The Effect of Analytics Tools on Energy Consumption of Websites

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***Abstract*—In this paper, we study the effect of the web analytics tools on the energy consumption of the website they are deployed on. Our test setting comprises of four identical Wordpress websites which were equipped with varying number of analytics tools. We used an automated script that performed similar actions on every website for predetermined number of times, a Raspberry Pi which was running the script, and a DC meter used to record the energy consumption of the Raspberry Pi during the script execution. Our results indicate that using the web analytics tools has a clear impact on the energy consumption of websites, and that this increase is more severe with increasing amount of analytics tools. On average, the energy consumption is estimated to increase by 8.14% when 10 analytics tools are used, 6.08% when 5 analytics tools are used and 3.48% when one analytics tool is in use. This suggests that the use of web analytics tools has a direct effect on the total global size of the carbon footprint of the internet usage. In the light of the ecological threats facing the world, our findings paint a dire picture of this aspect of the ICT industry.**

***Index Terms*—energy consumption, web analytics, carbon footprint, energy measurement, online privacy, user tracking**

I. Introduction

In the past decade, web analytics tools that monitor and track website user actions have become widespread, a de facto standard, and these kind of applications are found deployed on all kinds of websites [1]. During the same time period, calls for decreasing the energy usage and reducing the carbon footprint have risen as the threat of impending ecological catastrophe hangs above the fate of our planet. In this paper, we investigate the effects of web analytics tools on the energy consumption of the websites, by conducting a comparative study in a laboratory environment.

To the best of our understanding, the topic of energy consumption of web analytics has received very little previous attention from the scientific community. While we are not the first to study it, very few previous papers exist detailing this phenomena. This is mainly because the measurement of the energy consumption in computer devices is not easy to pinpoint to a specific source, and because there are lots of ”measurement noise”, i.e. background processes running on consumer computers, which may distort the results. To mitigate these effects we have chosen to run our experiments in a laboratory environment, in this case meaning that the browser accessing the websites was run on a Raspberry Pi, since it is much more feasible to control the number of background processes and other variables when using this kind of platform for the experiment.

Since this topic has not been studied in-depth before, and as there is a great society wide drive towards carbon neutrality, we feel that there is growing demand for scientific study in to what role the web analytics tools play in the overall carbon footprint of the ICT industry. After all, these kinds of applications have become ubiquitous and are found deployed from the majority of the websites globally. Thus, it is important to know, even through estimations, what their environmental impact is.

For this research, we created four identical Wordpress websites, which were equipped with varying number of web analytics. We then proceeded to execute an automation script that emulated the actions of the human user. The script was deployed on the Raspberry Pi. The script was executed 100 times for each website, and during the execution the energy consumption of the Raspberry Pi was measured with an attached DC meter. We show that using the web analytics tools has a clear effect on the energy consumption of the studied websites, and this impact gets more prominent when the number of analytics tools grows.

The rest of the paper is organized as follows. In Section II, we take a survey on similar studies done and their relation to our work. In Section III, we explain the study setting and the research methodology in detail. In Section IV, we present the results of our investigation. In Section V, we discuss the

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implications that arise from our results. Finally, in Section VI, we offer the definite conclusions that can be drawn from the current study.

II. Related Work

Despite the survey we conducted, we could find only one paper that addressed the issue we are studying in this research, the effect of analytics tools on the energy consumption of the website. However, studies have been done on the energy consumption of the Internet, web applications and the ICT infrastructure in general, and thus we will take a brief overview of them here. While these studies do not exactly focus on the same questions as we do in this paper, they still contextualize our research arrangement somewhat. We have narrowed this survey to those papers which have been published during the last decade, as papers older than that hardly reflect the realities of the modern world, due to the enormous growth in the use of and the evolution in the nature of the ICT technology in the past decade.

Perhaps most important for our own research of the works cited here, is the paper by Petalotis et al. [16], in which they studied the effect of advertisements and analytics tools on the energy consumption and execution time of the mobile applications run on smartphone browser. They concluded that of these two, the advertisements affect both metrics more, but that the analytics tools do have an effect. They also made an observation that the choice of browser affects how the analytics tools increase the energy consumption, with the effect being stronger in Google Chrome than in Opera. Petalotis et al. also discuss at length the potentially invalidating aspects of this kind of research, from how the measurement tools, the choice of platform on which to conduct the experiment and the subject matter, may affect the results of the measurements.

Many of these considerations are similar to what we have had to evaluate. However, they differ from our research because we have made different choices in regards to the experimental setting. For example, Petalotis et al. note that their choice of device, an Android tablet, used for the experiment has all kinds of background processes etc. which may affect the measurement outcome, and they describe different techniques of how to mitigate this threat to validity. On the other hand, we have chosen to solve this issue by running the experiments on Raspberry Pi, which is inherently an easier environment to control, allowing for better reproducibility of our experiment.

Capra et al. [3] studied the effect of software development frameworks and external libraries on the energy consumption, and discovered that such tools usually increase the energy consumption severely. Specifically this decrease in energy efficiency impacted larger applications, rather than smaller.

Singh et al. [18] developed a software-based metering tool for OS process energy consumption in response to the demands of the growing cloud service infrastructure, as the hardware-based metering tools were deemed by them to be too impractical for real-world scenarios.

Andrae and Edler published a paper in 2015 [2], in which they presented several scenarios for the growth of the energy consumption and the carbon footprint of the ICT industry up to the year 2030. In their worst estimations, by 2030, the energy consumption of the computer systems would be 51% of the whole global consumption, and even if all this energy would come from the renewable sources, the share of ICT -consequent carbon footprint would be 23%.

Ishii et al. [8] presented a model for estimation of the energy consumption of networks on a national scale. The chief motivator for this research was the perceived need for a system of estimating the growing energy demands of the network traffic, and the perceived practical difficulties in correctly estimating it with existing solutions, due to the nature of the network infrastructure.

Hindle [7] published a paper which investigated the various difficulties at advancing energy awareness in software engineering and research in to energy consumption of the software, and what should be done to improve this. He concluded that the main problems are the fragmentary nature of the community of researchers, that there is no sufficient co-operation between the people working in hardware design versus software development and that there are serious obstacles in accurately measuring the energy consumption, based on the lack of suitable tools.

In the same year, Hindle and Chowdhury [5] conducted another study, in which they developed GreenOracle, a machine-learning based system that can estimate the energy consumption of the software with 90% accuracy.

Romansky et al. [17] studied the effectiveness of estimation models in predicting the software energy consumption. They concluded that machine-learning based time series based models and long short-term memory (LSTM) based time series based models were often better at predicting the energy consumption than the prior estimation models.

Zaghdoudi [24] published a survey on the relationship between internet usage, economic growth, energy consumption and the use of renewable energy, based on statistical observations on 31 developed countries between the years 1990 to 2015. His findings indicate that the increase in internet usage has had impact on both the economic growth and the increase in energy consumption in these countries.

Morley et al. [12] researched the effect of Internet usage to the peak and total energy consumption. The study was a literature review in which they took an overview of existing research on Internet energy consumption, and concluded that no exact numbers can be given, due to the difficulties in studying phenomena this complex.

Lange et al. [9] published a paper in 2020, where they studied whether the growth of ICT sector ultimately increases or decreases the global energy consumption. Their findings indicate that overall, the growth of the ICT sector increases the energy demand, and that the digitalization does not have the decoupling effect on the relationship between economic growth and energy consumption.

Ournani et al. [13] conducted a qualitative research on the awareness of the software developers on the energy consumption of the software by interviewing 10 experienced developers. Their conclusion was that the knowledge about the software energy consumption among developers is very varied, with many respondents being completely ignorant of the topic, despite having worked relatively long in software industry. In general, there was no consensus among developers on what should be done to improve the situation.

Van Hasselt et al. [19] researched the difference in energy consumption between web applications written with JavaScript and WebAssemply compiled from C, and came to conclusion that the WebAssembly is always several degrees less energy consuming than the JavaScript. Similar results were obtained by Macedo et al. [6] when studying this same phenomena.

A recent paper by Oxenløwe et al. [14] investigated the energy consumption of the Internet services in general, and came to a conclusion that there is a pressing need to develop a framework through which the carbon emissions caused by them could be monitored.

While these studies have focused on slightly different subjects than ours, the central theme with all of them, as is in this paper, is on energy consumption in computer systems, how to measure it and what solutions could be implemented to decrease it. They form the background against which our results are projected, hopefully positioning our findings to a context from which they can be understood correctly.

III. Study Setting and Methodology

For the purpose of the current study, four identical Wordpress websites were created. All of the websites contained only those elements which were present in the Wordpress template which was used, and all of the websites used the same visual layout, shown in Figure 1. As can be seen in the upper right corner, there are four links: Home, About, Blog and Contact. In addition to this, each of the websites had a Search field, which is not shown in the screenshot due to being situated in the bottom of the page. The websites did not contain any other additional Wordpress plugins. One of the websites was left without any analytics. One was equipped with one analytics tool, which was Google Analytics. One was equipped with 5 analytics tools and one with 10 analytics tools. When designing the experiment we decided upon these numbers as they were perceived to have large enough difference between each other to potentially show relevant difference in the measurements; in other words, we did not create 11 websites with each having one analytic more than the previous one because the difference between having 2 or 3 analytical tools would most likely be quite indiscernible, whereas the difference between 1, 5 and 10 analytics would most likely be clearly visible, and thus more illustrative of how the increase in analytics affects the energy consumption. Like our results illustrate, this hypothesis was correct.

The analytics tools used for the website with 5 analytics tools were:

- Google Analytics[1]
- Matomo[2]
- Hotjar[3]
- Microsoft Clarity[4]
- Meta Pixel[5]

The analytics tools used for the website with 10 analytics were the aforementioned five, and the following:

- Crazy Egg[6]
- Gaug.es[7]
- Woopra[8]
- Open Web Analytics[9]
- Smartlook[10]

The main reason for choosing Wordpress as the website platform for this research is the fact that Wordpress is the most widely used website platform, with approximately 42% of all websites globally being powered by it[11]. Other major reason that informed the choice of using the Wordpress for the website template was because of its ease of use, which allowed for the setting up of the research environment with the least expenditure of resources. Since this is the reason why the Wordpress is the most used website platform in the first place, we do not feel that it would conflict with our research interests. We feel that conducting our experiment on such a widely adopted system makes our results more applicable, as they are obtained from fundamentally similar environment to the majority of the websites in actual use. The reason to not use any other plugins in the websites, apart from the ones which were required by the analytics tools, was due to mitigating the effect they might have had on the energy consumption measurements.

Likewise, the analytics tool deployed on the website which had only one such tool was chosen to be Google Analytics. The reason for this is quite straightforward: the Google Analytics is the most commonly used analytics tool globally, being found from 53.6% of all websites[12], and this makes it the perfect measuring stick unto which to compare the results from having none, or having more than one analytics tool. Combined with the Wordpress based website it was deployed on, we can argue that this setting simulates the average website found from the Internet quite well – being powered by Wordpress, and having Google Analytics present.

Meta Pixel is used on roughly 30%[13] of the world's most

[1] https://analytics.google.com/analytics/web/provision/#/provision
[2] https://matomo.org/
[3] https://www.hotjar.com/
[4] https://clarity.microsoft.com/
[5] https://www.facebook.com/business/tools/meta-pixel
[6] https://auth.app.crazyegg.com/v2/login
[7] https://get.gaug.es/
[8] https://www.woopra.com/
[9] https://www.openwebanalytics.com/
[10] https://www.smartlook.com/
[11] https://aovup.com/stats/wordpress/
[12] https://w3techs.com/technologies/details/ta-googleanalytics
[13] https://techhq.com/2023/07/why-is-the-meta-pixel-at-heart-of-data-privacy-cases/

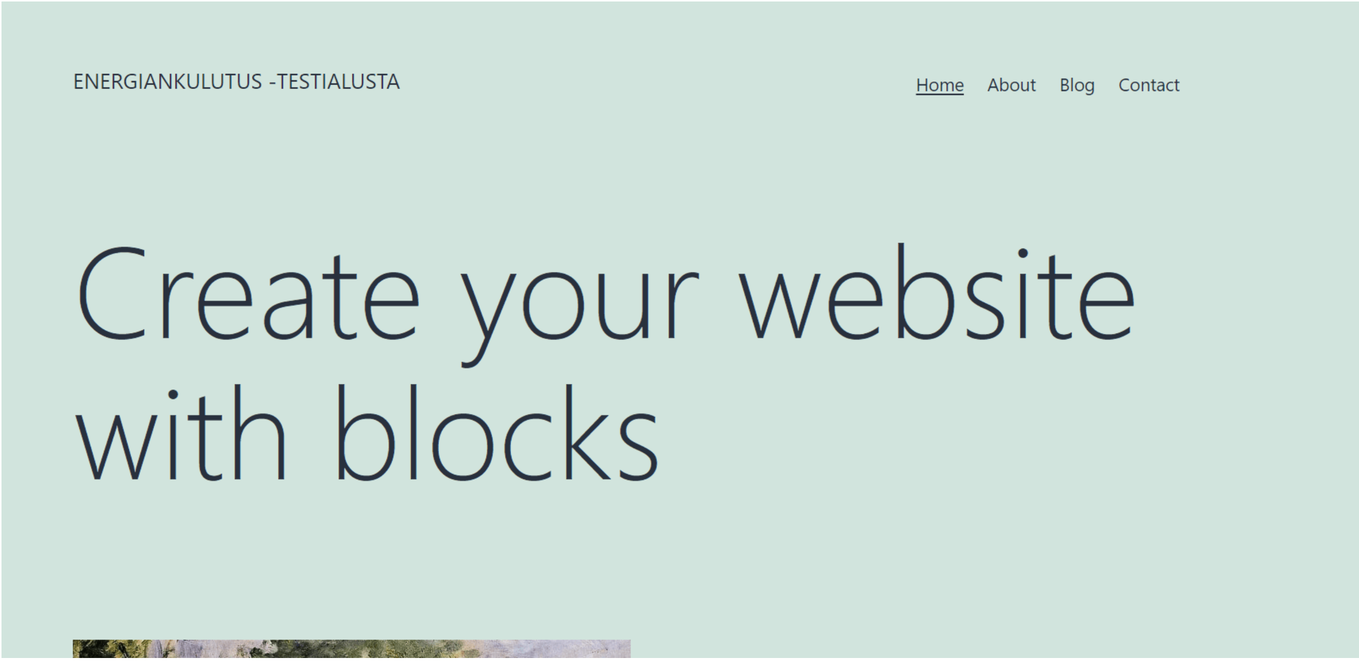

Fig. 1. A screenshot of the Wordpress website used in the experiment.

popular websites, putting it somewhat closer to the scale of Google Analytics, although it is still several degrees less popular of an option. The choice of the other web analytics tools used in this study was informed mainly by them being free-to-use, or at least having a free trial period which made them available for our use. With the exception of the aforementioned Meta Pixel, none of the other analytics providers have nowhere near the market share of the Google Analytics in the user tracking market, and thus the choice of particular brand of software was not deemed very important factor in regards to how representative of the real world situation the test setting was.

The physical test setup used in the empirical work is presented in Figure 2 and the abstract conceptual model for the setup in Figure 3. Our setup consisted of a HardKernel Smartpower 3[14] and the 19V/7A power brick sold as a bundle with the power meter, a Raspberry Pi 4 model B[15] (RPi), and a Dell Latitude laptop. Standard Cat 6, HDMI, and USB cables were used for communication, the DC for the RPi was fed through DIY banana connectors, a short (~30 cm) 0.75 mm^2 cable, and a 5.5/2.1 mm DC to USB-C adapter. The RPi was also equipped with small heatsinks sold with the bundle and a Kingston Class 10 / UHS-1 SD card. The Raspberry Pi also had external mouse, keyboard and desktop LCD (Dell 21") display connected, to simulate the energy consumption of the actual use scenario by human operator, and their energy consumption was considered in the measurement. The PSU provided by Odroid was used to power the SmartPower 3 unit, which in turn was powering the RPi unit. The RPi unit is the system under test (SUT) in this setup, executing both the test scripts for the test scenarios and the software meters for collecting data of the resource usage during the tests. A standard PC was also used as a controller for initiating the tests by starting the scripts via SSH. The controller PC also directly logged the data from SmartPower 3 via USB to avoid tainting the test process run by the SUT.

The scripts for driving the test scenarios were developed with Python programming language version 3.9.2 and Selenium WebDriver version 3.141.0, which is a library designed for development of testing scripts for browser-based software. We released the source code for the script publicly in GitLab, where it can be obtained for reproduction of our test scenario.[16] The script was designed to simulate the actions of human user on the website, in other words to click the links and input text in to the search field. The browser used by the script was Chromium version 106.0.5249.119. The script was deployed on the Raspberry Pi, and controlled through SSH connection. Raspbian Gnu/Linux version 11 Bullseye[17] was used as operating system on the SUT. Apart from the operating system and the script used in the experiment, only other program that was running during the experiment was the collectd[18], which was used to measure the processor engagement, memory usage and network traffic.

While Python is not the most energy efficient language available [15], we felt that the difference to other languages in this case would be relatively irrelevant, as the script in itself is very lightweight and does not affect the overall energy

[14]https://www.hardkernel.com/shop/smartpower-iii/
[15]https://www.raspberrypi.com/products/raspberry-pi-4-model-b/
[16]https://gitlab.utu.fi/tech/soft/mitvidi/software-measurement
[17]https://www.raspberrypi.com/news/raspberry-pi-os-debian-bullseye/
[18]https://www.collectd.org/

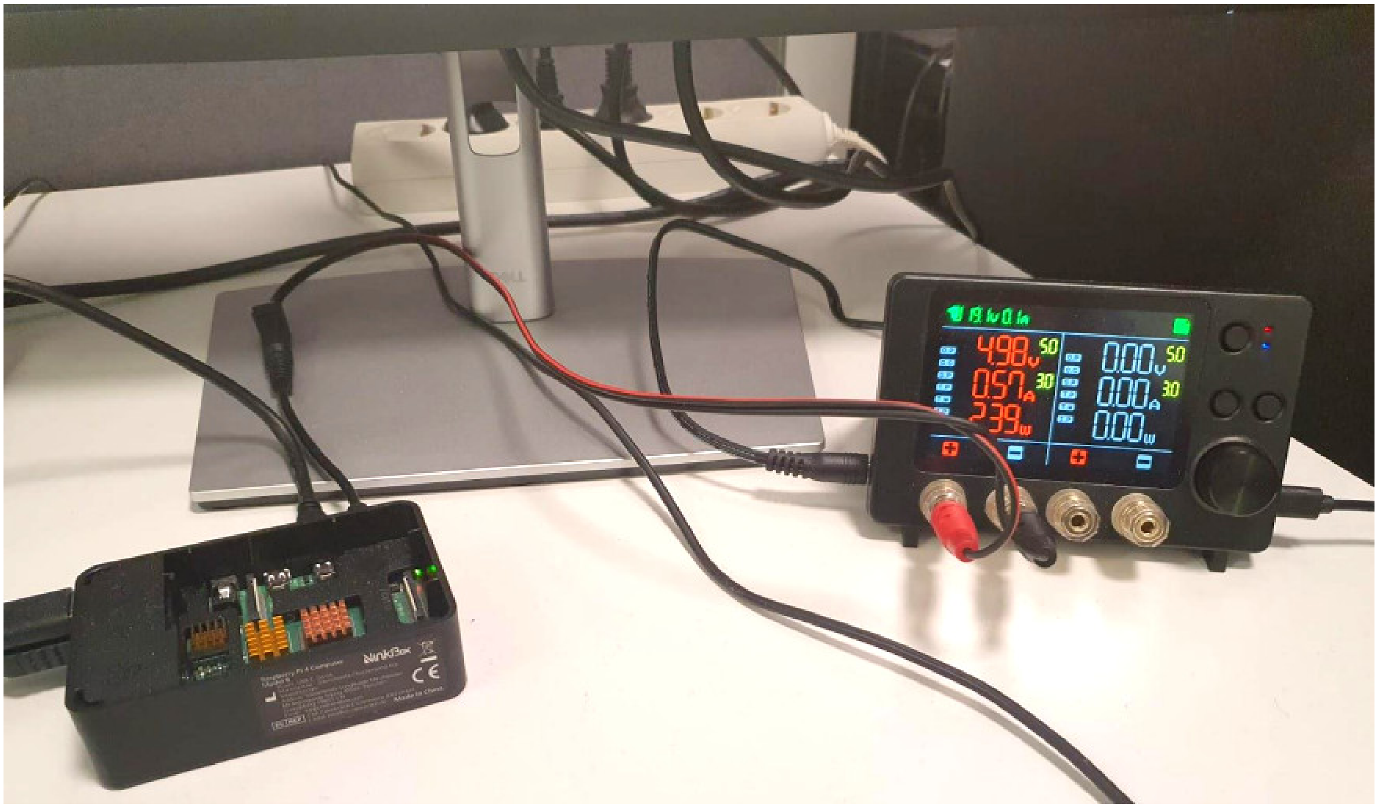

Fig. 2. Test setup with Raspberry Pi (left) and HardKernel SmartPower 3 (right).

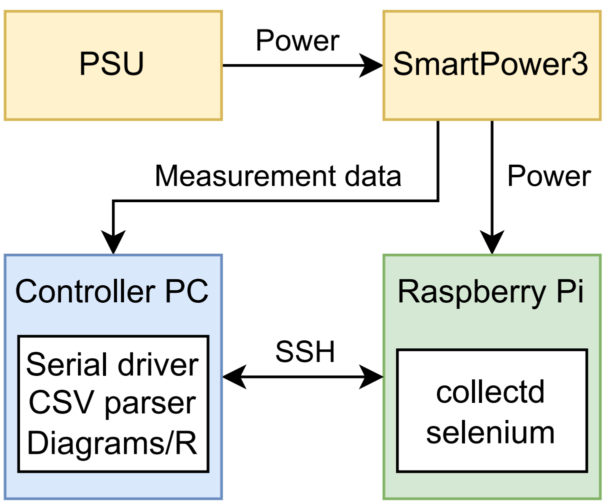

Fig. 3. Conceptual structure of the measurement setup.

consumption significantly. The basic consumption of the script in itself is visible in the idle consumption measured during the experiment, and as such it is unnecessary to try to subtract this from the measured points of activation, i.e. those caused by the website. In general, trying to measure the energy consumption of specific processes is not exactly a simple task in itself, which is why we have in this study measured the consumption as a whole.

The script accessed the website, then proceeded to click on all the clickable elements and use the search functionality of the website, while at the same time the energy consumption was measured with an external DC meter powering the Raspberry Pi. The data collected from the energy measurements was stored in CSV format. The choice of using Raspberry Pi for this experiment, and not actual workstation computer, was informed mainly because it makes the test scenario more reproducible. Desktop computers are much more complex devices, with various amounts of background processes running all the time, and thus it is not very viable to pinpoint the energy consumption happening at this or that moment to specific action by specific script. It is also quite hard to find two exactly similar computers hardware-wise, which would make the exact reproduction of the test environment practically impossible, or at the very least unfeasible.

However, this also means that the results we have obtained in this research are not directly relatable to the desktop computer environment, in other words we can not say that the energy consumption would increase relatively as much or as little when conducting this experiment on a normal consumer-grade desktop or laptop computer, tablet or a smartphone. However, it is certain that the energy consumption does increase with the use of the web analytics, that this increase is relatively quite severe. The increase is also clearly tied to the amount of web analytics tools in use.

The script was executed 100 times for all four websites to ensure that sufficient sample size was obtained to produce a meaningful average estimation of the energy consumption. Between each execution, the script waited until every element of the last execution had stopped, i.e. browser windows had been shut down etc. before the start of new execution. Each new execution was performed with disabled browser cache, to mitigate the effect any cached information would have had on the measurement results. Since the average script execution times were not consistent between the different setups, with those setups that had higher amount of analytics tools taking more time to execute the script, we applied polynomial regression and extrapolation to the results that had shorter execution times to make the averages comparable with each other.

In detail, to make the three scenarios where the execution times were shorter comparable to the longest one, we applied cubic polynomial regression to fit a curve to graph a function for average wattage and execution time. We found that linear and quadratic regression methods were insufficient since the change in wattage during execution time is neither linear or compliant to second degree polynomial. When the appropriate curves were fitted, we extrapolated those curves to find wattage values between the original finishing times and the finishing time of the longest scenario. The extended curves, however, did not capture the up-and-down motion visible in Figure 4 because the extrapolated wattage points are all found on the polynomial curve. Nonetheless, we found that this model still captured the average wattages because calculating an average between high points and low points eventually gives same answer as middle points would give. The polynomial regression and extrapolation were executed in RStudio (v2023.06.02) with R for Windows 4.3.1. The R-code used for finding polynomial functions and extrapolation of the functions is publicly available on GitHub.[19]

The connection between the specific actions executed by the script and their energy consumption was established with timestamps, which the script printed while executing the actions in the website. By using the timestamps it was possible to connect a specific action to a specific point in time, which enabled us to identify the actions that happened during the most energy-intensive points of the script execution.

IV. Results

First, it must be noted that the average script execution time was not consistent between the different analytics tool setups in the websites. The setups which had more analytics in use also took longer to execute the script, because the website response times were slower, and thus the script had to wait longer times between the actions. As can be seen from Figure 4, the average execution times were:

- **0 analytics:** 99 seconds
- **1 analytic:** 103 seconds
- **5 analytics:** 105 seconds
- **10 analytics:** 112 seconds

While the focus of this study is on the energy consumption of the web analytics tools, it is nevertheless an interesting observation that the use of analytics tools obviously makes the website respond slower, and that this slowing-down effect is directly proportionate to the number of analytics tools in use. These results, and other findings apart from the energy consumption, that we noted during the study are presented in Section IV-A.

The average wattage for the setup with 0 analytics tools was 2.58 W. The average wattage of the setup with ten analytics tools was 2.79 W. This makes the energy consumption increase between these two setups to be 8.14%, which can be considered to be significant increase. The average wattages of the other two setups were 2.737 W for 5 analytics tools in use (6.08% increase from 0 analytics) and 2.67 W for 1 analytics tool (3.48% increase from 0 analytics). It must be noted that the increase we see from the use of one analytical tool was due to Google Analytics, which suggests that it has a relatively higher energy consumption profile than other tools. Since it is the most used web analytics tool in the world this result has certain weight. However, it must be noted that these averages are obtained after applying polynomial regression and extrapolation to the shorter test series to be comparable with the longest, and thus they are estimations. Even so, they indicate that there is clear increase in the energy consumption when using the web analytics, and that this increase is obviously connected to the amount of the analytics tools in use.

As can be seen from Figure 4, the energy consumption had strong spikes, which were the result of the script clicking links and engaging the search functionality of the websites. The connection between the specific actions and the energy consumption can be seen exemplified in Figure 5. The graph depicts the setup with no web analytics. As can be seen in comparison to Figure 4, all of the test scenarios initially use quite similar amount of energy, presented as the first spike in the graph, but depending on the number of analytics tools in use starts to immediately differ from each other in this respect, when the script starts to execute the actions in the website. As we can see, for example the magnitude of the second spike in energy consumption, which marks the script navigating for the first time to the landing page of the website, is 3.4 W with no analytics, and 4.1 W with ten analytics. The increase in energy consumption at this point is thus 20.59%, which is substantial. This point of increase in energy consumption is most likely caused by the loading of the tracking cookies, which are at this point initialized for the first time.

On average the wattage at the spike peaks of the setup with 10 analytics is 3.56 W, while the average of the peaks of the setup with 0 analytics is 3.04 W, the increase between these two extremes thus being approximately 17.01%. The setups with 1 and 5 web analytics tools have the average spike wattage at 3.15 W and 3.36 W, respectively. From this we can

[19]https://gitlab.utu.fi/tech/soft/mitvidi/software-measurement/-/blob/main/analytics/Wattage_Extrapolations.R?ref_type=heads

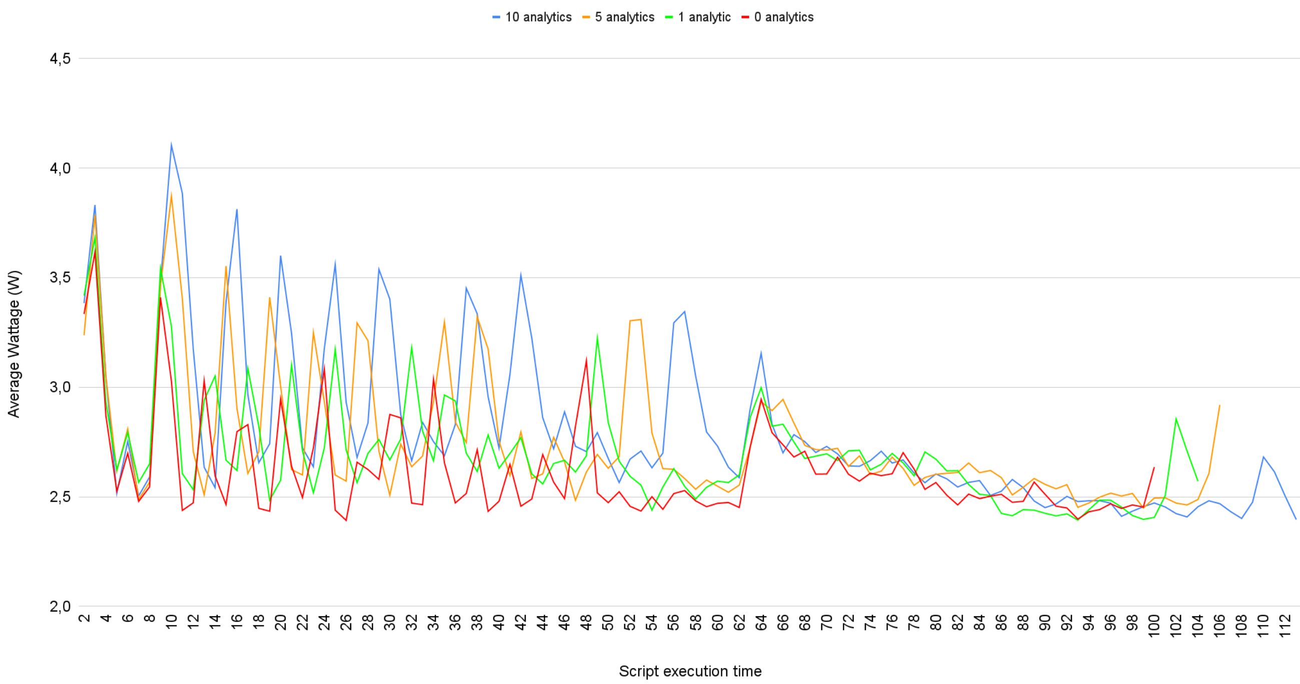

Fig. 4. The average power consumptions of all four setups during the script execution.

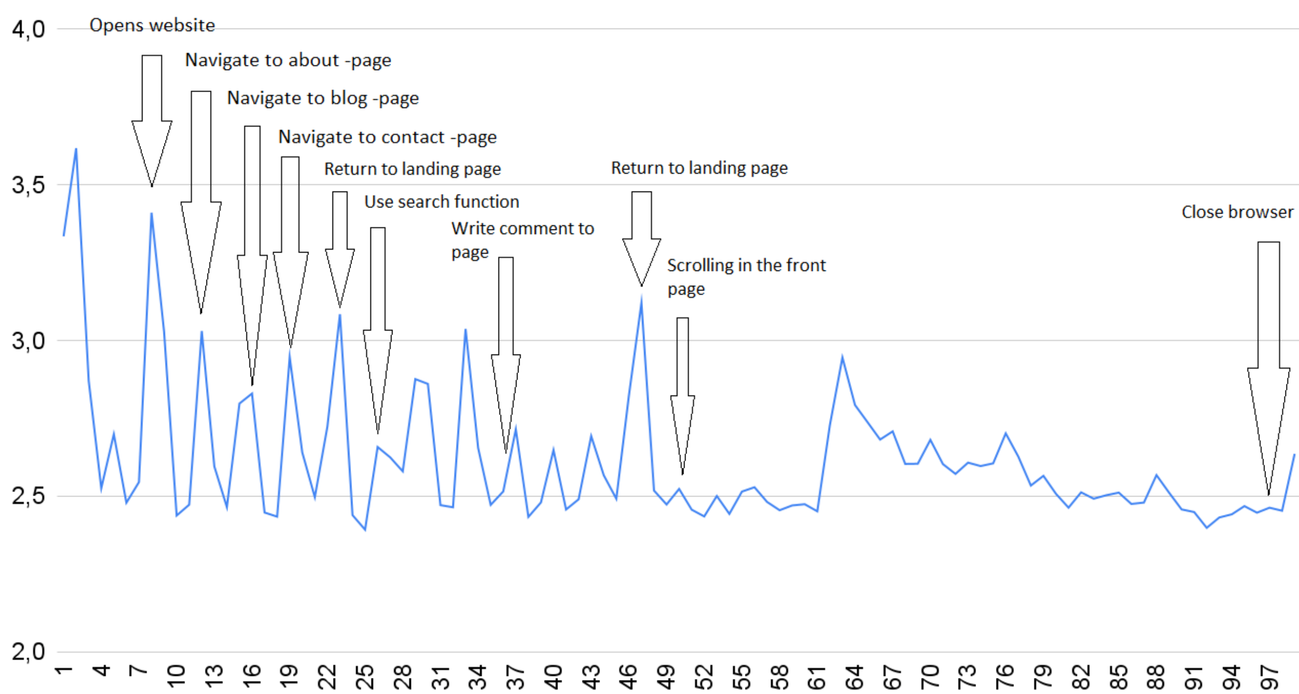

Fig. 5. Specific actions at energy intensive -moments of script execution.

see that the there is a clear connection between the amount of web analytics in use and the amount of energy consumed when performing actions in the website. Further on the timeline we can see that every time the script takes actions in the website the energy consumption spikes, and the websites with analytics tools (blue, green and orange graphs) consitently use more energy.

A. Other effects of web analytics

Apart from just the energy consumption, during the research we measured also several other aspects of hardware activation which we found relevant. The processor engagement, the network traffic and memory usage were all recorded during the script execution for further analysis. As they are related to the energy consumption, this section will provide an overview on how these metrics behaved.

The temporal discrepancy between the different graphs, i.e. that the graph denoting the website with 10 analytics is lagging behind the others in terms of when the spikes in energy consumption occur is due to the aforementioned phenomena of the website responding slower when it has more analytics tools deployed. As we can see from Figure 4, the average lag caused by the increase in analytics tools was 5.125 seconds for 10 analytics, 3 seconds for 5 analytics and 0.875 seconds for 1 analytics tool. These results suggest that not only does the use of web analytics tools cause the increase in energy consumption, but it also severely increases the response time of the website. Of course, again it must be noted that these results are obtained in a laboratory environment, and they are not directly representative of the lag happening on a consumer device. Still, it is obvious that the lag exists and corresponds to the number of the analytics tools.

In Figure 6, we can see the average network traffic in kilobytes per second. The graphs here are distinctly different from the ones that present the average energy consumption. At the beginning of the graph, we can see two small spikes, in the time-zones of 7–11 seconds, and later in the area between 27 and 35 seconds. First of these periods of network activity correlate with the script clicking the links in the website, and the second with the script using the search functionality of the website. Beyond these, there is one particularly intense moment of network activity, which peaks at 63 seconds.

As we can see, all graphs spike at this point sharply, although the one depicting the setup with 5 analytics tools relatively less than others. The action the script executes at this point is just scrolling in the main page of the website, so we make the assumption that this particularly intense network traffic is somehow caused by the web analytics that are deployed, although the mechanism is not exactly evident. However, what makes this point interesting is that the highest traffic levels were recorded from the setups with 10 and 1 analytics used, while the setup with 5 analytics tools had even lower amount of traffic than the one with no analytics at all. Since the setup with 1 analytics tool deployed used Google Analytics, it would be tempting to say that this similarity with the network traffic of 10 analytics tools at this point in time must be due to the fact that Google Analytics transmits particularly large amount of data. However, as the setup with 5 analytics tools also had the Google Analytics installed, this can not be the reason. All in all, this network traffic behaviour is anomalous, and we can not at the present moment offer an explanation for it.

Figure 7 depicts the average CPU load percentage during the script execution. Unsurprisingly, this graph is very similar to Figure 4, although not exactly identical. However, the almost exact similarity in the temporal axis and the somewhat less exact similarity in the resource consumption axis between these two graphs indicates that majority of the energy consumption is due to the processor engagement.

In Figure 8 we see the averages of the memory used while the script executes. As we can see, there are no strong spikes in memory usage at all during the script execution, with the usage increasing steadily, but showing relatively small differences between the different setups. Increase in the memory usage in all setups is fairly consistent, and just like the behavior of the network traffic, does not seemingly correlate with the actions the script executes on the website. Instead, the highest points of the memory usage are situated after the main actions performed by the script, at the point where the script is performing aimless scrolling around in the main page of the website.

V. Discussion

The key findings of the current study point towards direct correlation between the use of web analytics and a clear increase in energy consumption. While the results we have presented in this study were obtained in a laboratory environment with a setup that is not directly comparable to consumer devices, and thus are not directly applicable to give answers to what the increase would be in normal usage situation, it is obvious that the web analytics do affect the energy consumption by notably increasing it. Furthermore, there is obvious connection between this increase and the number of analytics tools being used. The difference between having no analytics tools present versus having them, especially in the case of 10 analytics, is very significant. While the average difference obtained, 8.14% increase in energy consumption between 0 and 10 analytics, might not feel that large, the implications that can be made from it, when projected into the global scale, are staggering. And it should be understood that this is only the increase we see in the client-side. In the server-side, there is massive back-end machinery devoted to processing the data extracted by the analytical tools, of which energy consumption we can not directly observe, or even estimate very well, but which is nonetheless one aspect of the total energy consumption caused by the analytical tools.

It is not known precisely how much energy the use of Internet consumes, as this topic is hard to study due to its scope, and because drawing boundaries on what exactly constitutes the use of Internet is not exactly agreed upon. The best estimates are roughly in the area between 5% to 9% [2], [10], [12], [20] of the total global energy consumption, but it must be noted that these results have been obtained in studies that are already almost decade old, or even older. Regardless, even if we would assume that the relative amount of consumption would not have risen in the past decade, we are talking about

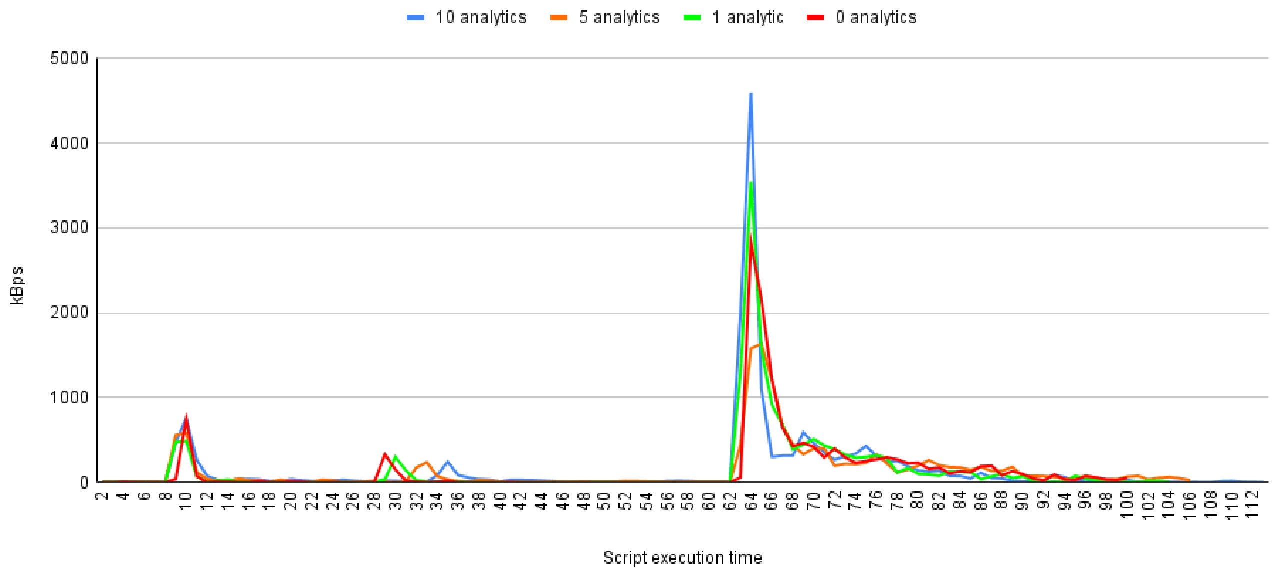

Fig. 6. The average network traffic during script execution.

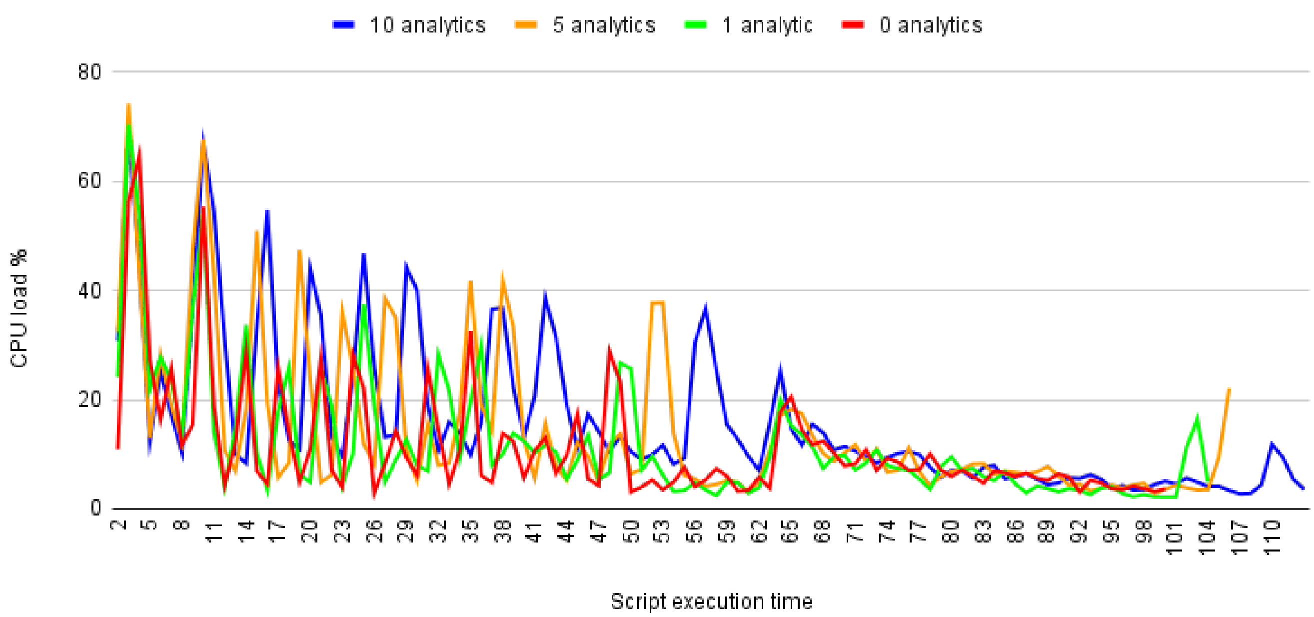

Fig. 7. The average CPU load percentage during script execution.

massive amounts of energy and consequently larger size of the carbon footprint. For example, the paper by Andrae and Edler estimated that the global energy consumption of the ICT systems would be even as high as 51% by 2030. [2]

Considering the times we are living right now, with the shadows of a global eco-catastrophe looming high over the horizon, it is highly questionable if this kind of consumption is justified, considering that the de facto purpose of web analytics tools is to drive economic profit. Their use is argued for by giving the website proprietors better data on their users, to tailor the services for them better. However, in reality the majority of the data extracted by these tools is used for other purposes such as directed marketing, either knowingly by the website proprietors themselves, or by third parties to whom this data is very often leaked. Regardless of who gets a hold of the data, it is ultimately used to actively generate profit, and there is even a whole branch of scientific research dedicated to studying and improving the effectiveness of analytics tools

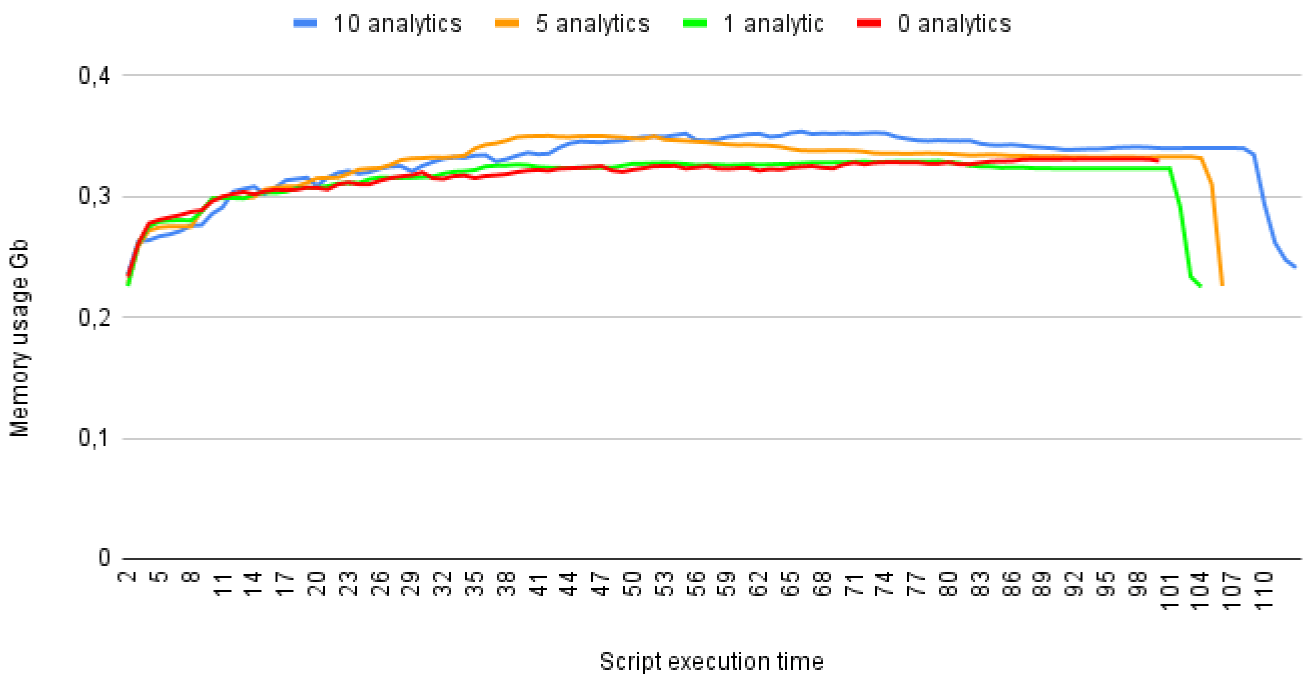

Fig. 8. Average memory usage during script execution.

towards this end. [11], [21], [23] While there is nothing inherently negative in making profit, if the analytics tools indeed come with as huge increase to the energy consumption as our results show, as a society we should be asking whether such practices should even be allowed, considering the very vocal drive towards carbon neutrality we have seen in past few years. It should also be remembered that not only does the use of website analytics increase the energy consumption, but it also has negative effects on the social sustainability, as is evidenced by several studies on the subject. [4], [22]

The aspect of data waste should also be considered here, as majority of the analytical tools collect essentially identical pieces of information about the website users, which are then stored in to multiple databases operated in myriads of data centers. All of this essentially means that large portion of the energy consumption increase we are seeing here is due to this kind of waste data accumulation. In the end, if we truly care about the fate of our planet, and are not just paying lip service to the goals of sustainability, is it really acceptable to use this much electricity just to increase the profits?

In the future, this research can be extended towards including periodical measurements from devices that are more representative of the real-world usage situations, and development of models through which these results would be comparable to the results obtained with the laboratory devices. The need for such models is obvious if we want to investigate the actual increase in energy consumption caused by the website analytics in consumer devices, as the nature of these devices makes it very hard to correctly estimate such things.

Other avenue of future research that we will be pursuing is the development of a benchmark database of the energy consumption levels of widely used software systems, to provide a baseline against which the energy consumption of other software implementations could be compared. One possible avenue of research would be the comparison between using the Selenium library in Python, versus other languages in which it is available, to determine if this has a significant effect on energy consumption.

VI. Conclusions

In this paper, we have presented the results we obtained by measuring what effect on energy consumption the use of web analytics tools have. Our observations indicate that the use of web analytics increases the energy consumption significantly and that this increase is connected to the amount of these tools in use. The average increase in energy consumption is as much as 8.14% with 10 analytics tools deployed at the website, and while this is result obtained in laboratory environment, it suggests that similar increase is present in consumer machinery also. The use of web analytics seems to increase the response time of the website, in effect slowing the website down. Further, these results imply that on the global scale, web analytics tools have severe effect on the carbon footprint of the internet usage, and that since these kind of technologies can hardly be considered essential to the website infrastructure, this casts a shadow of doubt on their use in times when energy efficiency and reducing the environmental impact are paramount.

REFERENCES

[1] Tom Alby. Popular, but hardly used: Has google analytics been to the detriment of web analytics? In *Proceedings of the 15th ACM Web Science Conference 2023*, pages 304–311, 2023.

[2] Anders SG Andrae and Tomas Edler. On global electricity usage of communication technology: trends to 2030. *Challenges*, 6(1):117–157, 2015.

[3] Eugenio Capra, Chiara Francalanci, and Sandra A. Slaughter. Is software "green"? application development environments and energy efficiency in open source applications. *Information and Software Technology*, 54(1):60–71, 2012.

[4] Robin Carlsson, Sampsa Rauti, and Timi Heino. Data leaks to third parties in web services for vulnerable groups. In *2023 46th MIPRO ICT and Electronics Convention (MIPRO)*, pages 1208–1212. IEEE, 2023.

[5] Shaiful Alam Chowdhury and Abram Hindle. Greenoracle: Estimating software energy consumption with energy measurement corpora. In *Proceedings of the 13th International Conference on Mining Software Repositories*, MSR '16, page 49–60, New York, NY, USA, 2016. Association for Computing Machinery.

[6] João De Macedo, Rui Abreu, Rui Pereira, and João Saraiva. Webassembly versus javascript: Energy and runtime performance. In *2022 International Conference on ICT for Sustainability (ICT4S)*, pages 24–34, 2022.

[7] Abram Hindle. Green software engineering: the curse of methodology. In *2016 IEEE 23rd International Conference on Software Analysis, Evolution, and Reengineering (SANER)*, volume 5, pages 46–55. IEEE, 2016.

[8] Kiyo Ishii, Junya Kurumida, Ken-ichi Sato, Tomohiro Kudoh, and Shu Namiki. Unifying top-down and bottom-up approaches to evaluate network energy consumption. *Journal of Lightwave Technology*, 33(21):4395–4405, 2015.

[9] Steffen Lange, Johanna Pohl, and Tilman Santarius. Digitalization and energy consumption. does ict reduce energy demand? *Ecological Economics*, 176:106760, 2020.

[10] Jens Malmodin, Åsa Moberg, Dag Lundén, Göran Finnveden, and Nina Lövehagen. Greenhouse gas emissions and operational electricity use in the ict and entertainment & media sectors. *Journal of Industrial Ecology*, 14(5):770–790, 2010.

[11] Bernard Marr. *Data strategy: How to profit from a world of big data, analytics and the internet of things*. Kogan Page Publishers, 2017.

[12] Janine Morley, Kelly Widdicks, and Mike Hazas. Digitalisation, energy and data demand: The impact of internet traffic on overall and peak electricity consumption. *Energy Research & Social Science*, 38:128–137, 2018.

[13] Zakaria Ournani, Romain Rouvoy, Pierre Rust, and Joel Penhoat. On reducing the energy consumption of software: From hurdles to requirements. In *Proceedings of the 14th ACM/IEEE International Symposium on Empirical Software Engineering and Measurement (ESEM)*, pages 1–12, 2020.

[14] Leif Katsuo Oxenløwe, Quentin Saudan, Jasper Riebesehl, Mujtaba Zahidy, and Smaranika Swain. Evaluating energy consumption of internet services. *IEICE Transactions on Communications*, advpub:2022OBI0001, 2023.

[15] Rui Pereira, Marco Couto, Francisco Ribeiro, Rui Rua, Jácome Cunha, João Paulo Fernandes, and João Saraiva. Ranking programming languages by energy efficiency. *Science of Computer Programming*, 205:102609, 2021.

[16] Christos Petalotis, Luka Krumpak, Maximilian Stefan Floroiu, Laréb Fatima Ahmad, Shashank Athreya, and Ivano Malavolta. An empirical study on the performance and energy costs of ads and analytics in mobile web apps. *Information and Software Technology*, 166:107370, 2024.

[17] Stephen Romansky, Neil C Borle, Shaiful Chowdhury, Abram Hindle, and Russ Greiner. Deep green: Modelling time-series of software energy consumption. In *2017 IEEE International Conference on Software Maintenance and Evolution (ICSME)*, pages 273–283. IEEE, 2017.

[18] Vivek Kumar Singh, Kaushik Dutta, and Debra VanderMeer. Estimating the energy consumption of executing software processes. In *2013 IEEE International Conference on Green Computing and Communications and IEEE Internet of Things and IEEE Cyber, Physical and Social Computing*, pages 94–101. IEEE, 2013.

[19] Max Van Hasselt, Kevin Huijzendveld, Nienke Noort, Sasja De Ruijter, Tanjina Islam, and Ivano Malavolta. Comparing the energy efficiency of webassembly and javascript in web applications on android mobile devices. In *Proceedings of the 26th International Conference on Evaluation and Assessment in Software Engineering*, pages 140–149, 2022.

[20] Ward Van Heddeghem, Sofie Lambert, Bart Lannoo, Didier Colle, Mario Pickavet, and Piet Demeester. Trends in worldwide ict electricity consumption from 2007 to 2012. *Computer Communications*, 50:64–76, 2014.

[21] Wouter Verbeke, Bart Baesens, and Cristián Bravo. *Profit driven business analytics: A practitioner's guide to transforming big data into added value*. John Wiley & Sons, 2017.

[22] Esko Vuorinen, Panu Puhtila, Sampsa Rauti, and Ville Leppänen. From whistle to echo: Data leaks in web-based whistleblowing channels. In *Nordic Conference on Secure IT Systems*, pages 37–53. Springer, 2023.

[23] Russell Walker. *From big data to big profits: Success with data and analytics*. Oxford University Press, 2015.

[24] Taha Zaghdoudi. Internet usage, renewable energy, electricity consumption and economic growth: Evidence from developed countries. *Economics Bulletin Access Econ*, 37(3):1612–1619, 2017.