and `vector`) and they showed that `malloc` is the most efficient in terms of energy and performance [1]. Chen and Zong showed by using Android Run Time environment instead of Dalvik, that the energy and performance implications of Java are similar

to C and C++ [5]. Rashid et al. compared the energy and performance impact of four sorting algorithms written in three different programming languages (ARM assembly, C/C++, and Java) and they found that Java consumes the most energy [14]. From all these studies it seems that Java and Python consume a lot of energy and perform slowly in comparison with C/C++ and Assembly.

Additionally, many empirical studies have assessed the impact of coding practices (e.g. the use of `for` loops, getters and setters, static method invocation, views and widgets, and so on) regarding energy consumption. Characteristically, Tonini et al. conducted a study on Android applications and found that the use of `for` loops with specified length and the access of class variables without the use of getters and setters can reduce the amount of the energy that the applications consume [15]. Furthermore, in their study, Linares-Vsquez et al. performed analysis over 55 Android applications from various domains and they reported the most energy consuming API methods [11]. For instance, they found that the 60% of the energy-greedy APIs, 37% were related to graphical user interface and image manipulation while the remaining 23% were associated with the database.

Contrary to previous works, here we compare energy consuming programming tasks in more than ten programming languages. Our results show that significant diverge with respect to energy consumption exist for interpreted programming languages. Moreover, we provide comparison in programming languages such as Go, Rust, VB.NET, and C# which is not available in prior work.

6 CONCLUSIONS AND FUTURE WORK

To this end, we conclude as follows. Compiler optimizations provides gains, in terms of energy consumption, for the tasks we tested. However, for most the programming languages such as C, C++, C#, Rust, and VB.NET optimization are not applied by default, therefore it is the user must set it. Prior work [2, 6] also evaluated the energy efficiency of compiled programming languages and showed that C and C++ were the most energy efficient compared to Java. In contrast, the tasks we compared show that Java's energy consumption does not diverge significantly from C and C++ results. Moreover, in tasks *url -decode* and *-encode*, Java achieves more energy efficiency than C and C++. In addition, we also compared Go which results to higher energy savings compared to C and C++ for all tasks apart from *insertion-sort*.

For interpreted programming languages, JavaScript consumes less energy for sorting tasks while Php does it for *classes* (object creation with method call), *array-concatenation*, *url -decode*, and *-encode*. In addition, our results show a huge difference among the interpreted programming languages energy dissipation.

For the selected tasks, we see a correlation between the execution time and the energy consumption of the interpreted programming languages, which is not the case for all the compiled and semi-compiled languages. In specific case, such as Rust and VB.NET, while the energy is increased the run-time performance is not affected. Therefore, the reasons for such a trend are still unknown to us and further investigation is necessary.

As for future work, we would like to test all the 29 collected tasks and, furthermore, to develop more such as exception and task for functional programming. Moreover, we will test the collected tasks in different CPU architectures such as AMD and ARM. In addition, we plan to collect resource usage to identify a possible relationship between programming languages and energy consumption.

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