The comparison of the energy consumption of different programming languages and programs

Lukas Koedijk
lukaskoedijk@gmail.com

July 5, 2019, 56 pages

Research supervisor: A. M. Oprescu, a.m.oprescu@uva.nl
Host/Daily supervisor: D. Stam, stam.dennis@kpmg.nl
Host organisation/Research group: KPMG Advisory N.V., www.kpmg.nl

Universiteit van Amsterdam
Faculteit der Natuurwetenschappen, Wiskunde en Informatica
Master Software Engineering
http://www.software-engineering-amsterdam.nl

Abstract

Here goes your abstract. Be concise, introduce context, problem, known approaches, your solution, your findings.

Contents

Chapter 1

Introduction

Currently more and more people are concerned with global warming. Global warming is partly the result of the emission of greenhouse gasses during energy generation of conventional energy options. Because of this a lot of people want to change to green energy generation to help solve this problem. Another solution is to decrease the energy consumption, which is not only good for the environment but can also save a lot of money on the energy bill. The energy consumption of communication networks, personal computers and data centers world wide is increasing over the years [1]. This happens at a growth rate of 10%, 5% and 4% respectively [1]. Therefore it is important to research ways of decreasing the energy consumption. In the field of hardware there is, according to Koomey's law, an increase of the number of computations per Joule. However this is not enough, because tasks need more computations to complete due to the confidence in the improvement of hardware [2]. For this reason we need to look at possibilities in decreasing the energy consumption from a software perspective.

1.1 Problem statement

The energy consumption of communication networks, personal computers and data centers are increasing yearly. There are two ways of decreasing the energy consumption, by decreasing the energy consumption of hardware or software. Scientific research is mostly focused on decreasing the energy consumption of hardware. There are also some papers about reducing the energy consumption in the software process and the decision making process. A small bit of research is done on the energy consumption of software, but their research goal is to estimate the energy consumption. This thesis aims to investigate good ways of writing code with regards to energy consumption.

1.1.1 Research questions

During this research we answer the following two existence questions: (1) **Is there a difference in the energy consumption of software projects in different programming languages that have the same functionality** and (2) **Is there a difference in energy consumption of different software projects (using the same programming language) that have the same functionality**? To answer these questions we first need to answer the three description and classification questions listed below.

- How can the energy consumption of a software project be measured?
- How do we prove that two programs have the same functionality?
- When is a difference in energy consumption significant?

Based on the results we find when answering the second existence question, we looked into what this difference is on code level. To do this we need to answer the descriptive/comparative question **what is the difference on code level between software project that are in the same programming language and have the same functionality, but have a difference in the energy consumption**? This question is only useful when there is a difference in the energy consumption of software projects in the same programming language that have the same functionality.

For the first research question the hypothesis is that there is a difference in the energy consumption

based on the programming language chosen. The hypothesis of the second research question is that there is a difference in the energy consumption of different software projects (in the same programming language) that have the same functionality.

1.1.2 Research method

As method we use a controlled experiment. In this experiment we will run different software projects to measure the energy consumption. Here the projects are the variable input, the energy consumption the output and environmental variable such as the compiler used and energy consumption calculations should be constant.

Data

For the first research question we need programs that have the same functionality, but are written in a different programming language. Possible resources for such programs are library code, interview code, student assignments and code from competitions solving math problems. We first looked at library code, but found that libraries most of the time don't use the same algorithm. This is a problem because the research question does not target comparing algorithms, but the way a programmer writes code. Therefor we used the *the computer language benchmark game* [3] as a source for programs that have the same functionality and use the same algorithm for solving the problem at hand. The second research question requires programs that offer the same functionality and are written in the same programming language. Here we could also use *the computer language benchmark game* as most programs are available in different programming languages.

When proving that all the programs have the same functionality we could have defined properties for the input and output and test if these properties hold for all the programs [4], but *the computer language benchmark game* already makes sure that the programs offer the same functionality. This research builds upon these validations.

To prove that the programs consume different amounts of energy we use the one sided Mann Whitney U test. This test has as its hypothesis that two distributions are from the same population.

Measuring energy consumption

When measuring the energy consumption of a project you have to take into account the energy consumption of CPU, memory and disk [5]. The measurements can be done with a hardware or software approach. A hardware approach is more accurate but also more expensive [5]. This research uses a hardware approach and utilizes the DAS-4 and DAS-5 systems. The DAS is a distributed system that can also do energy measurements [6]. The nodes that can measure the energy are located at the VU cluster. To measure the energy we need to run a job on the DAS-5 and use the DAS-4 to measure the energy consumption. When running a job we need to specify which node we want to run the job on, because not all nodes can be measured for the energy consumption.

Code level

When there is a difference in the energy consumption of different software projects in the same programming language we will look at the different projects on code-level. Here we will try to find what is causing a project to have a lower or higher energy consumption. There are too many combinations of programs and programming languages to look at, thus we need to make a selection. We choose to look at the programming languages that had the biggest range in energy consumption for all the problems, these languages are Python, Ruby and PHP. For every problem we looked to the two programs that differ the most for those three programming languages. Unfortunately not all the problems had enough implementations and some didn't have implementations where we could prove their energy consumption was different. We will look at the program combinations side by side and write down the differences that are observed. Then we analyze these differences and determine if some are occurring more often then others. This could get us a preliminary understanding of what causes the difference in energy consumption of different programs, but to really find out what causes the difference extended research should be done. We will perform a small scale example of such extended research by looking at two differences and implementing them in the well known nth prime number problem. These programs will each run 30 times and then we test if there is a difference and which one is performing better regards the energy consumption using the Mann Whitney U test.

1.2 Contributions

Our research makes the following contributions:

1. An energy consumption measurement set-up
2. A data set of software programs featuring the same functionality
3. Comparison of programming languages on energy consumption efficiency
4. Preliminary findings for writing good software regards the energy consumption

1.3 Outline

In chapter 2 we describe background knowledge that is needed to understand the rest of the thesis. Chapter 3 explains the energy measurement set-up we used and in chapter 4 we discuss the programs we choose to investigate. The results are shown in chapter 5 and in chapter 6 we discuss these results. In chapter 7 we discus papers related to our subject and lastly we conclude our research in chapter 8.

Chapter 2

Background

In this chapter we will explain the background information needed to understand the thesis. We start by looking at different sources that show which programming language is popular. Then we will look at the a source for programming languages that have the same functionality. After that we will look at a system that could be used for measuring the energy consumption. Finally we will delve into the different statistical tests used.

2.1 Programming languages

When looking into what the most used/popular programming languages are we find different results. Here are four different sources with their own opinion of what the most used/popular programming languages are.

Git-hub is a version control system where multiple programmers collaborate in a project. They looked at the amount of pull requests made for that language [7]. The thought was that the language that programmers work a lot with on git is the most popular, but this is based on only the public repositories. In the first quarter of 2019 the top ten according to this method is JavaScript, Python, Java, Go, C++, Ruby, PHP, TypeScript, C# and C.

Indeed is a job search site. They looked at the percentage of jobs with a programming language in their name in the tech software category [8]. Thus the more job offering for a programming language the more popular that programming language is. The problem with this method is that job offerings do not show how many people work with a programming language, but only which programming language has a shortage in programmers. Based on data from September 2018 the top ten according to this method is Java, JavaScript, HTML, Python, C#, C++, XML, Ruby, PHP and Perl.

TIOBE is a software quality company. They looked at the amount of hits they got when searching "[Language] programming" on a lot of different search engines [9]. There are rules which a search engine needs to comply with for it to be used in the calculations and they also look a what type of hits they find to determine whether or not to use it in the calculations. The pitfall of this method is the favouritism for complex languages. When a language is more difficult to understand, more page of tutorials are needed and more questions about this language will be asked. As of April 2019 the top 10 according to this method is Java, C, C++, Python, Visual Basic .NET, C#, JavaScript, SQL, PHP and Assembly language.

PYPL index stands for the PopularitY Programming Language index. They look at how many times a language tutorial is searched [10]. This method also has favouritism for complex languages, where programmers need to use the tutorials a lot because of the difficulty. Based on data form April 2019 the top ten according to this method is Python, Java, JavaScript, C#, PHP, C/C++, R, Objective-C, Swift and Matlab.

2.2 The computer language benchmark game

The computer language benchmark game, also called the famous programming language shootout, compares different programs and languages based on their run time, memory usage, zipped program size and CPU usage [3]. The project features ten different problems with a variety of programs from different languages. Everyone can submit a program if it holds to the two requirements: follow the same algorithm and result in the correct output. This is important because we want to compare the way of writing a program and the difference in programming language, but not the difference in algorithm used. For every program featured, the correct output and required steps to compile the program are listed.

In the previous chapter we found that the energy consumption of a program is the sum of the CPU, memory and disk energy consumption [5]. To get a good view on what influences the energy consumption, our problems need to be diverse when it comes to these three categories. The problems that we looked into are called Binarytrees, Fannkuchredux, Fasta, Mandelbrot, Nbody, Revcomp and Spectralnorm. For the Binarytrees problem a lot of trees are allocated and deallocated in memory and thus this is a memory intensive task. The fannkuchredux problem does a lot of calculations on all permutations and is thus CPU intensive. The Fasta problem creates and saves a large DNA sequence and is memory intensive. For the Mandelbrot problem a large bitmap is saved and thus is it memory intensive. The Nbody problem models the orbit of Jovian planets and is CPU intensive. The Revcomp problem reads a DNA sequences line by line, transforms them and writes the result to output. Therefor the Revcomp problem is disk intensive. For the Spectralnorm problem a lot of calculations are done on a large matrix and is thus CPU intensive. A more extensive explanation of the problems can be found on the computer language benchmark game website [3]. An overview of category and problem is shown in table 2.1.

Category	**Problems**
CPU	Fannkuchredux, Nbody, Spectralnorm
Memory	Binarytrees, Fasta, Mandelbrot
Disk	Revcomp

Table 2.1: The job intensive categories the different problems are in.

2.3 DAS

The Distributed ASCI Supercomputer (DAS) is used for scientific experiments and was designed by the Advance School for Computing and Imaging (ASCI) [6]. There are six organisations involved, all having their own cluster, namely the *Universiteit van Amsterdam* (UvA), *Vrije Universiteit* (VU), *Universiteit Leiden* (UL), *Technishe Universiteit Delft* (TUD), *ASTRON* and *The MultimediaN Consortium* (UvA-MN). Each cluster has different nodes and hardware available, we used the cluster of the VU. Each cluster has a head node where all the users connect to. Here the users can reserve nodes and add jobs to the queue. There are multiple releases of the DAS, currently only DAS-4 and DAS-5 are in use. On the VU DAS-5 cluster we have a total of six nodes available for measuring the energy consumption, because they are connected to a Power Distribution Unit (PDU). This PDU is from Racktivity and has an error marge of 1%. To connect to this PDU we need to make a connection from the DAS-4 through the use of the Simple Network Management Protocol (SNMP). These six node each have different hardware specifications and therefor it is important to distinguish between the nodes. The nodes we used are *node28* and *node29*, where the hardware specifications for *node28* are a GPU node with an Nvidia Tesla K20 (with 6 GB onboard memory), an Xeon Phi and a michost and for *node29* are a GPU node with an Nvidia GTX980 (with 4 GB onboard memory) and an TitanX-Pascal.

2.4 Statistics

Not understanding the terminology of statistics may lead to confusion, therefor here are some basic principles in statistics. When performing a statistical test we have a null hypothesis and an alternative hypothesis. Every test has it specific null and alternative hypothesises and the goal of the test is to reject the null hypothesis. Rejecting the null hypothesis is done by looking at the resulting p-value of the test. The p-value is the chance that the value of the statistical test occurs if the null hypothesis is true on a

zero to one scale. We therefor reject the null hypothesis if we think this chance in too low, thus below a certain threshold. This threshold is determined beforehand and is called the *alpha*-value, a common value for *alpha* is 5%. When we cannot reject the null hypothesis, thus the p-value is not below 0.05, it does not necessarily mean that the null hypothesis is true. It could be the case that the test is not powerful enough or the data set used to validate the hypothesis is too small.

2.4.1 Normal distribution

When choosing a statistical test we have to take into consideration the preconditions for using the test. The most common precondition is that the data follows a normal distribution. The Shapiro-Wilk test has more power then the other normality tests [11] and therefor this test was used. The Shapiro-Wilk test calculates a statistic by dividing the the summation to the power of two of every point times a coefficient by the summation of every point minus the mean to to the power of two [12]. This formula is shown in equation 2.1. The null-hypothesis of the Shapiro-Wilk test is that the data is normally distributed. This means that when the null-hypothesis gets rejected the data does not follow a normal distribution. For this test we used an *alpha*-value of 0.01, because distributions that are close to normally distributed can still be used in some of the statistical tests. When testing if the energy measurements from a single program on a single node follow the normal distribution using the Shapiro-Wilk test we get that not all programs measurements are normally distributed. From the 269 different programs 183 were not normally distributed on node029 and 38 on node028. Therefor we need to choose statistical test that don't assume the data to be normally distributed.

$$W = \frac{(\sum_{i=1}^{n} a_i x_{(i)})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{2.1}$$

2.4.2 Same distribution

When comparing different programs, that are in the same language and have the same functionality, we need to find out if there is a significant difference concerning the energy consumption. This can be tested by looking at the two different distributions and testing if they are from the same population. Here the null hypothesis is that the distributions are from the same population. As the data does not follow the normal distribution, the students t-test cannot be applied. An alternative is the Mann whitney U test [13], which looks if the chance that a random variable from the first distribution is greater than a random variable from the second distribution. When this chance is 50%, then the two different distributions belong to the same population. Another test that we could have used was the students t-test. This test however has the preconditions that the means of the two distributions should follow the normal distribution and the variance of the two distributions should be equal. Our data doesn't match these precondition and therefor we chose to use the Mann Whitney U test.

There are two versions of the Mann Whitney U test, the one-sided and the two-sided test. For the two-sided Mann Whitney U test the alternative hypothesis is that the distributions are from the same population, but if you want to know the direction of this comparison you need to use the one-sided Mann Whitney test [14]. Which means that the alternative hypothesis for the one-sided Mann Whitney U test is that the first distribution is stochastically larger than the second distribution [14]. Because rejecting the null hypothesis holds more power than not rejecting the null hypothesis, a one-sided Mann Whitney U test was used twice. We tested if the first distribution was stochastically larger than the second distribution and if the second distribution was stochastically larger than the first, with an *alpha*-value of 0.05. If both these tests cannot reject the null hypothesis then we still don't know for certain that the distributions are from the same population.

We also used the two sample Kolmogorov-Smirnov test to find out if two distributions are from the same population. This test also has as its null hypothesis that the two distributions are from the same population and we used an *alpha*-value of 0.05. The Kolmogorov-Smirnov test compares the empirical distribution functions of the two distributions.

2.4.3 Correlation

A commonly known method for calculating the correlation is called the Pearson coefficient. The Pearson coefficient uses the covariance of two variables to calculate its correlation score [15]. For this method the

following assumptions should hold, the correlation is linear and the data follows a normal distribution. Our data however does not meet these assumptions for all programs and therefor we needed to look at a different method. The Kendall Tau coefficient calculates a ranked correlation coefficient and does not assume that the data follows a normal distribution [16], therefor this method was used. The Kendall Tau method looks at how many pairs of points follow the same order. For example points (x_i, y_i) and (x_j, y_j) follow the same order if $x_i > x_j$ and $y_i > y_j$ or if $x_i < x_j$ and $y_i < y_j$. Because every pair needs to be checked this could get computational heavy for large number of points, luckily that is not the case in this research project.

The coefficient is in the range of one to minus one, where at zero there is no correlation and at one or minus one there is. But what about the scores in between? According to the standard Guilford scale the range $0 - 0.2$ means slight correlation, $0.2 - 0.4$ means low correlation, $0.4 - 0.7$ means moderate correlation, $0.7 - 0.9$ means high correlation and $0.9 - 1$ means very high correlation [17]. Because the minus in the coefficient shows which direction the correlation is in, we can use the absolute value to determine in which range of correlation a negative number is.

2.4.4 Anomaly detection

An anomaly, also called outlier, is a point that does not behave like the rest of the points in the results. These anomalies can be detected by using a clustering algorithm like DBSCAN [18]. The DBSCAN algorithm goes though every point and counts how many other points are in a predefined area around the point. If there are more or equal to the minimum amount of points needed in this area then this point is labelled as a core point. Points that are not core points but are in the predefined area around a core point are labelled border points, all the other points are anomalies [19]. This is visualized in figure 2.1, where all red dots are core points, yellow dots border points and blue dots anomalies. The minimum amount of points needed around a point and the predefined area around a point are the input variables of this algorithm, which is the disadvantage of this method.

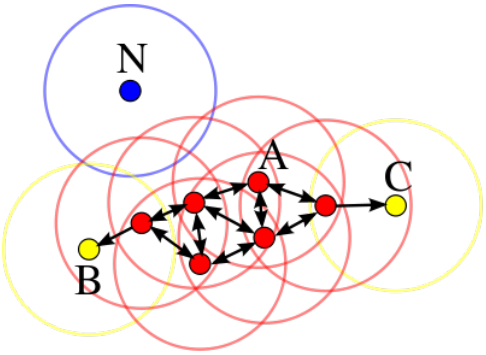


Figure 2.1: The labels according to DBSCAN algorithm with minimum points is four, where the red dots are core points, yellow dots border points and blue dots anomalies. Core points are points that have within a certain distance a minimum amount of points. Border points don't have the minimum amount, but are within reach of a core point. Anomalies don't have the minimum amount of points in a certain area and are not reachable from a core point. (source: `https://en.wikipedia.org/wiki/DBSCAN`**)**

Input variables

According to [19] we can set the minimum amount of points a core point needs in his area to four for two dimensional data. However for the area we need to calculate the radius, also called the eps variable. This eps is calculated by first calculating the distance to the fourth nearest neighbour for every point. These distances are then sorted and plotted. The value for eps can then be read from the graph looking at the first valley [19]. In our implementation we calculated this eps automatically for every single program. To retrieve the first valley we looked at the differences between the slopes around a point. The point with the biggest difference in slopes was in the valley and was used as our eps variable for that specific program.

These two parameters have a big influences on how the clusters are divided and which points are labelled as an anomaly. When the minimum amount of points gets smaller more clusters will be formed and when it gets larger less clusters will be formed, assuming eps stays the same. When eps gets smaller more points will be labelled as anomalies and when eps get larger less points will be labelled as anomalies, assuming the minimum points parameter stays the same.

2.4.5 Clustering

When trying to find clusters in our data we were searching for a specific amount of clusters. Because the amount of clusters was known before clustering the k-means clustering algorithm was used. This algorithm begins by randomly assigning means for the amount of clusters specified. Then all the points are passed and divided into a cluster based on which mean has the shortest euclidean distance. After this the mean of the clusters is calculated and these will be the new means. This will iterate till a local maximum is found or the maximum amount of iterations has passed. The maximum amount of iterations was left to the default of 300 form the *sklearn* python packages.

Chapter 3

Energy measurement

In this chapter we discus the approach used around the energy measurement. We first look into the possibilities that are available to use. After that we will look at options and issues the energy measurement approach has. Finally we show an overview of the set-up used to measure the energy consumption.

When doing energy measurements it is important to not only measure the energy consumption of the CPU, but also of the memory and disk [5]. You can use a hardware method to measure the energy consumption or use a software method to estimate the energy consumption. Using a hardware method is more accurate, but also more expensive [5]. This research uses a hardware approach and utilizes the DAS-4 and DAS-5 systems.

There were two kind of energy measurement values we could retrieve from the PDU, the current power (Watt) and the energy consumption (kWh) from when the node was plugged-in till the moment this value is retrieved. Both methods have a disadvantage when applied. When using the current power one needs to retrieve the power constantly and some accuracy is lost because we don't know what happens with the power draw in between two measure points. The method of measuring the energy consumption has the problem of showing a number that is too large, the numbers are in kWh with a low precision. Thus the lowest decimal shows Watt per hour. We found that for small programs it is not sufficient to only measure in Watt per hour, because of the short run times. We tested this with three programs, an idle program where the only command was *sleep* and two programs that calculates the 10.000th prime one recursively and optimized. The results of this test are shown in figure 3.1. Here we see that the difference of 0.001 kWh is a large difference when working with numbers that are of scale 0.005 kWh. There isn't a clear difference between primes optimized and the sleep that takes close to the same amount of seconds as the primes optimized. Because of these results we choose to go with the power measurement method.

	Idle	**Prime**	**PrimeOpt**
Time	8m0.002s	7m58.443s	1m2.394s
Energy	0.033 kWh	0.037 kWh	0.005 kWh
Time	1m2.002s	7m59.611s	1m2.220s
Energy	0.004 kWh	0.037 kWh	0.005 kWh
Time	1m2.002s	7m58.503s	1m2.235s
Energy	0.005 kWh	0.036 kWh	0.004 kWh

Table 3.1: A test done using the energy measurement in kWh with three different programs.

When using the power measurement method we determine a large number of measurements, where each point has a timestamp and a power value. An example of a measurement and these points are shown in figure 3.1. To calculate the total energy consumed during this program we need to calculate the surface beneath the graph. To do this we calculate the surface between two points and add all surfaces together. When two points do not have the same value we choose the average between the two to use for the surface. For this it is important to have a small interval between measurement points such that the error marge is as small as possible. When looking at the different nodes we see that they all

have a different idle power state. To help compare between the nodes and reduce the difference between the measurement moments we removed the idle state from the energy consumption. To do this we measured the idle state one minute before the first program and after the last program of a single run of all the programs. The average power was then calculated and subtracted from every measurement. These calculations resulted in the following formula 3.1.

$$E = \sum (t_{n+1} - t_n) * \frac{(p_n - p_{idle}) + (p_{n+1} - p_{idle})}{2} \tag{3.1}$$

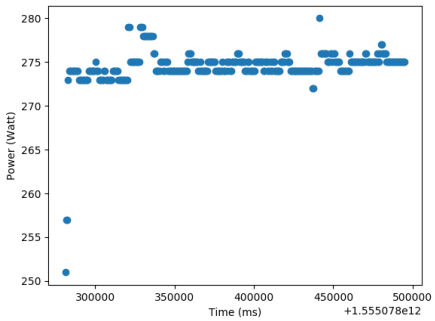


Figure 3.1: An example measurement of the primesOpt program.

An overview of the energy measurement set-up can be seen in figure 3.2 and we created this set-up together with Stephan Kok. Here we can see that from the DAS-5 a job is sent to one of the energy measurement nodes. This is done by using the *prun* command and specifying which node to use. The job we send to this node is a bash script that runs all the programs in our data set. In this job we sleep for ten seconds in between the measurements of the programs to give the node time to go back to its idle state. After these ten seconds the measure script on the DAS-4 is started and then the program we want to measure the energy consumption for starts to run on the node. Immediately after the program ends the measure script is stopped. This measure script on the DAS-4 constantly sends a *snmp* message to the PDU and writes the values to an output file. Due to the other nodes constantly being occupied and the long run time, every program was able to run 27 times on *node28* and 22 times on *node29*.

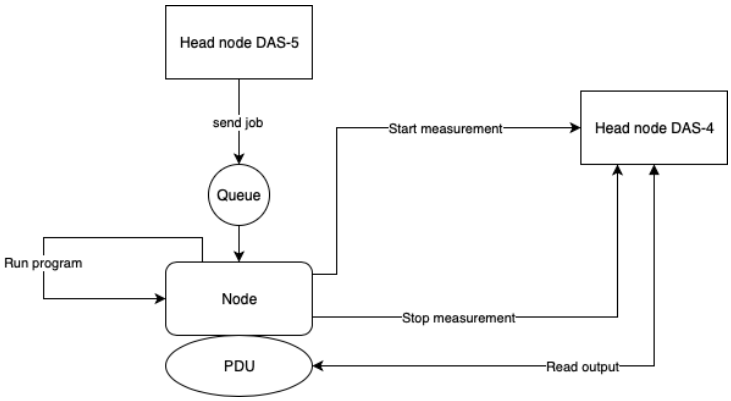


Figure 3.2: The structural overview of how we used the DAS to measure the energy consumption. From the head node of the DAS5 we send jobs to the queue of a certain node we want to measure on. This job will then run on that node when its available. In the job we send a message to the DAS4 to starts its energy measurement, then we run the programs and after that we send a message to the DAS4 to stop the energy measurement. The DAS4 retrieves the energy measurements from the PDU via constant smtp requests.

Our script on the DAS-4 uses *snmpwalk* to retrieve the values from the PDU. The time it takes to retrieve the data from the PDU using *snmpwalk* is not constant. This means that we need to take into account that we have some loss of information and in some cases even too few measure points. When

there are less then 30 energy measurements for a program, that specific programs will run again until it has enough measure points. In figure 3.3 the average time between two measure points is shown alongside the standard deviation, the maximum and minimum time difference. There we can see that the average time between two measures is really fast, but the largest time period between two measures is really long.

```
The mean of the time difference: 0.102455347255
The standart deviation of the time difference: 0.0593552869984
The maximum time difference: 11.888
The minimum time difference: 0.067
```

Figure 3.3: Some statistics of the time between two energy measurement in seconds.

Chapter 4

Data

In this chapter we show the approach followed when selecting the data used for testing. We first discus which programming languages we should investigate. After that we discus what the source is for our programs and which issues we came across when using those programs.

4.1 Programming languages

To find data we first need to decide which programming languages to choose for testing. We did this by looking into what the most popular and most used programming languages are. For this question it depends who you ask which result you get. Therefor four sources were used to determine which programming language to use. The four sources are git-hub, indeed, TIOBE and PYPL.

When languages are in all the top tens of the four sources they were labelled as popular and these are the languages included in this research, thus the languages Java, JavaScript, Python, C#, C++ and PHP. We also choose to investigate C and Ruby. C because it was in three of the four top tens and it is well-established and known for a high level of control over available resources, thus having a potential impact on the energy consumption. Ruby was in two of the top tens, but also 13th according to TIOBE and 12th in the PYPL index. Thus Ruby was close to be in all the top tens and therefor also chosen to be investigated.

4.2 Gathering data

To be able to compare different programs they need to have the same functionality. A source for programs that have the same functionality is *the computer language benchmark game* [3]. All the programs for the ten problems in our seven programming languages were downloaded. These programs were then tested to see if they could compile, run and result in the correct output. This was all done on the DAS5 to make sure there were no local dependencies. All the programs that did not compile, or resulted in run time errors or incorrect output were excluded from the data set. There were three problems, Knucleotide, Pidigits and Regexredux, that for different programming languages use a partly different algorithm because of different library implementations. Therefor we excluded these problems from the data set. At the time of conducting the research, no working JavaScript implementations of the Mandelbrot problem were available. Nonetheless this problem will still be used and we will just have an empty spot in our results.

Before running all the programs some needed to be compiled first. The compilation step of languages that have a separated compilation step were not included in the energy measuring. The reason for this is that a finished program is compiled once and then could be used multiple times. This does mean that the languages JavaScript, Python, PHP and Ruby have a bit of a disadvantage, because they don't have a separate compilation step. The compiler can nowadays do a lot of optimizations of the code. During this research we want to see the result of user decisions on the energy consumption. Therefore besides testing the programs with the compilation flags used on the language benchmark game we also tested with as few flags as possible. This means that we removed all the optimization flags except the ones needed for the compilation. Also the compiler version of the different languages is important. To

give a good pictures of were we stand today we need to use the most recent stable version and also the most commonly used one. Unfortunately it isn't that easy to update the language versions on the DAS. Therefore I used the versions that were already on their and these programming language versions are listed alongside the compiler used in table 4.1.

Languages	**Compiler**	**Version**
Java	javac	1.8.0_161
JavaScript	node	6.12.3
Python	python	3.4.5
PHP	php	5.4.16
C	gcc	6.3.0
C++	gcc	6.3.0
C#	mcs	5.10.1.20
Ruby	ruby	2.0.0

Table 4.1: All the different compilers and versions of the programming languages used.

This all resulted in a large data set of 202 programs with 67 programs that had to run twice, once with and once without flags. Running all these programs takes about eight hours to complete. Unfortunately we were only allowed to use a node on the DAS for 30 minutes to run one script during working hours. This means that we had to run it at night and in the weekend, which limited the amount of data points that were measured. Of course running programs more often would give more accurate results, but this was just too time consuming.

Some programs were too fast to get a good amount of energy measurement points. To solve this problem those programs were run for multiple times during one measurement and then afterwards their energy consumption was divided by the amount of times the programs was run. Another problem that occurred was that retrieving a measure point takes a variable amount of time. This caused some programs to still not have a good amount of energy measurement points. Therefor I decided to set a minimum amount of 30 of measurement points needed in order for it to be used.

Chapter 5

Results

In this chapter we show the results from our experiments. From running all the experiments we got a lot of raw data. This data alongside all the programs tested are on a publicly available git repository. On that git repository you can also find the programs used to do the measurements, the calculations of various statistical tests and all the intermediate results. The link to this repository is `https://github.com/lukaskoedijk/Green-Software`. The ordering of the chapter will be as followed, where we first take a loot at the anomaly detection that was done. Secondly we show the results from the experiments concerning the programming languages. After that we will show the results of the experiments when looking at programs. Finally some additional results are shown.

5.1 Anomalies

We checked for anomalies using DBSCAN. An example of the results we got from this approach is shown in figure 5.1. There we can see in the top graph the distribution of measurements for a single program on one of the two nodes on the DAS. The red dots are the measurements DBSCAN labelled as an anomaly. In the bottom graph we see from every measurement point its distance to its fourth nearest neighbour. This is sorted and the red dot is the choice of the input variable of DBSCAN called *eps* and is calculated by finding the first valley.

For *node28* there were a total of 345 anomalies from 7263 measurement points, which is roughly 4.8%. In the measurements from *node29* there were a total of 305 anomalies from 5918 measurement points found, which is roughly 5.1%. Even though there are more anomalies found than programs, there was not for every program an anomaly detected. All the anomalies found were removed from further results.

5.1.1 Two clusters

During the processing of the information from the anomaly detection we saw only on *node29* that the resulting measurements for some programs could be clustered. We looked further into this and found that where we found two clusters it seemed to follow an ordering based on the moment of measuring. With clusters based on the moment of measuring we mean that in the first cluster all measurements were done before a certain date and in the second cluster after that date. The DBSCAN algorithm found for *node28* seven times two clusters in the measurements for a single program, none of which follow the moment of measuring, and 58 times for *node29* of which 53 follow the moment of measuring. At *node29* for all of these 53 programs the null hypothesis that they're from the same distribution can be rejected. We then instead of letting a clustering algorithm cluster first and then check if the clusters follow the moment of measuring, clustered ourselves based on the moment of measuring. We find that for *node28* 218 programs and for *node29* 41 programs the null hypothesis that the two moment of measuring clusters are from the same population can't be rejected. Because of the large amount of programs where the clusters were not from the same population at *node29*, we decided to run another clustering algorithm named k-means. We set the amount of clusters the k-means algorithm will search for at two, because we wanted to find these two moment of measuring clusters. We then found that there were zero programs that had clusters based on moment of measuring for *node28* and 63 programs for *node29*. These 63 programs all rejected the null hypothesis that the two clusters were from the same population. When looking at the programming languages and problems these 63 programs entail, we saw a good representation of the programming

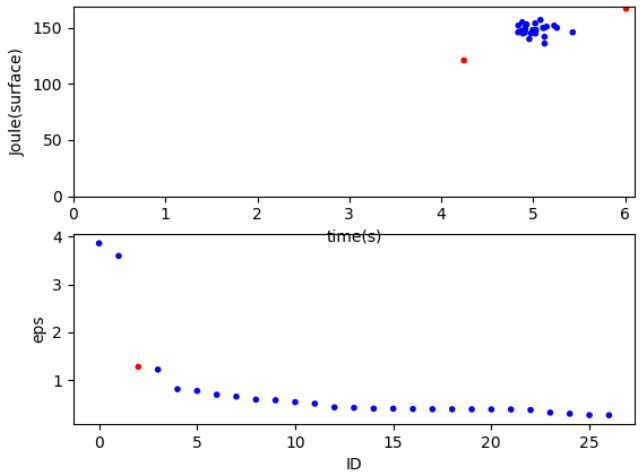


Figure 5.1: In the top graph the distribution of measurements from program java-3 on the Binarytrees problem on *node28* is shown. The bottom graph shows the sorted fourth nearest neighbour graph. The red dots at the top are measurements labelled as an anomaly and at the bottom is the choice for the *eps*-value.

languages and different problems. There were no indications of suspecting some programming language or problem specific cause for this difference. There still could be some other commonality between these programs, but it is too difficult to find this between the 63 programs. Therefor we left it like this with on *node28* no difference in the moment of measuring and on *node29* only a difference in some of the programs.

5.2 Programming Languages

After all the measurements were done we wanted to compare the programming languages. This was done by filtering out one problem and selecting every measurement of a program that solves this problem. This resulted in a lot of points per language and these are plotted in a box-plot. There are seven problems and thus also seven box-plots. An example of one of these box-plots is shown in figure 5.2. Here the box is from the first quartile till the third quartile and a line at the median. The dots are measurement points laying outside the fences that are located at $Q1 - 1.5(Q3 - Q1)$ and $Q3 + 1.5(Q3 - Q1)$. The whiskers show the range of points that are outside the box but inside the fences. All the graphs are shown in appendix A for *node28* and appendix B for *node29*.

In the box-plot we can't always clearly see which programming language is using less energy. To find out what the relationship is between two programming languages we used twice the one-sided Mann Whitney U test. This we calculated for every language with every other language and because of the fact that if one is smaller the other should be larger this table should be inverted around the diagonal zero's, thus a + changes into a -. An example of this is shown in table 5.1. In that table a + means that the programming language on the row is performing better than the programming language on the column, i.e. the programming language on the row consumes less energy. The - means the opposite, a *0* means equal and *unknown* means that both one-sided Mann Whitney U tests could not be rejected. All the tables are shown in appendix A for *node28* and appendix B for *node29*.

Using these tables we can see which language is performing better compared to others, but only for a single problem at a time. To give a total overview of problems and programming languages we calculated a score for every combination. One point was rewarded when there was a plus, one point was subtracted when there was a minus and nothing was added or subtracted in the case of a zero or unknown. With the use of these scores we made a heatmap, where green means a high score and red a low. This heatmap is shown in figure 5.3. Here the programming languages with a lot of green in their row, or a lot of red in their column, are performing better than most programming languages. We also wanted to see which

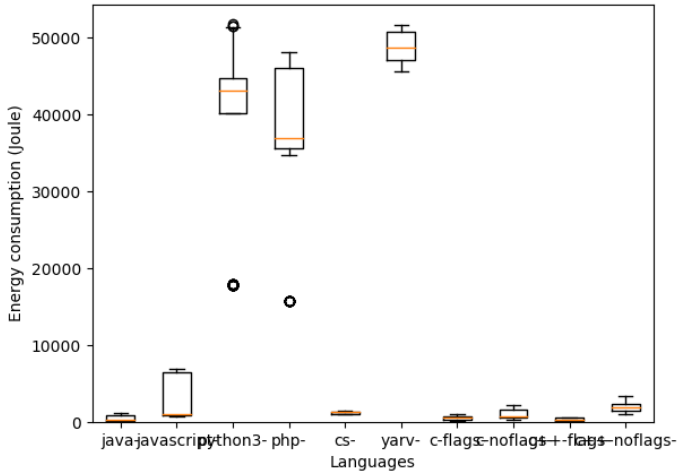


Figure 5.2: The box plot of the different programs in a programming language for the problem Fannkuchredux on *node28*.

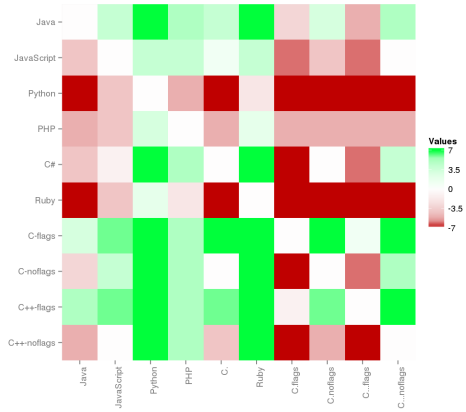
	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	+	+	+	+	+	-	+	-	+
JavaScript	-	0	+	+	+	+	-	+	-	+
Python	-	-	0	-	-	-	-	-	-	-
PHP	-	-	+	0	-	-	-	-	-	-
C#	-	-	+	+	0	+	-	+	-	+
Ruby	-	-	+	+	-	0	-	-	-	-
C-flags	+	+	+	+	+	+	0	+	Unknown	+
C-noflags	-	-	+	+	-	+	-	0	-	+
C++-flags	+	+	+	+	+	+	Unknown	+	0	+
C++-noflags	-	-	+	+	-	+	-	-	-	0

Table 5.1: The comparison of the different languages for the Nbody problem on *node28*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -, and the *Unknown* means that we could not reject the null hypothesis.

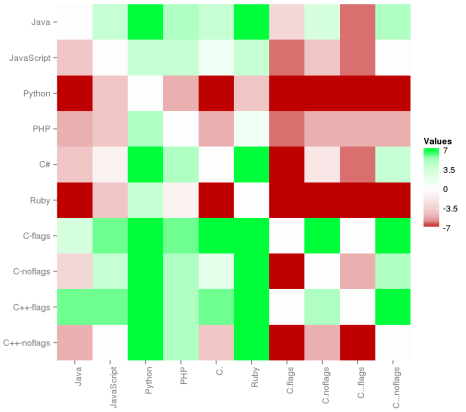
programming language combination resulted the most in an *unknown*, thus which combination could not reject the null hypothesis the most. For this we also created a heatmap where a one was added for every *unknown* found. This resulted in figure 5.4.

5.3 Programs

When comparing programs that are written in one language and solve the same problem, we can also use a box-plot. An example of such a box plot is shown in figure 5.5. Here we can't always see which program is performing better concerning the energy consumption. Therefor we also used the one-sided Mann Whitney U test twice here. For some combination of two programs we weren't able to reject both the Mann Whitney U tests. All these program combinations and their p-values are listed in table A.8 for *node28* and in table B.8 for *node29* in respectively appendix A and B. There were a total of 24 program combinations on *node28* and 59 on *node29* where the null hypothesises could not be rejected. We tried to also use Kolmogorov-Smirnov test to see if we would get less cases of uncertainty. This resulted in a total of 33 program combinations for *node28* and 61 for node29. But when we look at the overlap we see that there are only 24 program combinations for *node28* and 50 for *node29*. Thus this second test removed the uncertainty of nine program combinations on *node29*.



(a) The heatmap of *node28* of the relationship between the programming languages for all problems combined. A green box means that the language on the row has a lower energy consumption over all the programs than the language in the column, red is the reverse.



(b) The heatmap of *node29* of the relationship between the programming languages for all problems combined. A green box means that the language on the row has a lower energy consumption over all the programs than the language in the column, red is the reverse.

Figure 5.3

5.3.1 Code level

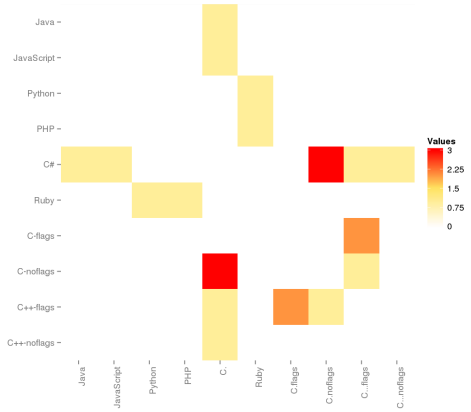
When comparing the different programs we found the differences shown in table D.1 in appendix D. Here we find for most comparisons multiple differences. If there are multiple differences found we can't be sure that a specific difference has an influence on the energy consumption, but if we only see one difference that does not mean that there aren't any other differences. Another problem with multiple differences is that the difference is relative. One way of writing code can be better then a second way of writing code, but worse than a third regards the energy consumption. When looking at table D.1 we see that multithreading is a lot of times a difference, but it occurs in both the good and bad programs. This can also be said for the difference between a while and for-loop. We also see that using a library instead of implementing it yourself is beneficial concerning the energy consumption.

It is really hard to exactly point out what causes the programs to be different, a better approach would be to make a small change in one program when you have two exactly the same programs. To give an example of how this is done we did this for two small changes. The first change we choose was the difference between while and for-loop, because we saw in the table that both occurred in the good and bad section. For the second change we choose the difference between an if-statement with condition and body on different lines and an if-statements with condition and body on the same line, because we expected this to not have an effect. These four programs are shown in D. When we measure the energy consumption 30 times each for these four programs we get the results show in figure **??**. Using the Mann Whitney U test we find that there is a significant difference between the *for-loop* program and the *while-loop* program, but we couldn't reject the null hypothesis when comparing the *sameline* and *diffline* programs.

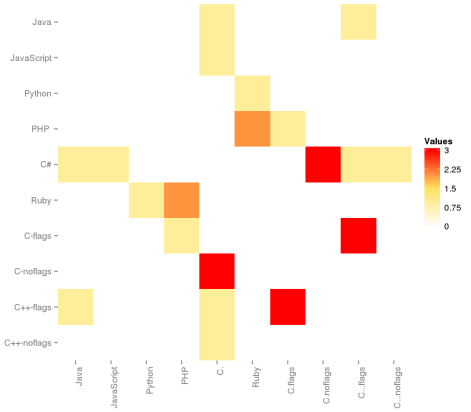
5.4 Additional Findings

5.4.1 Hardware

Our measurements were run on two different nodes, which had different hardware specifications. To find out how big of an influence the node is we wanted to compare the measurements between the two nodes for a single program. We first used the one-sided Mann Whitney U test and found that for two programs we couldn't reject the null hypothesis that they're from the same distribution. For most programs their energy consumption highly depends on which node they were run on. To see if only the height is different, but still follow the same trend we calculated the correlation. This correlation was calculated between the



(a) The heatmap of *node28* of the the amount of times we could not reject the null hypothesis for the relationship between the programming languages for all problems.



(b) The heatmap of *node29* of the the amount of times we could not reject the null hypothesis for the relationship between the programming languages for all problems.

Figure 5.4

different programs and an example of the results is shown in figure 5.7a. In this figure we have positive and negative numbers, this only shows the direction of the correlation. Thus the correlation number 0.7 and -0.7 have the same correlation strength. All the other graphs of the other problems are shown in appendix C. In all these graphs we see that most scores are low. Because the distribution of the programs are small we decided to check the correlation of all the measurements in one language for one problem. These are also all listed in appendix C and an example is show here in figure 5.7b. There we see that in most cases the Kendall correlation score is higher.

5.4.2 Time

Because of some statements in related work, we also wanted to investigate the relationship between the energy consumption and the run time. We plotted a separate graph for every problem every measurement from both the nodes, where on the x-axis is the run time and on the y-axis the energy consumption. This graph is shown in figure 5.8. Looking at these graphs we see a line through the points and based on the Kendall tau scores the run time and energy consumption have a high correlation according to the Guilford scale. In some of the case we also see a second line, which means that a lower run time not necessarily result in a lower energy consumption.

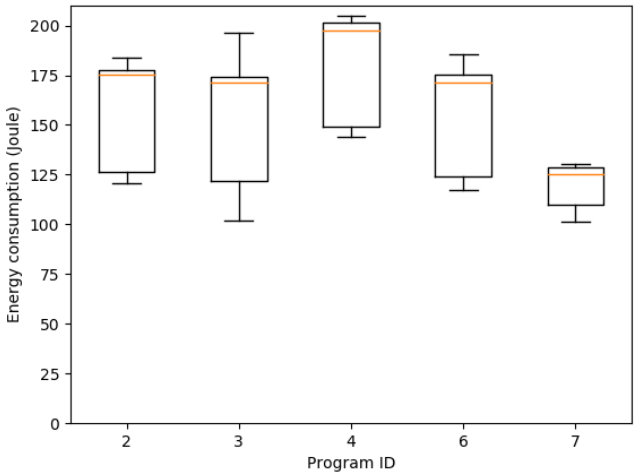


Figure 5.5: The box-plot for the programming language Java comparing the measurements of different programs that solve the Binarytrees problem and are measured on *node28*.

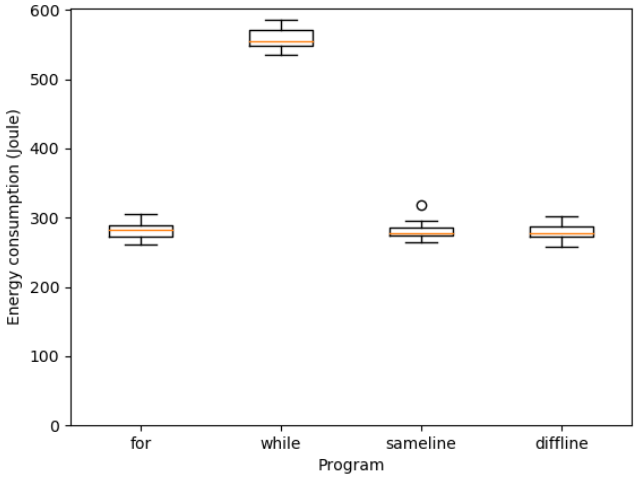
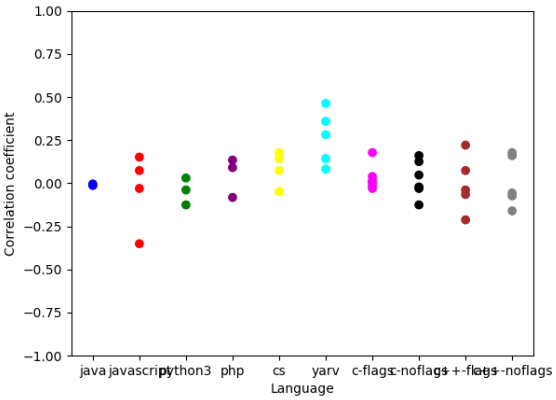
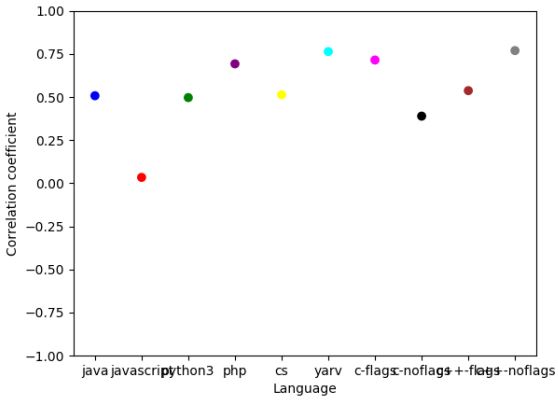


Figure 5.6: The box-plot comparing two programs that have a small difference on code level when solving the 10000th prime number problem. The measurements were done on *node28* and the program were measured 30 times each.

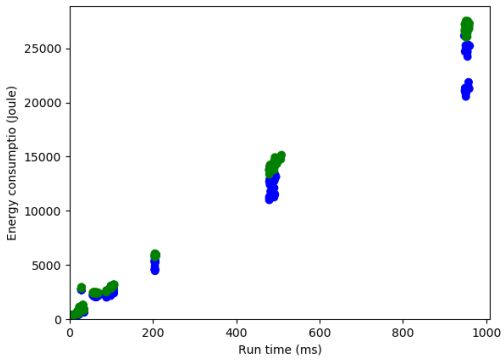


(a) The Kendall correlation score for every single program that solves the Fasta problem.

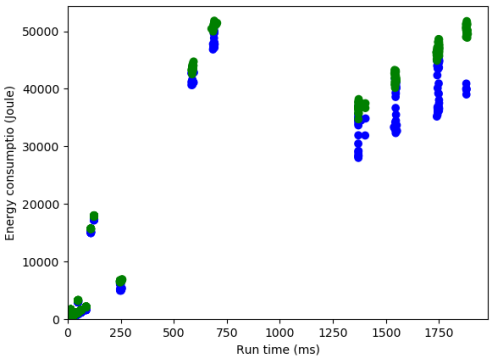


(b) The Kendall correlation score for every programming language that solves the Fasta problem.

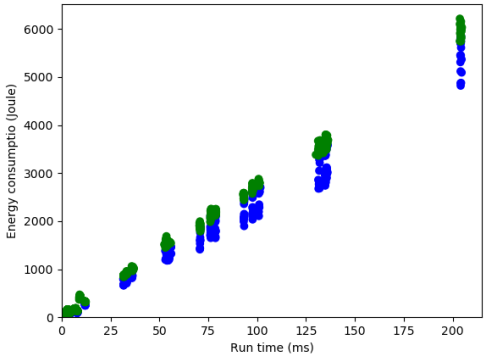
Figure 5.7



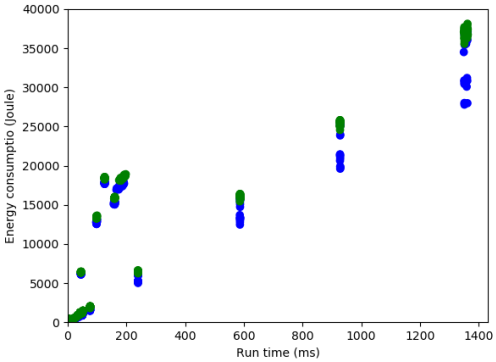
(a) Binarytrees, tau=0.85



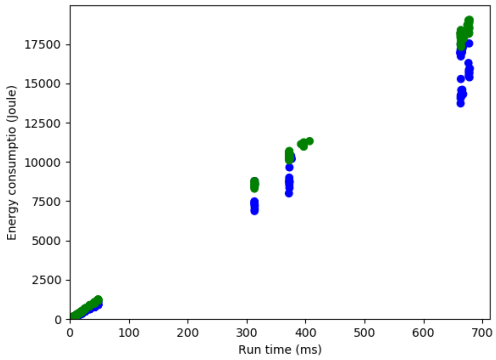
(b) Fannkuchredux, tau=0.72



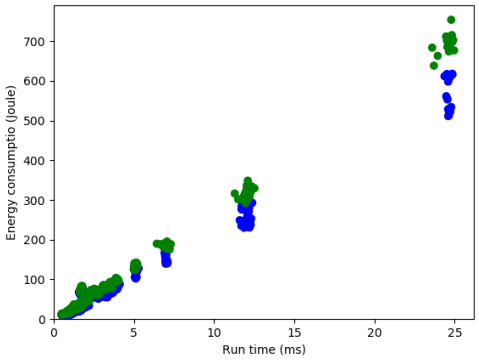
(c) Fasta, tau=0.84



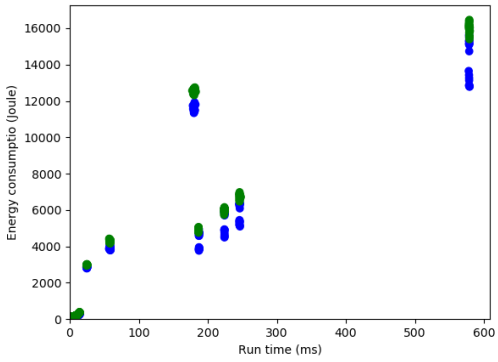
(d) Mandelbrot, tau=0.84



(e) Nbody, tau=0.89



(f) Revcomp, tau=0.82



(g) Spectralnorm, tau=0.85

Figure 5.8: All the energy measurements and their corresponding run times for every problem. Here the green points are the measurements from *node28* and the blue from *node29*.

Chapter 6

Discussion

In this chapter we discuss the various results from the different experiments. First we will look at the results we got from comparing programming languages to each otter. Then we will discuss the results from comparing programs to each otter. Finally we will discuss some additional results we found.

6.1 Programming Language

Comparing the programming languages to each otter showed that most had a difference in their energy consumption, for 12 and 15 combinations on *node28* and *node29* respectively we could prove a difference. The combination of programming languages where we couldn't prove the difference for the most problems was C-noflags with C on *node28* and C-noflags with C and C++-flags with C-flags on *node29*. When looking at which programming language preforms the best confirm the energy consumption for every problem, we observe that C-flags and C++-flags are the best. This let us to conclude findings 1 and 2.

Finding 1: There choice of programming language has an influence on the energy consumption of a program.

Finding 2: Programming languages C and C++ perform the best concerning the energy consumption.

Because we see notice the difference between programming languages that have a pre-compilation phase and those that don't, we also looked at the no pre-compilation programming languages separately. Here we observe that JavaScirpt performs better than the otter programming languages without a pre-compilation phase. Which let us conclude finding 3.

Finding 3: From the programming languages that don't have a pre-compilation phase JavaScript performs the best concerning the energy consumption.

We expected the compilation flags to play a part in the energy consumption of C and C++. When looking at the results we see that the measurements from C and C++ with compilation flags perform better concerning the energy consumption than the measurements from C and C++ without compilation flags. This let us to conclude finding 4.

Finding 4: Programs in the language C and C++ consume more energy when the amount of compilation flags are minimized.

6.2 Programs

We observe that only a small amount of the energy measurements are labelled as anomalies, 4.8% and 5.1% for *node28* and *node29* respectively. We also see a difference in the behaviour of 63 programs based on the moment of measuring on *node29*. Finally we see that when comparing programs that solve the same problem and are written in the same programming language most have a difference in their energy consumption, for 24 and 50 programs on *node28* and node29 respectively we can't prove their different. This let us to conclude finding 5.

Finding 5: The way a program is written influences the energy consumption of that program.

When comparing two programs, where we introduced a small difference, we found that a for-loop use less energy than a while-loop. We also compared the difference between having the body and condition of an if-statement on the same or different lines. Here we couldn't reject the null-hypothesis and thus it looks like the placement of the body doesn't matter. This let us conclude findings 6 and 7.

Finding 6: A for-loop consumes less energy than a while-loop.

Finding 7: Regards the energy consumption it doesn't matter if the body of an if-statement is on the same or different line as the condition.

6.3 Additional Findings

When comparing the measurements from both the different measurement nodes to each otter, we find that all but two programs have a difference in their energy consumption based on which node the program is run on. When comparing measurements from specific programs to each otter we observe a slight to low correlation and when we compare all programs in one language that solve one problem we observe a moderate to high correlation. This let us to conclude finding 8.

Finding 8: The hardware has an influence on the energy consumption of a program running on it.

If we look at the correlation between the energy consumption and the run time separately for every single problem, we observe that they all have a high correlation. At three problems we see not one but two trends, which shows that a point with a faster run time does not necessarily consume less energy. This let us to conclude finding 9.

Finding 9: The run time of a program has an influence on the energy consumption, but a shorter run time does not always mean a lower energy consumption.

6.4 Threads to validity

We used programs listed on the *the computer language benchmark game* which gave us a large amount of programs with the same functionality. These programs could be submitted by everyone and were checked to make sure they use the same algorithm and have the same output. For some programming languages there were more submissions than others, there were cases that for a problem there was only one submission for a programming language. Here we can't be certain that this one program represents the whole language for this problem, maybe we were just lucky and got the best performing program in that programming language confirm the energy consumption. This uncertainty could be decreased by finding more programs and measuring those for the energy consumption.

The languages that normally have a pre-compilation phase have an advantage because the energy consumption of this pre-compilation was not measured. This approach was chosen for we found that this was a programming language feature and we wanted to mirror the real world use of the languages as close as possible. But there are ways of pre-compiling the other languages or improving the following runs by caching. This could improve the energy consumption of the no pre-compilation phase programming languages, resulting in a different comparison between the languages.

Before the first program and after the last program of a single run we measured the idle state. This idle state was then used to subtract from the measurements to be able to compare the two different nodes. The time between the before and after idle measurement is eight hours. Maybe the idle state fluctuates so much that we were better of calculating the idle state before and after every single program. However we did not choose this option because it would increase the run time even more.

Because of the long run time and the restrictions of only being able to measure outside of working hours we measured each program 27 times on *node28* and 22 times on *node29*. After this for most programs we decreased this number for they were detected as anomalies. This sample size could be on the small size giving less accurate results.

Chapter 7

Related work

To get an overview of the related research we made the table 7.1 where we are comparing different related papers. Most research is about reducing the energy consumption of a specific piece of hardware, for example scheduling on a multi-core processor. There are also some papers about reducing the energy consumption in the software and the decision making process. There is also some research done on the energy consumption of software, but their research goal was to estimate the energy consumption.

Papers	**Type of Research**	**Unit of Analysis**	**Goal**
[2]	Controlled Experiment	Deployment strategies, releases and use case scenarios	Finding optimal energy consumption
[20]	Case Study & Controlled Experiment	HPC bag of task applications	Finding optimal energy consumption
[5]	Case Study	Small functions	Estimating energy consumption
[21]	Case Study & Controlled Experiment	Small functions	Estimating energy consumption
[22]	Case Study	Task on complex micro-architectures	Estimating worst-case energy consumption
[23]	Controlled experiment	I/O application tasks	Estimating energy consumption of I/O tasks
[24]	Empirical Study	Six commonly used refactorings	Finding impact of refactorings on energy consumption
[25]	Controlled experiment	Programming languages	Rank programming languages based on speed, memory usage and energy consumption
[26]	Case Study	Multi-core processor scheduling	Efficient workload partitioning
[27]	Case Study	Cache storage management algorithms	Power aware cache management
[28]	Case Study	Java applications	Framework to automate decision-making support regarding energy consumption
[29]	Case Study	Software process	Two level green software model

Table 7.1: Overview of related research

7.1 Finding optimal energy consumption

The paper [2] looks at the impact of releases and deployment strategies of a software product on the energy consumption. They used a controlled experiment where the variables they changed where deployment strategies, releases and use case scenarios. The variables they measured during their tests were power consumption and execution time. They saw that both the releases and deployment strategies impacted the energy consumption and that this impact was influenced by which use case scenario they used. Therefore they concluded that there is no absolute optimal option for releases and deployment strategies with respect to energy consumption. They also found that the execution time had a bigger impact on the energy consumption than the power consumption, because of the low variability in power consumption.

The paper [20] looks at the scheduling of bags of task application in High performance Computing (HPC). They delved into the trade-off between energy consumption and performance by finding a optimal point for both variables. This was calculated by designing a dynamic Hill Climbing algorithm.

Their algorithm uses less then 12% of the resources an exhausted search would use to find a majority of points close to the optimal for the trade-off in 10 of the 12 scenarios. They validated their algorithm by implementing it and running a wide range of HPC bag of task applications. They found that the estimations of their algorithm have an error below 5%.

7.2 Estimating energy consumption

The paper [5] looks at different techniques to measure the power consumption. Then they propose a model to measure the power consumption and they used this model in their implementation named *Tool to Estimate Energy Consumption* (TEEC). They test their implementation against a power meter, but they do not mention how accurate their implementation is. The figure they use at the validation is also not clear, they just state that it shows the same behaviour as TEEC. They find that the power consumption of unoptimized code is higher and has a longer execution time than the optimized code. They do not mention it, but looking at their graphs the unoptimized and optimized code seem to have the same peaks where the only difference is the time steps and that the optimized code is faster.

The paper [21] estimates the energy consumption by developing a model which can be applied at instruction set simulation level. This was done by designing a translation from instruction set architecture code to Horn-clause representation and this model is called in the paper *Instruction Set Simulation* (ISS). They also use the CiaoPP general resource analysis framework, which is low level, to model the energy consumption. They named it *Static Resource Analysis* (SRA) in the paper. In their experiments they only use small functions to test and the results were compared to a mathematical equation. They found that the ISS function is less accurate when the value of N increases and that the SRA function is not accurate for small values of N. Here N is the input value of the function that is tested for its energy consumption.

The paper [22] estimates the worst-case energy consumption of a task on complex micro-architectures. This is important for battery-operated embedded devices, where we don't what the battery to drain empty before a critical task is completed. They test their result against a commonly used benchmark and they find that their values have at most 33% difference with the benchmark.

The paper [23] looks at two applications that are I/O heavy. Different tasks were run for these applications and the energy consumption was measured. Another variable in their experiments was the amount of cores used. They compared the energy values measured with a commonly used estimation scheme for the energy consumption which only looks at the CPU utilization. They noticed a difference in energy consumption and the correlation between power consumption and CPU utilization was close to zero. The reason for this was that the estimation scheme didn't factor in the energy consumption of I/O operations. Therefor they came up with a scheme that factors in the CPU utilization and the I/O operations. This scheme used values from the tests to put in different values in the formula and was tested against the two applications and they found a small error. This is an issue, because you expect the data you used to create a model to fit the model. A better approach would have been to use one application for calculating the values and the other for the validation.

7.3 Measuring energy consumption

The paper [24] addresses the lack of information about the energy impact of code refactorings. They did this by testing the energy impact of 197 projects when the using six commonly used refactorings. From this test they found that refactorings can influence the energy consumption. Also they find that one refactoring does not necessarily have the same influence on the energy consumption when used with different projects.

The paper [25] tries to find a connection between the speed, memory usage and energy consumption of a programming language. They do this by choosing the fastest implementation of the exact same algorithm, defined in the computer language benchmarks game, in different programming languages. From these programs they measured the execution time, memory usage and energy consumption. They

used Intel's Running Average Power Limit (RAPL) tool to measure the energy consumption and for the memory usage and execution speed they used the *time* command available in Unix-based systems. They find that a faster programming language does not necessarily have a lower energy consumption and memory usage does not relate to energy consumption. A big problem with this paper is that in their threads to validity paragraph they defend their implementation instead of stating what could be wrong with their implementation.

7.4 Hardware

The paper [26] proposes an algorithm to makes sure all cores in a multi-core processor have the same workload. This is reducing energy consumption because multiple single core processors consume more energy.

The paper [27] tries multiple algorithms for storage cache management to decrease the energy consumption. One algorithm is an offline greedy algorithm and they also propose an online algorithm. They evaluate their algorithms by simulating a complete storage system, enhancing the DiskSim simulator. Their greedy algorithm results in 16% less energy used then the LRU algorithm. They also find that the cache policy write-back can use 20% less energy then write-through.

7.5 Other

The paper [28] implements a framework that automatically optimizes the energy consumption of a Java software project. The framework does this by running multiple different given options and testing which option consumes the least amount of energy. Thus as input the framework needs a list of possible changes. Because the framework needs possible changes we don't know if the resulting code is the most energy efficient version, only that it is more energy efficient then the other input. They showed that by letting their framework chose which library to use they reduced their energy consumption by 17%.

The paper [29] makes a two level green software model. The first level is about making the software process more energy efficient. This new process is a hybrid of the sequential, iterative, and agile development processes. The second level is about the role software tools can have on improving the energy efficiency of software. They also discus the relationship between the two levels.

Chapter 8

Conclusion

We looked at the impact the choice of programming language and way of coding has on the energy consumption. This was measured using a PDU and a distributed node system called DAS. These measurements were compared using the one sided Mann Whitney U test twice and in most cases we could reject one of the two null hypothesises.

When looking into the first research question (1) **Is there a difference in the energy consumption of software projects in different programming languages that have the same functionality**? we find that we cannot make a conclusion for all the problems for all the programming language combination. In the most cases we find a difference, but this difference could not be proven for every programming language combination for every problem. However for some problems on a specific node we can. There is a difference in the energy consumption of different programming languages that solve the problem Binarytrees, Fannkuchredux and Fasta on *node28* and Binarytrees for *node29*.

For the second research question (2) **Is there a difference in energy consumption of different software projects (using the same programming language) that have the same functionality** we find that we cannot make a conclusion for all the projects. In most cases there is a difference in software projects that solve the same problem and are written in the same programming language, but not for all of the software projects combinations. We did find that there seemed to be a good representation of programming languages and problems for the cases where we could not prove they were different.

8.1 Future work

In future research we would like to further investigate the difference on code level has on the energy consumption. This could be done by looking by having two identical programs and then slightly change one of them. Measure them both for the energy consumption, proof that they are different and show which one consumes less energy. When this is done for a lot of different small changes we could get a clearer view on how to write code in such a way that we consume less energy.

We would also like to investigate what happens to the energy consumption when we add a precompilation phase to the programming languages that normally don't have this phase. It is also interesting to investigate what happens when we do other optimizations like caching of programs.

Acknowledgements

If so inclined, thank people. Kees Verstoep

Bibliography

[1] W. Van Heddeghem, S. Lambert, B. Lannoo, D. Colle, M. Pickavet, and P. Demeester, "Trends in worldwide ict electricity consumption from 2007 to 2012", *Computer Communications*, vol. 50, pp. 64–76, 2014.

[2] R. Verdecchia, G. Procaccianti, I. Malavolta, P. Lago, and J. Koedijk, "Estimating energy impact of software releases and deployment strategies: The kpmg case study", in *Proceedings of the 11th ACM/IEEE International Symposium on Empirical Software Engineering and Measurement*, IEEE Press, 2017, pp. 257–266. DOI: 10.1109/ESEM.2017.39.

[3] I. Gouy, *The computer language benchmarks game*, Accessed: 26-04-2019. [Online]. Available: https://benchmarksgame-team.pages.debian.net/benchmarksgame/.

[4] T. Mens and T. Tourwé, "A survey of software refactoring", *IEEE Transactions on software engineering*, vol. 30, no. 2, pp. 126–139, 2004.

[5] H. Acar, G. Alptekin, J.-P. Gelas, and P. Ghodous, "The impact of source code in software on power consumption", *International Journal of Electronic Business Management*, vol. 14, pp. 42–52, 2016.

[6] H. Bal, D. Epema, C. de Laat, R. van Nieuwpoort, J. Romein, F. Seinstra, C. Snoek, and H. Wijshoff, "A medium-scale distributed system for computer science research: Infrastructure for the long term", *Computer*, vol. 49, no. 5, pp. 54–63, 2016.

[7] C. Zapponi, *Githut 2.0 - a small place to discover languages in github*, Accessed: 16-04-2019, Apr. 2019. [Online]. Available: https://madnight.github.io/githut/#/pull_requests/2019/1.

[8] A. D. Rayome, *The 10 most in-demand programming languages of 2018*, Accessed: 16-04-2019, Sep. 2018. [Online]. Available: https://www.techrepublic.com/article/the-10-most-in-demand-programming-languages-of-2018/.

[9] TIOBE, *TIOBE index for april 2019*, Accessed: 16-04-2019, Apr. 2019. [Online]. Available: https://www.tiobe.com/tiobe-index/.

[10] P. Carbonnelle, *PYPL popularity of programming language*, Accessed: 16-04-2019, Apr. 2019. [Online]. Available: http://pypl.github.io/PYPL.html.

[11] N. M. Razali, Y. B. Wah, *et al.*, "Power comparisons of shapiro-wilk, kolmogorov-smirnov, lilliefors and anderson-darling tests", *Journal of statistical modeling and analytics*, vol. 2, no. 1, pp. 21–33, 2011.

[12] S. S. Shapiro and M. B. Wilk, "An analysis of variance test for normality (complete samples)", *Biometrika*, vol. 52, no. 3/4, pp. 591–611, 1965.

[13] H. B. Mann and D. R. Whitney, "On a test of whether one of two random variables is stochastically larger than the other", *The annals of mathematical statistics*, pp. 50–60, 1947.

[14] N. Nachar *et al.*, "The mann-whitney u: A test for assessing whether two independent samples come from the same distribution", *Tutorials in quantitative Methods for Psychology*, vol. 4, no. 1, pp. 13–20, 2008.

[15] E. S. Pearson, "Some notes on sampling tests with two variables", *Biometrika*, pp. 337–360, 1929.

[16] M. G. Kendall, "A new measure of rank correlation", *Biometrika*, vol. 30, no. 1/2, pp. 81–93, 1938.

[17] J. P. Guilford, "Fundamental statistics in psychology and education", 1942.

[18] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection: A survey", *ACM computing surveys (CSUR)*, vol. 41, no. 3, p. 15, 2009.

[19] M. Ester, H.-P. Kriegel, J. Sander, X. Xu, *et al.*, "A density-based algorithm for discovering clusters in large spatial databases with noise.", in *Kdd*, vol. 96, 1996, pp. 226–231.

[20] A. V. Filip, A.-M. Oprescu, S. Costache, and T. Kielmann, "E-bats: Energy-aware scheduling for bag-of-task applications in hpc clusters", *Parallel Processing Letters*, vol. 25, no. 03, p. 1 541 005, 2015.

[21] U. Liqat, S. Kerrison, A. Serrano, K. Georgiou, P. Lopez-Garcia, N. Grech, M. V. Hermenegildo, and K. Eder, "Energy consumption analysis of programs based on xmos isa-level models", in *International Symposium on Logic-Based Program Synthesis and Transformation*, Springer, 2013, pp. 72–90.

[22] R. Jayaseelan, T. Mitra, and X. Li, "Estimating the worst-case energy consumption of embedded software", in *Real-Time and Embedded Technology and Applications Symposium, 2006. Proceedings of the 12th IEEE*, IEEE, 2006, pp. 81–90.

[23] R. Ferreira da Silva, A.-C. Orgerie, H. Casanova, R. Tanaka, E. Deelman, and F. Suter, "Accurately simulating energy consumption of I/O-intensive scientific workflows", in *2019 International Conference on Computational Science (ICCS)*, 2019.

[24] C. Sahin, L. Pollock, and J. Clause, "How do code refactorings affect energy usage?", in *Proceedings of the 8th ACM/IEEE International Symposium on Empirical Software Engineering and Measurement*, ACM, 2014, p. 36.

[25] R. Pereira, M. Couto, F. Ribeiro, R. Rua, J. Cunha, J. P. Fernandes, and J. Saraiva, "Energy efficiency across programming languages: How do energy, time, and memory relate?", in *Proceedings of the 10th ACM SIGPLAN International Conference on Software Language Engineering*, ACM, 2017, pp. 256–267.

[26] M. Zakarya, N. Dilawar, M. A. Khattak, and M. Hayat, "Energy efficient workload balancing algorithm for real-time tasks over multi-core", *World Applied Sciences Journal*, vol. 22, no. 10, pp. 1431–1439, 2013.

[27] Q. Zhu, F. M. David, C. F. Devaraj, Z. Li, Y. Zhou, and P. Cao, "Reducing energy consumption of disk storage using power-aware cache management", in *Software, IEE Proceedings-*, IEEE, 2004, pp. 118–118.

[28] I. Manotas, L. Pollock, and J. Clause, "Seeds: A software engineer's energy-optimization decision support framework", in *Proceedings of the 36th International Conference on Software Engineering*, ACM, 2014, pp. 503–514.

[29] S. S. Mahmoud and I. Ahmad, "A green model for sustainable software engineering", *International Journal of Software Engineering and Its Applications*, vol. 7, no. 4, pp. 55–74, 2013.

Appendix A

Node28

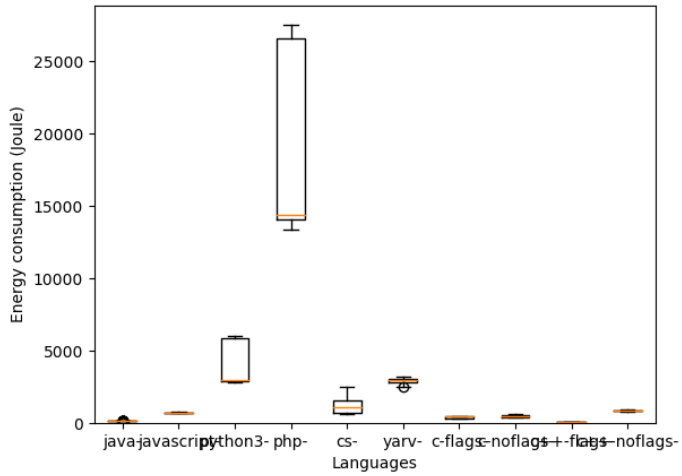


Figure A.1: The box plot of the different programs in a programming language for the problem Binarytrees on *node28*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	+	+	+	+	+	+	+	-	+
JavaScript	-	0	+	+	+	+	-	-	-	+
Python	-	-	0	+	-	-	-	-	-	-
PHP	-	-	-	0	-	-	-	-	-	-
C#	-	-	+	+	0	+	-	-	-	-
Ruby	-	-	+	+	-	0	-	-	-	-
C-flags	-	+	+	+	+	+	0	+	-	+
C-noflags	-	+	+	+	+	+	-	0	-	+
C++-flags	+	+	+	+	+	+	+	+	0	+
C++-noflags	-	-	+	+	+	+	-	-	-	0

Table A.1: The comparison of the different languages for the Binarytrees problem on *node28*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -.

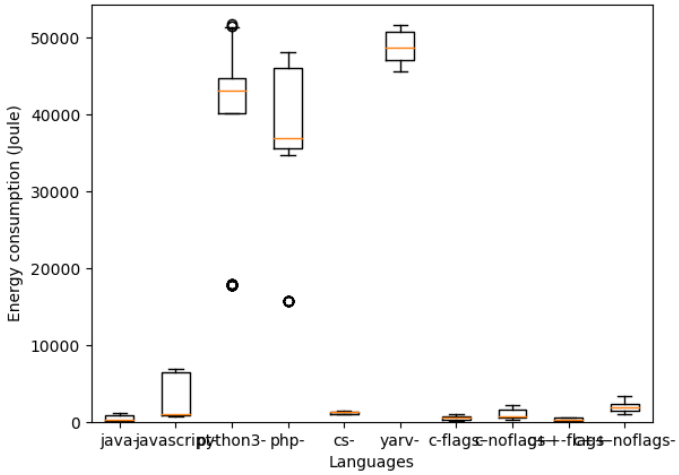


Figure A.2: The box plot of the different programs in a programming language for the problem Fannkuchredux on *node28*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	+	+	+	+	+	+	+	+	+
JavaScript	-	0	+	+	+	+	-	-	-	+
Python	-	-	0	-	-	+	-	-	-	-
PHP	-	-	+	0	-	+	-	-	-	-
C#	-	-	+	+	0	+	-	-	-	+
Ruby	-	-	-	-	-	0	-	-	-	-
C-flags	-	+	+	+	+	+	0	+	-	+
C-noflags	-	+	+	+	+	+	-	0	-	+
C++-flags	-	+	+	+	+	+	+	+	0	+
C++-noflags	-	-	+	+	-	+	-	-	-	0

Table A.2: The comparison of the different languages for the Fannkuchredux problem on *node28*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -.

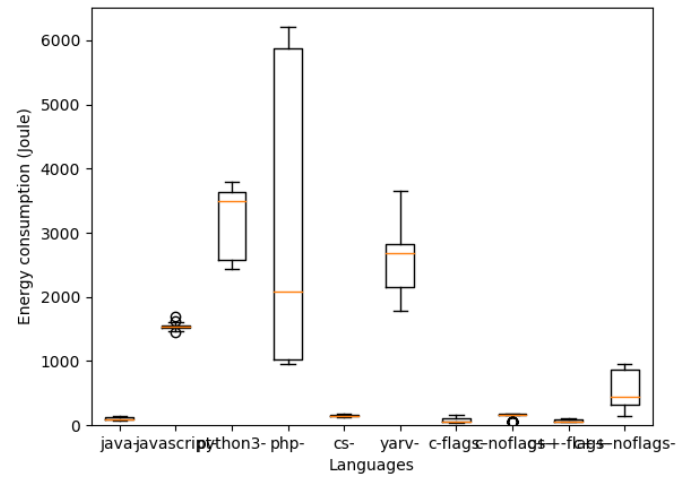


Figure A.3: The box plot of the different programs in a programming language for the problem Fasta on *node28*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	+	+	+	+	+	-	+	-	+
JavaScript	-	0	+	+	-	+	-	-	-	-
Python	-	-	0	-	-	-	-	-	-	-
PHP	-	-	+	0	-	+	-	-	-	-
C#	-	+	+	+	0	+	-	+	-	+
Ruby	-	-	+	-	-	0	-	-	-	-
C-flags	+	+	+	+	+	+	0	+	+	+
C-noflags	-	+	+	+	-	+	-	0	-	+
C++-flags	+	+	+	+	+	+	-	+	0	+
C++-noflags	-	+	+	+	-	+	-	-	-	0

Table A.3: The comparison of the different languages for the Fasta problem on *node28*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -.

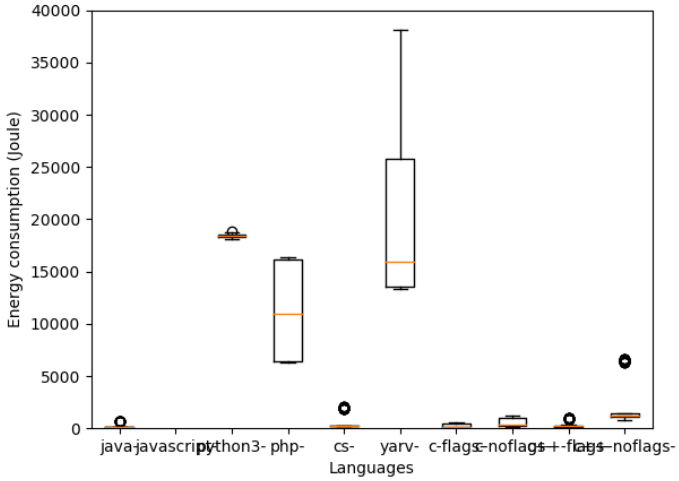


Figure A.4: The box plot of the different programs in a programming language for the problem Mandelbrot on *node28*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0		+	+	+	+	-	+	-	+
JavaScript										
Python	-		0	-	-	Unknown	-	-	-	-
PHP	-		+	0	-	+	-	-	-	-
C#	-		+	+	0	+	-	Unknown	-	+
Ruby	-		Unknown	-	-	0	-	-	-	-
C-flags	+		+	+	+	+	0	+	Unknown	+
C-noflags	-		+	+	Unknown	+	-	0	-	+
C++-flags	+		+	+	+	+	Unknown	+	0	+
C++-noflags	-		+	+	-	+	-	-	-	0

Table A.4: The comparison of the different languages for the Mandelbrot problem on *node28*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -, and the *Unknown* means that we could not reject the null hypothesis.

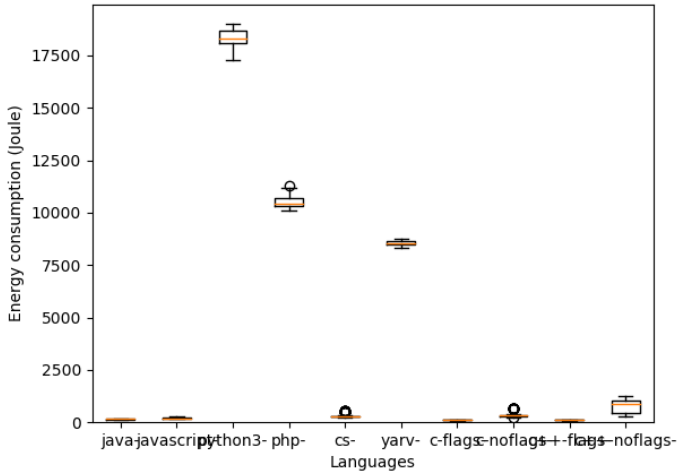


Figure A.5: The box plot of the different programs in a programming language for the problem Nbody on *node28*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	+	+	+	+	+	-	+	-	+
JavaScript	-	0	+	+	+	+	-	+	-	+
Python	-	-	0	-	-	-	-	-	-	-
PHP	-	-	+	0	-	-	-	-	-	-
C#	-	-	+	+	0	+	-	+	-	+
Ruby	-	-	+	+	-	0	-	-	-	-
C-flags	+	+	+	+	+	+	0	+	Unknown	+
C-noflags	-	-	+	+	-	+	-	0	-	+
C++-flags	+	+	+	+	+	+	Unknown	+	0	+
C++-noflags	-	-	+	+	-	+	-	-	-	0

Table A.5: The comparison of the different languages for the Nbody problem on *node28*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -, and the *Unknown* means that we could not reject the null hypothesis.

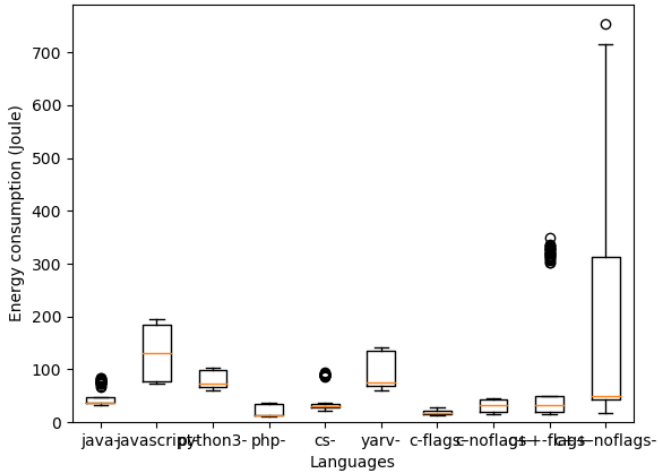


Figure A.6: The box plot of the different programs in a programming language for the problem Revcomp on *node28*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	+	+	-	-	+	-	-	-	+
JavaScript	-	0	-	-	-	-	-	-	-	-
Python	-	+	0	-	-	+	-	-	-	-
PHP	+	+	+	0	+	+	+	+	+	+
C#	+	+	+	-	0	+	-	Unknown	Unknown	+
Ruby	-	+	-	-	-	0	-	-	-	-
C-flags	+	+	+	-	+	+	0	+	+	+
C-noflags	+	+	+	-	Unknown	+	-	0	Unknown	+
C++-flags	+	+	+	-	Unknown	+	-	Unknown	0	+
C++-noflags	-	+	+	-	-	+	-	-	-	0

Table A.6: The comparison of the different languages for the Revcomp problem on *node28*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -, and the *Unknown* means that we could not reject the null hypothesis.

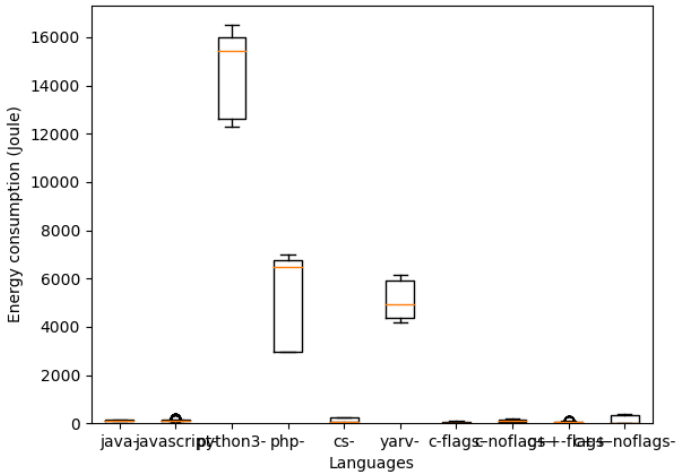


Figure A.7: The box plot of the different programs in a programming language for the problem Spectralnorm on *node29*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	-	+	+	Unknown	+	-	-	-	-
JavaScript	+	0	+	+	Unknown	+	-	-	-	-
Python	-	-	0	-	-	-	-	-	-	-
PHP	-	-	+	0	-	Unknown	-	-	-	-
C#	Unknown	Unknown	+	+	0	+	-	Unknown	-	Unknown
Ruby	-	-	+	Unknown	-	0	-	-	-	-
C-flags	+	+	+	+	+	+	0	+	+	+
C-noflags	+	+	+	+	Unknown	+	-	0	-	-
C++-flags	+	+	+	+	+	+	-	+	0	+
C++-noflags	+	+	+	+	Unknown	+	-	+	-	0

Table A.7: The comparison of the different languages for the Spectralnorm problem on *node28*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -, and the *Unknown* means that we could not reject the null hypothesis.

Program 1	Program 2	p-less	p-greater
java-3.problem0	java-6.problem0	0.266	0.740
javascript-1.problem2	javascript-2.problem2	0.829	0.176
javascript-1.problem2	javascript-3.problem2	0.413	0.594
javascript-2.problem2	javascript-3.problem2	0.197	0.808
javascript-1.problem6	javascript-3.problem6	0.532	0.475
javascript-1.problem6	javascript-5.problem6	0.272	0.734
javascript-3.problem6	javascript-5.problem6	0.243	0.763
python3-2.problem3	python3-5.problem3	0.488	0.520
cs-3.problem3	cs-4.problem3	0.088	0.915
cs-3.problem4	cs-5.problem4	0.622	0.385
cs-4.problem4	cs-6.problem4	0.493	0.515
c-noflags-1.problem2	c-noflags-2.problem2	0.882	0.122
c-flags-2.problem4	c-flags-3.problem4	0.230	0.776
c-noflags-1.problem4	c-noflags-6.problem4	0.218	0.787
c-flags-3.problem5	c-flags-6.problem5	0.175	0.830
c-noflags-4.problem5	c-noflags-5.problem5	0.090	0.912
c++-flags-1.problem0	c++-flags-8.problem0	0.571	0.436
c++-noflags-1.problem0	c++-noflags-3.problem0	0.883	0.121
c++-noflags-1.problem0	c++-noflags-8.problem0	0.874	0.130
c++-noflags-3.problem0	c++-noflags-8.problem0	0.453	0.555
c++-flags-1.problem2	c++-flags-2.problem2	0.317	0.690
c++-flags-3.problem4	c++-flags-8.problem4	0.168	0.837
c++-flags-4.problem4	c++-flags-6.problem4	0.225	0.781
c++-noflags-5.problem6	c++-noflags-6.problem6	0.374	0.633

Table A.8: The programs result from *node28* where the null hypothesis that they are from the same distribution could not be reject for the Mann Whitney U one-sided test less and bigger.

Appendix B

Node29

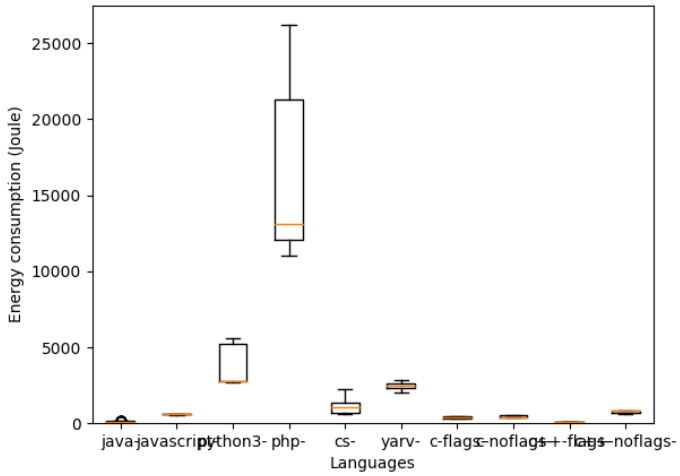


Figure B.1: The box plot of the different programs in a programming language for the problem Binarytrees on *node29*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	+	+	+	+	+	+	+	-	+
JavaScript	-	0	+	+	+	+	-	-	-	+
Python	-	-	0	+	-	-	-	-	-	-
PHP	-	-	-	0	-	-	-	-	-	-
C#	-	-	+	+	0	+	-	-	-	-
Ruby	-	-	+	+	-	0	-	-	-	-
C-flags	-	+	+	+	+	+	0	+	-	+
C-noflags	-	+	+	+	+	+	-	0	-	+
C++-flags	+	+	+	+	+	+	+	+	0	+
C++-noflags	-	-	+	+	+	+	-	-	-	0

Table B.1: The comparison of the different languages for the Binarytrees problem on *node29*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -.

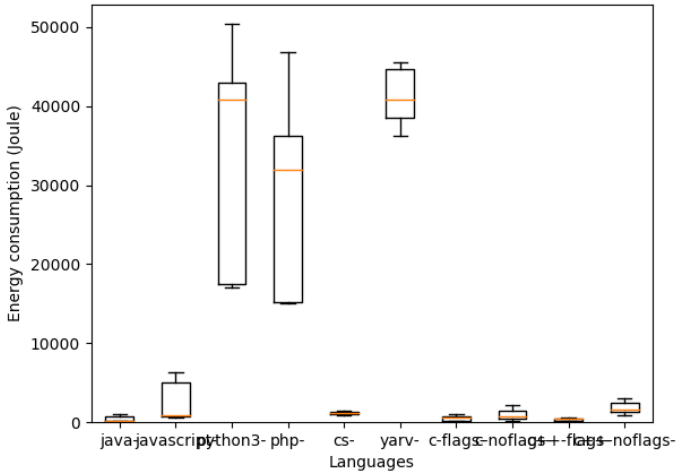


Figure B.2: The box plot of the different programs in a programming language for the problem Fannkuchredux on *node29*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	+	+	+	+	+	+	+	Unknown	+
JavaScript	-	0	+	+	+	+	-	-	-	+
Python	-	-	0	-	-	Unknown	-	-	-	-
PHP	-	-	+	0	-	+	-	-	-	-
C#	-	-	+	+	0	+	-	-	-	+
Ruby	-	-	Unknown	-	-	0	-	-	-	-
C-flags	-	+	+	+	+	+	0	+	-	+
C-noflags	-	+	+	+	+	+	-	0	-	+
C++-flags	Unknown	+	+	+	+	+	+	+	0	+
C++-noflags	-	-	+	+	-	+	-	-	-	0

Table B.2: The comparison of the different languages for the Fannkuchredux problem on *node29*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -.

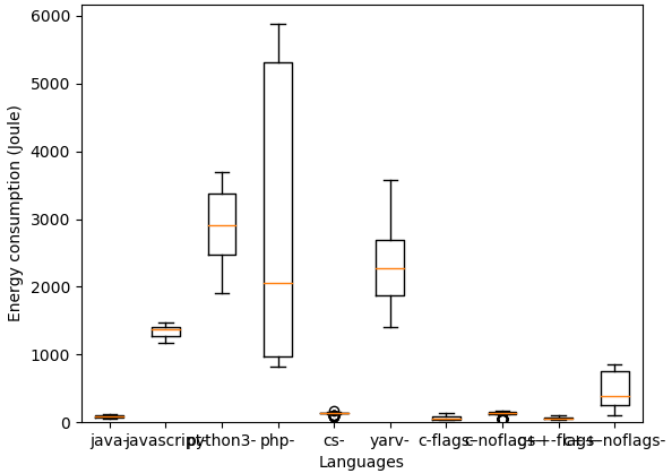


Figure B.3: The box plot of the different programs in a programming language for the problem Fasta on *node29*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	+	+	+	+	+	-	+	-	+
JavaScript	-	0	+	+	-	+	-	-	-	-
Python	-	-	0	-	-	-	-	-	-	-
PHP	-	-	+	0	-	Unknown	-	-	-	-
C#	-	+	+	+	0	+	-	Unknown	-	+
Ruby	-	-	+	Unknown	-	0	-	-	-	-
C-flags	+	+	+	+	+	+	0	+	Unknown	+
C-noflags	-	+	+	+	Unknown	+	-	0	-	+
C++-flags	+	+	+	+	+	+	Unknown	+	0	+
C++-noflags	-	+	+	+	-	+	-	-	-	0

Table B.3: The comparison of the different languages for the Fasta problem on *node29*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -, and the *Unknown* means that we could not reject the null hypothesis.

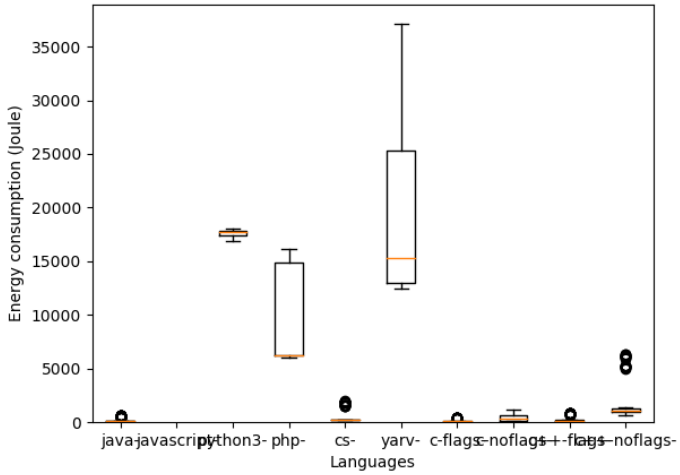


Figure B.4: The box plot of the different programs in a programming language for the problem Mandelbrot on *node29*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0		+	+	+	+	-	+	-	+
JavaScript										
Python	-		0	-	-	-	-	-	-	-
PHP	-		+	0	-	+	-	-	-	-
C#	-		+	+	0	+	-	Unknown	-	+
Ruby	-		+	-	-	0	-	-	-	-
C-flags	+		+	+	+	+	0	+	Unknown	+
C-noflags	-		+	+	Unknown	+	-	0	-	+
C++-flags	+		+	+	+	+	Unknown	+	0	+
C++-noflags	-		+	+	-	+	-	-	-	0

Table B.4: The comparison of the different languages for the Mandelbrot problem on *node29*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -, and the *Unknown* means that we could not reject the null hypothesis.

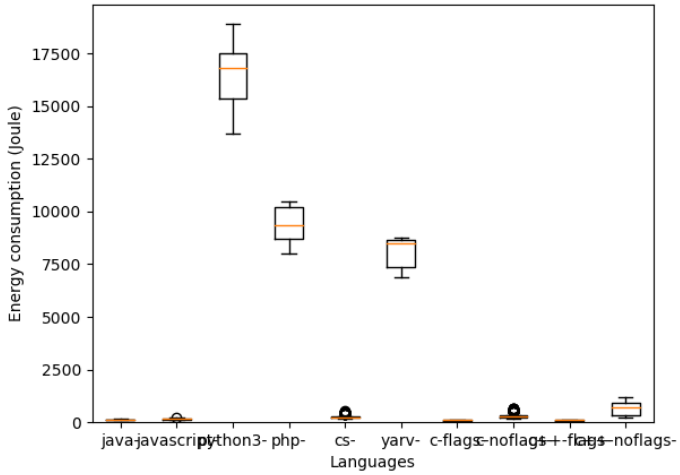


Figure B.5: The box plot of the different programs in a programming language for the problem Nbody on *node29*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	+	+	+	+	+	-	+	-	+
JavaScript	-	0	+	+	+	+	-	+	-	+
Python	-	-	0	-	-	-	-	-	-	-
PHP	-	-	+	0	-	-	-	-	-	-
C#	-	-	+	+	0	+	-	+	-	+
Ruby	-	-	+	+	-	0	-	-	-	-
C-flags	+	+	+	+	+	+	0	+	Unknown	+
C-noflags	-	-	+	+	-	+	-	0	-	+
C++-flags	+	+	+	+	+	+	Unknown	+	0	+
C++-noflags	-	-	+	+	-	+	-	-	-	0

Table B.5: The comparison of the different languages for the Nbody problem on *node29*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -, and the *Unknown* means that we could not reject the null hypothesis.

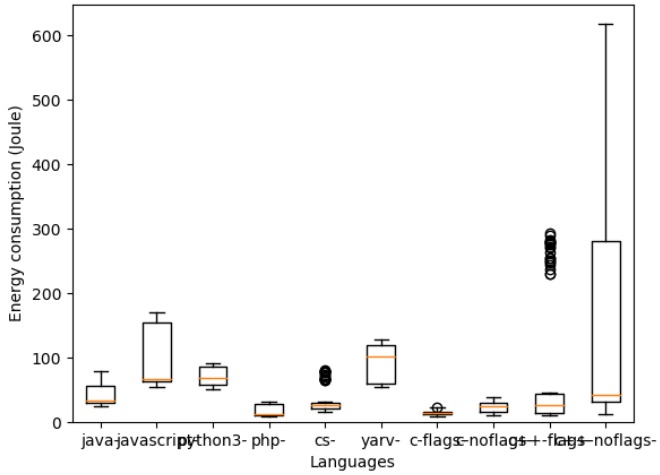


Figure B.6: The box plot of the different programs in a programming language for the problem Revcomp on *node29*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	+	+	-	-	+	-	-	-	+
JavaScript	-	0	-	-	-	-	-	-	-	-
Python	-	+	0	-	-	+	-	-	-	-
PHP	+	+	+	0	+	+	Unknown	+	+	+
C#	+	+	+	-	0	+	-	-	Unknown	+
Ruby	-	+	-	-	-	0	-	-	-	-
C-flags	+	+	+	Unknown	+	+	0	+	+	+
C-noflags	+	+	+	-	+	+	-	0	+	+
C++-flags	+	+	+	-	Unknown	+	-	-	0	+
C++-noflags	-	+	+	-	-	+	-	-	-	0

Table B.6: The comparison of the different languages for the Revcomp problem on *node29*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -, and the *Unknown* means that we could not reject the null hypothesis.

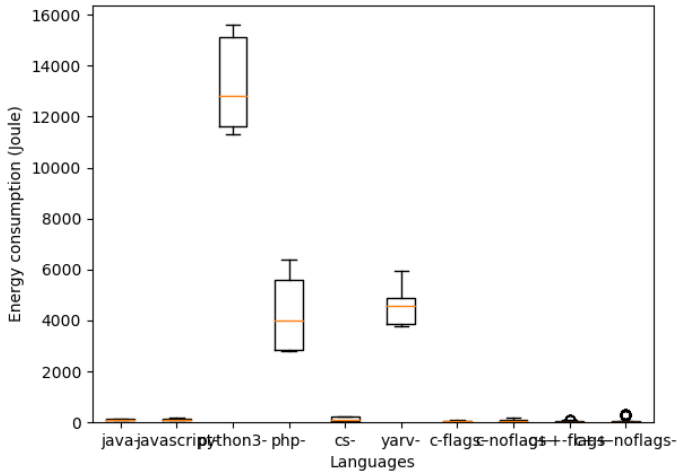


Figure B.7: The box plot of the different programs in a programming language for the problem Spectralnorm on *node29*.

	Java	JavaScript	Python	PHP	C#	Ruby	C-flags	C-noflags	C++-flags	C++-noflags
Java	0	-	+	+	Unknown	+	-	-	-	-
JavaScript	+	0	+	+	Unknown	+	-	-	-	-
Python	-	-	0	-	-	-	-	-	-	-
PHP	-	-	+	0	-	Unknown	-	-	-	-
C#	Unknown	Unknown	+	+	0	+	-	Unknown	-	Unknown
Ruby	-	-	+	Unknown	-	0	-	-	-	-
C-flags	+	+	+	+	+	+	0	+	+	+
C-noflags	+	+	+	+	Unknown	+	-	0	-	-
C++-flags	+	+	+	+	+	+	-	+	0	+
C++-noflags	+	+	+	+	Unknown	+	-	+	-	0

Table B.7: The comparison of the different languages for the Spectralnorm problem on *node29*. A + means that the language on the row has a lower energy consumption then the language on the column, the opposite for -, and the *Unknown* means that we could not reject the null hypothesis.

Program 1	Program 2	p-less	p-greater	K-S test
java-2.problem0	java-3.problem0	0.937	0.066	Unknown
java-2.problem0	java-6.problem0	0.820	0.186	Unknown
java-3.problem0	java-6.problem0	0.164	0.842	Unknown
java-2.problem3	java-4.problem3	0.514	0.495	Unknown
java-2.problem4	java-3.problem4	0.864	0.142	Unknown
java-4.problem5	java-5.problem5	0.732	0.276	Unknown
java-5.problem5	java-6.problem5	0.915	0.089	Unknown
javascript-1.problem2	javascript-2.problem2	0.174	0.832	Unknown
javascript-1.problem2	javascript-3.problem2	0.106	0.898	Unknown
javascript-2.problem2	javascript-3.problem2	0.305	0.704	Unknown
javascript-3.problem2	javascript-4.problem2	0.120	0.884	Unknown
javascript-1.problem4	javascript-4.problem4	0.060	0.943	Unknown
javascript-1.problem4	javascript-5.problem4	0.053	0.950	Unknown
javascript-4.problem4	javascript-5.problem4	0.401	0.609	Unknown
javascript-1.problem6	javascript-3.problem6	0.658	0.352	Unknown
javascript-1.problem6	javascript-5.problem6	0.628	0.382	Unknown
javascript-3.problem6	javascript-5.problem6	0.495	0.516	Unknown
cs-1.problem1	cs-3.problem1	0.609	0.400	Rejected
cs-1.problem1	cs-4.problem1	0.606	0.404	Rejected
cs-2.problem1	cs-5.problem1	0.793	0.214	Rejected
cs-2.problem1	cs-6.problem1	0.909	0.095	Rejected
cs-1.problem3	cs-4.problem3	0.756	0.252	Unknown
cs-3.problem3	cs-4.problem3	0.372	0.638	Unknown
cs-3.problem3	cs-6.problem3	0.877	0.128	Rejected
cs-4.problem3	cs-6.problem3	0.855	0.151	Unknown
cs-2.problem4	cs-3.problem4	0.952	0.050	Unknown
cs-3.problem4	cs-5.problem4	0.882	0.123	Unknown
cs-4.problem4	cs-6.problem4	0.430	0.580	Unknown
cs-4.problem4	cs-8.problem4	0.945	0.058	Unknown
cs-6.problem4	cs-8.problem4	0.952	0.050	Unknown
cs-1.problem5	cs-5.problem5	0.907	0.097	Unknown
cs-2.problem5	cs-5.problem5	0.157	0.849	Unknown
yarv-1.problem1	yarv-2.problem1	0.825	0.190	Unknown
c-flags-2.problem2	c-flags-5.problem2	0.292	0.716	Rejected
c-noflags-1.problem2	c-noflags-2.problem2	0.525	0.485	Unknown
c-noflags-1.problem2	c-noflags-5.problem2	0.200	0.806	Unknown
c-noflags-1.problem2	c-noflags-7.problem2	0.582	0.427	Unknown
c-noflags-2.problem2	c-noflags-5.problem2	0.224	0.783	Unknown
c-noflags-2.problem2	c-noflags-7.problem2	0.690	0.319	Unknown
c-noflags-5.problem2	c-noflags-7.problem2	0.861	0.145	Unknown
c-flags-2.problem4	c-flags-3.problem4	0.657	0.352	Unknown
c-flags-2.problem4	c-flags-6.problem4	0.470	0.540	Unknown
c-flags-3.problem4	c-flags-6.problem4	0.311	0.698	Unknown
c-noflags-1.problem4	c-noflags-6.problem4	0.410	0.599	Unknown
c-flags-3.problem5	c-flags-6.problem5	0.278	0.730	Unknown
c-noflags-4.problem5	c-noflags-5.problem5	0.300	0.708	Unknown
c-noflags-4.problem6	c-noflags-5.problem6	0.401	0.609	Rejected
c++-noflags-1.problem0	c++-noflags-3.problem0	0.340	0.669	Unknown
c++-noflags-1.problem0	c++-noflags-8.problem0	0.212	0.795	Unknown
c++-noflags-3.problem0	c++-noflags-8.problem0	0.398	0.612	Unknown
c++-flags-4.problem1	c++-flags-6.problem1	0.244	0.763	Rejected
c++-flags-1.problem2	c++-flags-2.problem2	0.676	0.333	Unknown
c++-flags-1.problem2	c++-flags-6.problem2	0.903	0.102	Rejected
c++-flags-2.problem3	c++-flags-5.problem3	0.790	0.217	Unknown
c++-noflags-8.problem3	c++-noflags-9.problem3	0.272	0.736	Unknown
c++-flags-3.problem4	c++-flags-8.problem4	0.642	0.367	Unknown
c++-flags-4.problem4	c++-flags-6.problem4	0.473	0.538	Unknown
c++-noflags-1.problem4	c++-noflags-6.problem4	0.277	0.731	Unknown
c++-noflags-7.problem4	c++-noflags-8.problem4	0.910	0.094	Unknown

Table B.8: The programs result from *node29* where the null hypothesis that they are from the same distribution could not be reject for the Mann Whitney U one-sided test less and bigger.

Appendix C

Correlation

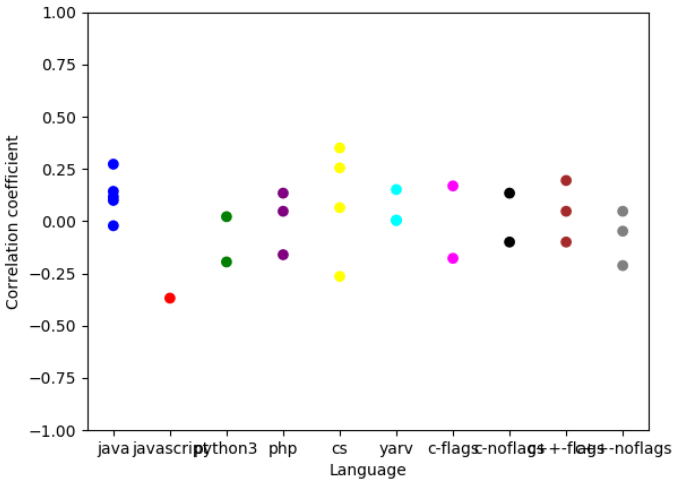


Figure C.1: The Kendall correlation score for every single program that solves the Binarytrees problem.

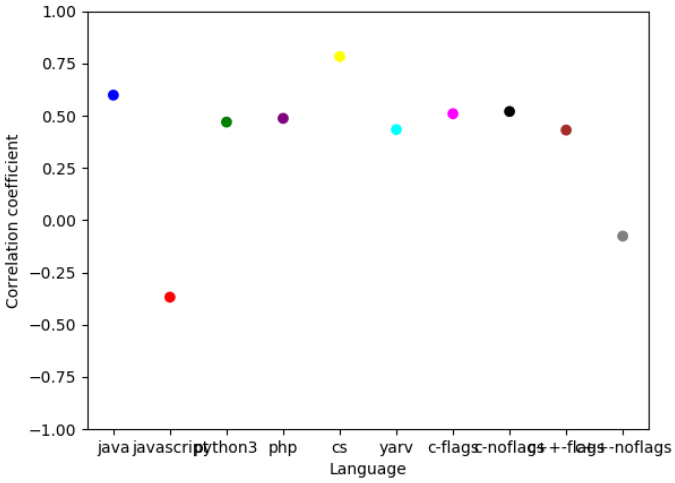


Figure C.2: The Kendall correlation score for every programming language that solves the Binarytrees problem.

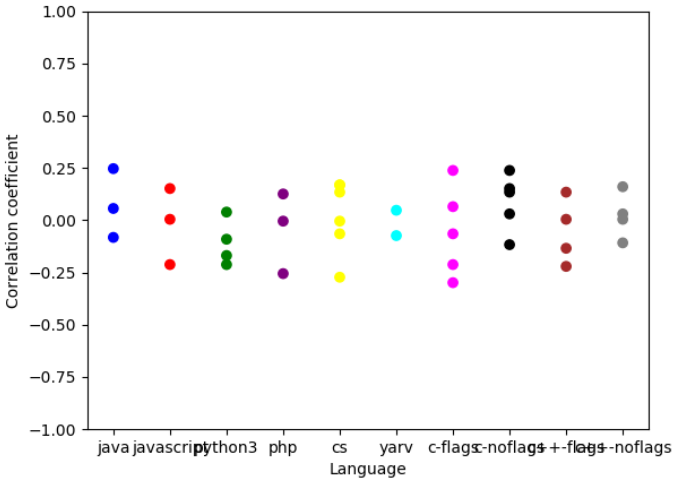


Figure C.3: The Kendall correlation score for every single program that solves the Fannkuchredux problem.

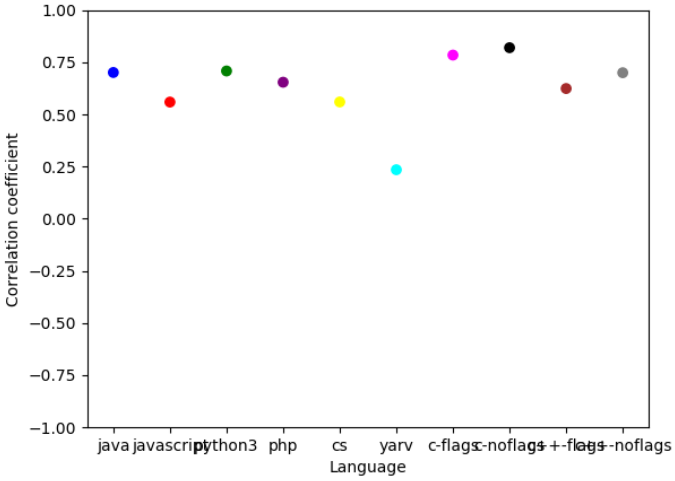


Figure C.4: The Kendall correlation score for every programming language that solves the Fannkuchredux problem.

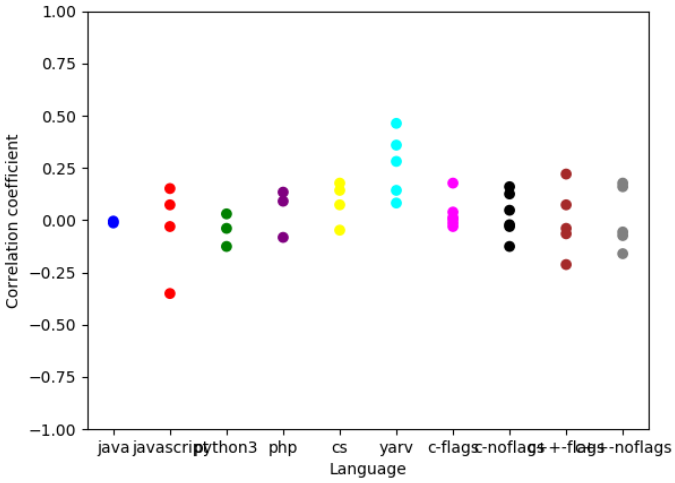


Figure C.5: The Kendall correlation score for every single program that solves the Fasta problem.

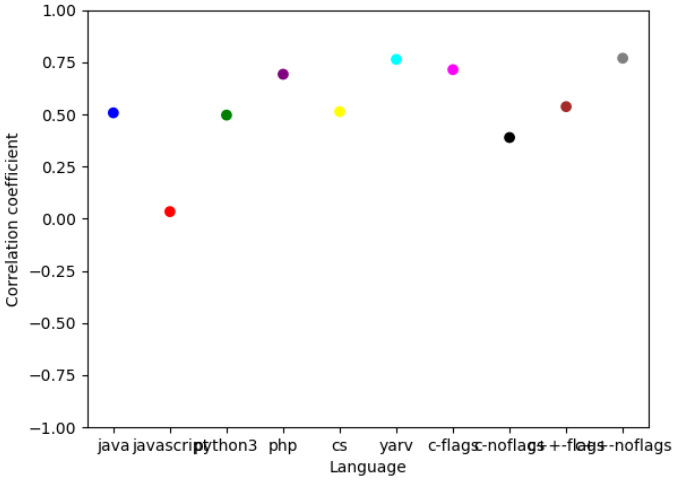


Figure C.6: The Kendall correlation score for every programming language that solves the Fasta problem.

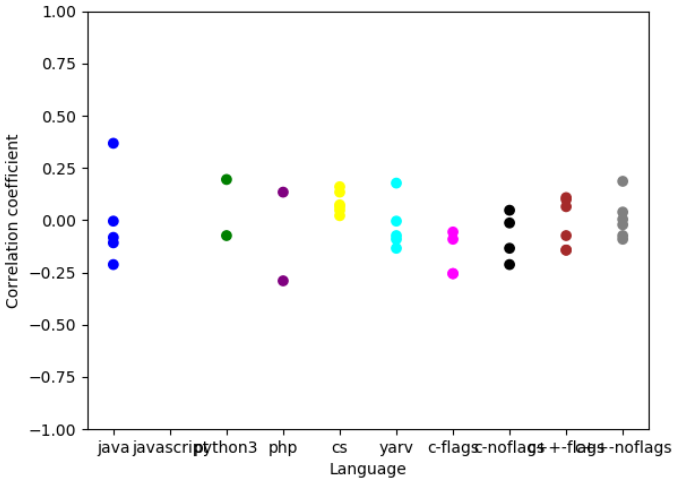


Figure C.7: The Kendall correlation score for every single program that solves the Mandelbrot problem.

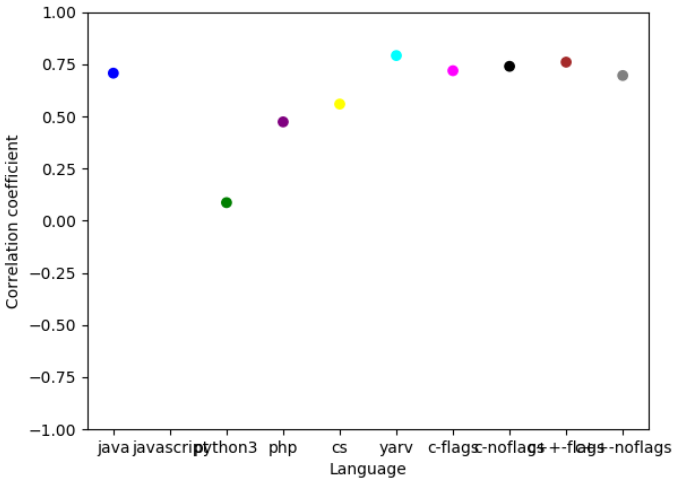


Figure C.8: The Kendall correlation score for every programming language that solves the Mandelbrot problem.

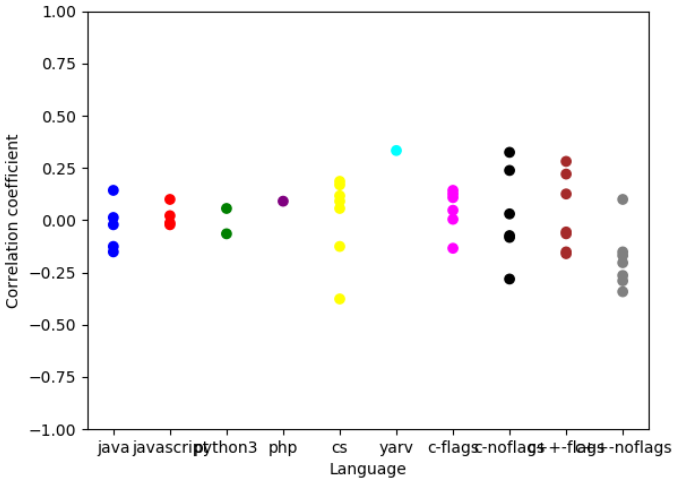


Figure C.9: The Kendall correlation score for every single program that solves the Nbody problem.

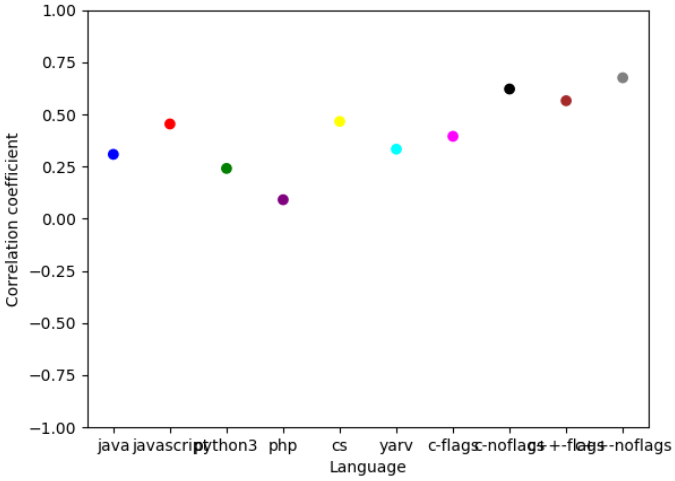


Figure C.10: The Kendall correlation score for every programming language that solves the Nbody problem.

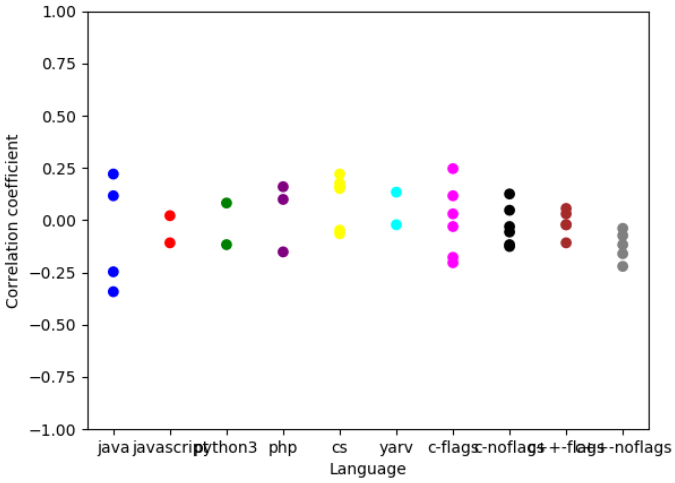


Figure C.11: The Kendall correlation score for every single program that solves the Revcomp problem.

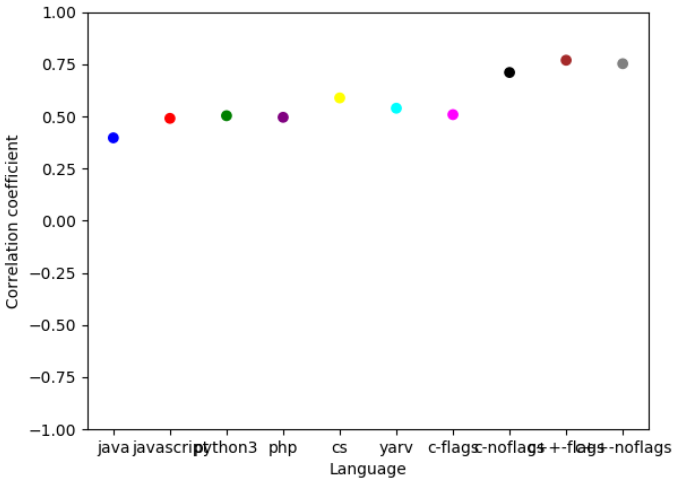


Figure C.12: The Kendall correlation score for every programming language that solves the Revcomp problem.

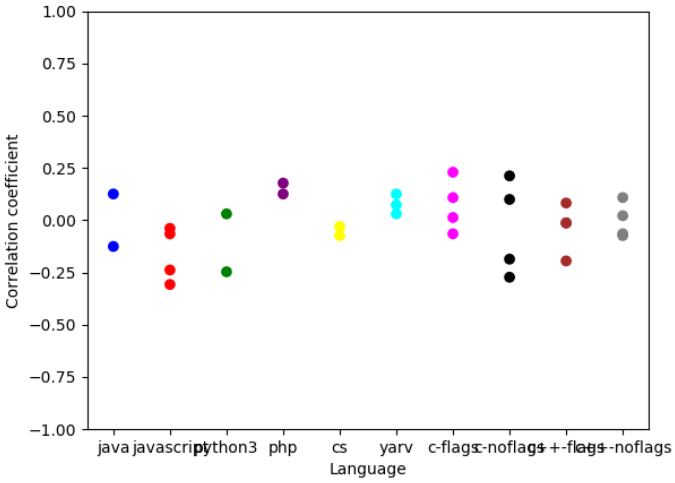


Figure C.13: The Kendall correlation score for every single program that solves the Spectralnorm problem.

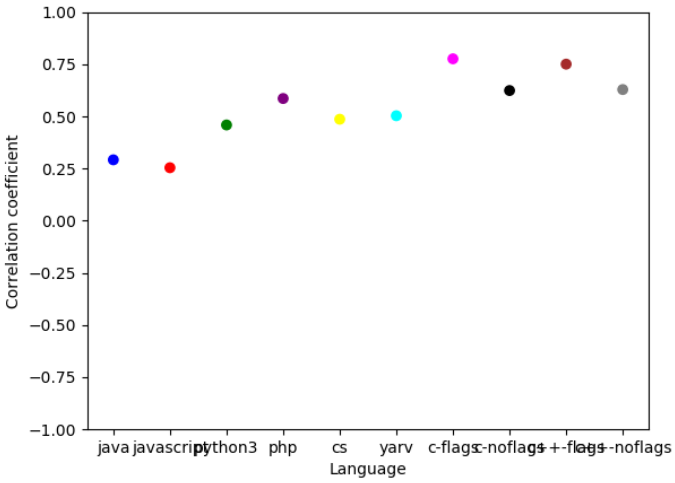


Figure C.14: The Kendall correlation score for every programming language that solves the Spectralnorm problem.

Appendix D

Code-level

Better program	Worse program	Better code-level	Worse code-level
python3-1.problem0	python3-2.problem0	Body below the condition of if statement	Condition and body of if statement on same line
		More functions and main function	Less functions and no main function
		Uses map	Doesn't use map
python3-4.problem1	python3-1.problem1	Doesn't use classes	Uses classes
		Uses libraries, math.factorial, itertools.islice and itertools.starmap	Doesn't use libraries
python3-3.problem2	python3-2.problem2	Uses while-loop	Uses for-loop
		Uses no additional function	Uses additional function
python3-2.pronlem4	python3-1.problem4	Uses library math.sqrt	Doesn't use library math.sqrt
		Less depth in main var	More depth in main var
python3-6.problem5	python3-4.problem5	Uses library itertools.starmap	Doesn't use library itertools.starmap
		Reading data from stdin.buffer	Reading data from stdin
python3-5.problem6	python3-6.problem6	More separate functions	Less separate functions
		Separate for-loop and list comprehension	Nested list comprehension
		Multithreading	Not multithreading
php-2.problem0	php-3.problem0	Uses classes	Doesn't use classes
php-3.problem1	php-1.problem1	Uses for-loop	Uses while true
php-4.problem2	php-2.problem2	Less bigger functions	More smaller functions
		Uses for-each-loop	Use for-loop
		Uses output buffer and implicit flushing	Doesn't use output buffer and implicit flushing
php-3.problem3	php-1.problem3	Doesn't use output buffer and implicit flushing	Uses output buffer and implicit flushing
		Multithreading	Not multithreading
php-1.problem5	php-3.problem5	Uses echo	Uses fwrite
		Not multithreading	Multithreading
php-3.problem6	php-2.problem6	Multithreading	Not multithreading
yarv-4.problem0	yarv-3.problem0	Uses return-statement in body of if-statement	Uses return-statement and then if-statement on same line
		Doesn't use garbage collection	Uses garbage collection
		Uses .each do	Uses while
yarv-1.problem1	yarv-2.problem1	Assigns values to var in condition of if and while statements	Doesn't assign values to var in condition of if and while statements
		Uses while	Uses upto
yarv-3.problem2	yarv-2.problem2	Uses classes	Doesn't use classes
yarv-6.problem3	yarv-1.problem3	Uses classes and functions	Doesn't use classes
		Multithreading	Not multithreading
yarv-3.problem5	yarv-2.problem5	Multithreading	Not multithreading
		Read input via: $stdin.each_line('>')	Read input via: STDIN.each
yarv-5.problem6	yarv-1.problem6	Uses .each do	Uses for-loop
		Multithreading	Not multithreading

Table D.1: The differences we found when looking at two programs that had a difference in their energy consumption. The better program consumes less energy then the worse programs.

```
import sys

n = int(sys.argv[1])

lastPrime = 2
```

```
prime = [lastPrime]

while len(prime) < n:
    lastPrime += 1
    possiblePrime = True
    i = 0
    while i < len(prime):
        if lastPrime % prime[i] == 0:
            possiblePrime = False
            break
        i += 1
    if possiblePrime:
        prime.append(lastPrime)

print(prime)
```

Listing D.1: The program that solves the nth prime number using a while loop.

```
import sys

n = int(sys.argv[1])

lastPrime = 2
prime = [lastPrime]

while len(prime) < n:
    lastPrime += 1
    possiblePrime = True
    for i in range(len(prime)):
        if lastPrime % prime[i] == 0:
            possiblePrime = False
            break
    if possiblePrime:
        prime.append(lastPrime)

print(prime)
```

Listing D.2: The program that solves the nth prime number using a for loop.

```
import sys

n = int(sys.argv[1])

lastPrime = 2
prime = [lastPrime]

while len(prime) < n:
    lastPrime += 1
    possiblePrime = True
    for i in range(len(prime)):
        if lastPrime % prime[i] == 0: possiblePrime = False; break
    if possiblePrime: prime.append(lastPrime)

print(prime)
```

Listing D.3: The program that solves the nth prime number using if-statements where the body and the condition are on the same line.

```
import sys

n = int(sys.argv[1])

lastPrime = 2
prime = [lastPrime]

while len(prime) < n:
    lastPrime += 1
    possiblePrime = True
    for i in range(len(prime)):
        if lastPrime % prime[i] == 0:
            possiblePrime = False
            break
```

```
    if possiblePrime:
        prime.append(lastPrime)

print(prime)
```

Listing D.4: The program that solves the nth prime number using if-statements where the body and the condition are on a different line.