Zurich University of Applied Sciences

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SPECIALIZATION PROJECT 2

Title

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Abstract

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The accompanying source code for this thesis, including all deployment and automation scripts, is available in the **PowerStack**[1] repository on GitHub.

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Chapter 1

Introduction and Context

1.1 Introduction and Context

1.1.1 Cloud Computing and its impact on the global energy challenge

Global energy consumption is rising at an alarming pace, driven in part by the accelerating digital transformation of society. A significant share of this growth comes from data centers, which form the physical backbone of cloud computing. While the cloud offers substantial efficiency gains through resource sharing and dynamic scaling, its aggregate energy footprint is growing rapidly. While data center accounted for around 1.5% (around 415 TWh) of the worlds electricity consumption in 2024, they are set to more than double by 2030[2]. That is slightly more than Japans's current electricity consumption today.

This increase is fueled by the rising demand for compute-heavy workloads such as artificial intelligence, large-scale data processing, and real-time services. Meanwhile, traditional drivers of efficiency—such as Moore's law and Dennard scaling—are slowing down[3, 4]. Improvements in data center infrastructure, like cooling and power delivery, have helped reduce energy intensity per operation[5], but these gains are approaching diminishing returns. As a result, total data center energy use is expected to grow faster than before, even as efficiency per unit of compute continues to improve more slowly[6].

1.1.2 Rise of the Container

Containers have become a core abstraction in modern computing, enabling lightweight, fast, and scalable deployment of applications. Compared to virtual machines, containers impose less overhead, start faster, and support finer-grained resource control. As such, they are widely used in microservice architectures and cloud-native environments[7].

This trend is amplified by the growing popularity of Container-as-a-Service (CaaS) platforms, where containerized workloads are scheduled and managed at high density on shared infrastructure. Kubernetes has become the de facto orchestration tool for managing such workloads at scale. While containers are inherently more energy-efficient than virtual machines in many scenarios[8], their widespread use presents a new challenge: understanding and attributing their energy consumption accurately.

1.1.3 Container Energy Consumption Measurement Challenges

Knowing the energy consumed by a container on a server is the essential elemenent to a container-level energy efficiency assessment of both the container itself, as well as the environment surrounding it. An accurate energy consumption estimation is therefore required to validate and improve any potential energy efficiency improvements of a container enviromnent, from kubernetes system components (e.g. Kubernetes Schedulers) to the containers themselves.

Energy consumption in containerized systems is inherently hard to measure due to the abstraction layers involved. Tools like RAPL (Running Average Power Limit) expose component-level energy metrics on modern Intel and AMD CPUs, but this information is not accessible from within containers or virtual machines. In public cloud environments, such telemetry is either not exposed or aggregated at coarse granularity, making direct measurement infeasible.

Containers further complicate attribution: because they share the kernel and hardware resources, it is difficult to isolate the energy impact of one container from another. Only indirect metrics—such as CPU time, memory usage, or performance counters—are available, and even these may be incomplete or noisy depending on system configuration and workload behavior. Various tools exist that attempt to model container power usage based on these inputs, but rarely are their produced metrics transistent and verified.

1.1.4 Problem Definition

The growing importance of containers in cloud environments, combined with the difficulty of directly measuring their energy usage, motivates this work. In particular, this thesis investigates the questions:

Question 1: Which measuremnt methods, metrics or models allow for reliable container-level power estimation?

Question 2: How should a software-based container energy consumption estimation tool be implemented?

Question 3: How can existing container energy consumption estimation tools be validated?

To answer these questions, this study explores methods of measuring server energy consumption, analyzes container workload metrics, and evaluates modeling techniques that aim to bridge the gap between raw energy data and container-level attribution. **The focus is on bare-metal Kubernetes environments, where full system observability allows for deeper analysis and model validation, serving as a foundation for future energy-aware cloud architectures.**

1.1.5 Context of this thesis

This thesis is part of the Master's program in Computer Science at the Zurich University of Applied Sciences (ZHAW) and represents the second of two specialization projects ("VTs"). The preceding project (VT1) focused on the practical implementation of a test environment for energy efficiency research in Kubernetes clusters. This

thesis (VT2) is meant to explore theoretical and methodolocical aspects of container energy consumption measurements in detail.

Furhtermore, this thesis builds upon prior works focused on performance optimization and energy measurement. EVA1 covered topics such as operating system tools, statistics, and eBPF, while EVA2 explored energy measurement in computer systems, covering hardware, firmware, and software aspects. These foundational topics provide the basis for the current thesis but will not be revisited in detail.

1.1.6 Use of AI Tools

During the writing of this thesis, *ChatGPT*[9] (Version 4o, OpenAI, 2025) was used as an auxiliary tool to enhance efficiency in documentation and technical writing. Specifically, it assisted in:

- Structuring and improving documentation clarity.
- Beautifying and formatting smaller code snippets.
- Assisting in LaTeX syntax corrections and debugging.

All AI-generated content was critically reviewed, edited, and adapted to fit the specific context of this thesis. **ChatGPT was not used for literature research, conceptual development, methodology design, or analytical reasoning.** The core ideas, analysis, and implementation details were developed independently.

1.1.7 Project Repository

All code, configurations, and automation scripts developed for this thesis are publicly available in the PowerStack[1] repository on GitHub. The repository contains Ansible playbooks for automated deployment, Kubernetes configurations, monitoring stack setups, and benchmarking scripts. This allows for full reproducibility of the test environment and facilitates further research or adaptation for similar projects.

Chapter 2

State of the Art and Related Research

2.1 Energy consumption measurement and efficiency on data center level

Energy consumption and efficiency on a data center level has been well-studied to the point where various Literature reviews were published[10, 11]. The bigger part of this research is focused on the data center infrasturture (cooling and power), and with good reason, as the data center infrastructure is responsible for a large part of the energy consumption. While a large number of coarse-, medium- and fine-grained metrics for data center energy consumption exist, most data center operators have focused on improving coarse-grained mertrics (especially the *Power Utilization Effectiveness, PUE*) with improvements to infrastructure. This has resulted in a PUE of 1.1 or lower in some cases[5]. Meanwhile, server energy efficiency has substantially improved, especially for partial load and idle power[12]. This has allowed data center operators to improve energy efficiency by simply installing more efficient cooling and power systems and servers. Fine-grained metrics such as server component utilization rates or speed were generally not used in the context of energy efficiency, but rather as performance metrics to ensure customer satisfaction.

2.2 Energy consumption measurement on a server level

As a result of the energy efficiency improvements of both data center infrastructure and server hardware mentioned in the previous section, a shift has started towards evaluating the actual server load energy efficiency. Efficiency gains on this level compound into further gains at the data center level. The method of resource-sharing of modern cloud computing (and especially the use of containers) have created great opportunities for server workload optimitation for energy efficiency, which in turn require power consumption measurements for evaluation. In the context of containers on multi-core processors, measuring the energy consumption of the entire server is insufficient, since it does not allow the attribution of consumped energy to specific containers or processes. While component-level power measurements provide finer measurements that could theoretically be modelled to display container energy consumption, they drastically raise the complexity for a number of reasons:

- Component-level energy consumption measurement without external tools is far from easy. While some components provide estimation models (e.g. Intel RAPL or *Nvidia Management Library* (NVML)), others can only be estimated using their performance metrics. This will invariably lead to large measurement uncertainties, especially with the component hardware differences between generations and manufacturers.

- The problem of attributing measured or estimated energy consumption to individual containers is in itself non-trivial: It not only requires a fine-grained time synchronization of energy consumption and used container resources due to the fast-switching nature most server components during any sort of multitasking.

- A deep understanding of dynamic or static energy consumption is required: Depending on the energy consumption attribution model, a container might not only account the energy it actively used, but potentially also account for a fraction of the energy consumed for any shared overhead such as shared hardware components, or system resources (such as the Kubernetes system architecure). This idea can be further extended: containers could potentially be penalized for any unused server resources, as these unused capacity still consume energy. These different attribution models lead to a larger debate about the goals of the measurements.

- Any server-level power models used to estimate the relation of individual component energy consumption suffers from the varity of different server configurations due to server specialization, such as Storage-, GPU-, or Memory-optimized servers.

-

The following sections of this chapter aim to present the current state-of-the-art in the various fields of research of the problem domains listed above.

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx here, a sentence will introduce the subsections:

- Hardware components: CPU / RAM / SoC / GPU / ...

-

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx

Finally, section xxxxxxxxxxxxxxxxxxxxxxxxxxxxx aims to give an overview of the currently existing implementations of software-based container-level energy consumption estimation.

2.3 Overview of Power Data collection

In a systematic review cloud servers power models, Lin et al[13] categorize power collection methods into 4 categories:

Key	Value	Description	Deployment Difficulty	Data Granularity	Data Credibility
Based on instruments	Installation of extra devices	Bare-metal machines	Easy	Machine Level	Very high
Based on dedicated aquisition system	Specialized systems	Specified models of machines	Difficult	Machine or component-level	High
Based on software monitoring	Build-in power models	Bare-metal and virtual servers	Moderate	Machine, component, or VM level	Fair
Based on simulation	System simulation	Machine, component or VM level	Easy	Machine, component, or VM level	Low

TABLE 2.1: Comparison of power collection methods for cloud servers

2.3.1 Instrument-based power data aquisition

Instrument-based Data collection aquisition produces the hightest data credibility at a low granularity: These devices, installed externally (measuring the power supplied to the PDU) or internally (measuring the power flow between the PDU and motherboard) have been the source of information for a number of studies. The approach to simply measure electric power at convenient hardware locations using dedicated equipment can of course be extended to provide additional granularity: For example, Desrocher et al[14] custom-created a DIMM extender custom-fitted with Hall-sensor resistors and a linux measurement utility to measure power consumed by a DIMM memory module at 1kHz sampling rate using a *WattsAppPro?* power meter and a *Measurment Computing USB.1208FS-Plus* data aquisition board.

This of course highlights a fundamental truth of instrument-based data collection: While it is possible to implement a measuring solution that provides high-granular and high-sampling rate power data, it is paired with an immense effort since solutions like this are not provided off-the-shelf. Unsuprisingly, this is most valuable for benchmarking or validation (Desrochers et al used their setup to validate Intel RAPL DRAM power estimations on three different systems). However, this methodology is (currently) unsuitable for deployment to data center servers due to its bad scalability and prohibitive costs. Hence, the primary role of instrument-based power data aquisiton is as a benchmarking and validation tool for research and development.

2.3.2 Dedicated Aquisition systems

2.3.2.1 BMC Devices, IPMI and Redfish

Some manufacturers have developed specialized power data aquisition systems for their own server products. The baseboard management controller (BMC) is a typical dedicated aquisition system usually integrated with the motherboard, usually as part of the intelligent platform management interface (IPMI)[13]. It can be connected to the system bus, sensors and a number of components to provide power and temparature information about the CPU, memory, LAN port, fan, and the BMC itself. Some comprehensive management systems such as Dell iDRAC or Lenovo xClarity have been further developed to provide high-quality, fine-grained power data due to their close interoperation between system software and underlying hardware. BMC devices on modern servers often offer IPMI- or Redfish interfaces. While these interfaces use the same physical servers, their implementation differ significantly, where Redfish generally offers higher accuracy (e.g through the use of higher-bit formats, whereas IPMI often uses 8-bit raw numbers).

In the context of container power consumption estimation, IPMI-implementations occupy an interesting role. In 2016, Kavanagh et al[15] found the accuracy of IMPI

power data to be relatively inaccurate when compared with an external power meter, mainly due to the large measurement window size of 120 to 180 seconds and the inaccurate assessment of the idle power. They concluded that IMPI power data was still useful when a longer averaging window was used, and the initial datapoints discounted. In a later study, they suggest combining the measurements of IPMI and Intel RAPL (which they find to underestimate the power consumption) for a reasonable approximation of true measurement[16]. Kavanagh's findings have been cited in various studies, often to negate the use of IPMI for power measurement. When used, it sometimes is chosed because it was the "simplest power metric to read"[17] in the context of entire data centers.

Redfish is a modern Out-of-band Management System, first released in 2015 explicitely to replace IPMI [18]. It uses a RESTful API and JSON data format, making queries with code easier. In 2019, Wang et al[19] directly compared IPMI and redfish power data to a reading of a high accuracy power analyzer, and found Redfish to be more accurate than IPMI, with a MAPE of 2.9%, while also finding a measurement latency of about 200ms. They also found measurements to be more accurate in higher power ranges, which they attribute to the improved latency.

In conclusion, BMC power data aquired over Redfish provides a simple simple and comparatively easy way to measure system power based on various physical system sensors. Its biggest strenght lies in easy implementation and general availability. In the context of container energy consumption, BMC power data lacks the short sampling rates necessary to measure a a highly dynamcic container setup, but can prove useful as a validation or cross-reference dataset for longer intervals exceeding 120 seconds. Unfortunately, the data quality of BMC power data depends on the actual system, and power models can be significantly improved by initial calibration with an external power measurement device[15].

2.3.3 Intel RAPL

Intel Running Average Power Level (RAPL) is a Power Monitoring Counter (PMC)-based feature introduced by Intel and provides a way to monitor and control the energy consumption of various components within their processor package[20]. An adaptation of RAPL for AMD processors uses largely the same mechansms and the same interface[21], although it provides less information than Intel's RAPL, providing no DRAM energy consumption[22]. Unfortunately RAPL does not have a detailed low-level implementation documentation, and the exact methodology of the RAPL calculations remain unknown[23].

Intel RAPL has been used extensively in research to measure energy consumption[24] despite some objections about its accuracy, which will be discussed sections 2.3.3.2 and 2.3.3.3. The general concencus is that RAPL is *good enough* for most scientific work in the field of server energy consumption and efficiency. As Raffin et at[25] point out, it is mostly used *like a black box without deep knowledge of its behavior*, resulting in implementation mistakes. For this reason, the next section 2.3.3.1 presents an overview of the RAPL fundamentals.Finally, section 2.7.1 discusses the currently available RAPL-based tools.

2.3.3.1 RAPL measurement methods

This subsection provides an overview of how RAPL works and is used. It is based on the Intel rchitectures Software Developer's Manual[26, Section 16.10] and the works of Raffin et al [25] (2024) and Schöne et al [27] (2024).

Running Average Power Limit (RAPL) is a power management interface in Intel CPUs. Apart from power limiting and thermal management, it also allows to measure the energy consumed by various components (or *domains*). These domains individual CPU cores, integrated graphics (in non-server CPUs) and DRAM, as well as *package*, refering to the whole CPU die. While it initially used models to estimate energy use[28], it now uses physical measurements. The processor is divided into different power domains or "planes", representing specific components, seen in figure 2.1. Notably, not all domains are present in all systems: Both client-grade systems feature the *Package* and *PP0 core* domains, server grade processors typically don't show the *PP1 uncore*-domain typically used for integrated GPUs, and client-grade processors don't show the *DRAM* domain. The *PSYS* domain for the "whole machine" is ill defined and only exists on client-grade systems. In an experiment with recent Lenovo and Alienware laptops, Raffin et al found that the *PSYS* domain reported the total consumption of the laptop, including display, dedicated GPU and other domains. Regardless, this thesis will focus on the RAPL power domains available to server-grade processors.

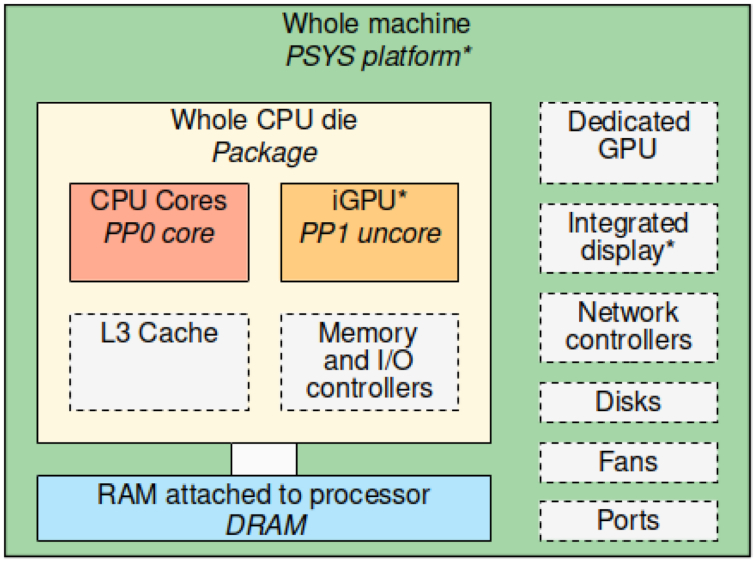


FIGURE 2.1: Hierarchy of possible RAPL domains and their corresponding hardware components. Domain names are in italic, and grayed items do not form a domain on their own, items with an asterisk are not present on servers[25].

RAPL provides hardware counters to read the energy consumption (and set power limits) for each domain. The energy consumption is measured in terms of processor-specific "energy units" (e.g. 61μJ for Haswell and Skylake processors). The counters are exposed to the operating system through model-specific registers (MSRs) and are updated approximately every millisecond. The main advantages of RAPL are that no external powermeters are required, nor a privileged access to the BMC (which could be used to power off the server). RAPL is more accurate than any untuned statistical estimation model.

Various measurement methods can be used to extract RAPL measurements. In a detailed comparison, Raffin et al[25] outline their individual features and tradeoffs, which are summarize in figure 2.2b:

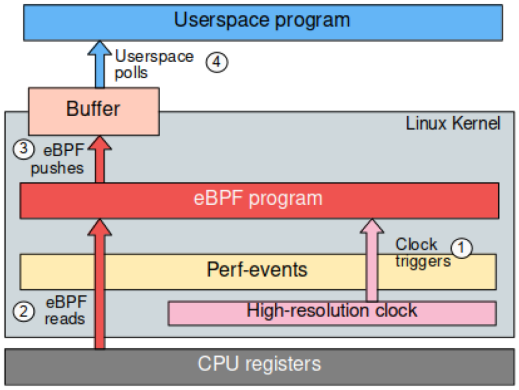
- **Lacking documentation:** Since there is no publicly available documentation of the low-level RAPL implementation, implementations are bound to suffer inaccuracies and inconsistencies due to a lack of understanding.

- The **Model-Specific Register (MSR)** interface provides low-level access to RAPL energy counters but is complex and hardware-dependent. Developers must manually determine register offsets and unit conversions based on processor model and vendor documentation. This method lacks safeguards, requires deep processor knowledge, and is error-prone, with incorrect readings difficult to detect. Although read-only access poses no risk to system stability, MSRs expose sensitive data and are thus restricted to privileged users (e.g., `root` or `CAP_SYS_RAWIO`). Fine-grained access control is not supported natively, though the `msr-safe` module offers limited mitigation.

- The **Power Capping (powercap)** framework is a high-level Linux kernel interface that exposes RAPL energy data through the sysfs filesystem, making it accessible from userspace. It simplifies energy measurements by automatically handling unit conversions and domain discovery, requiring minimal hardware knowledge. Though domain hierarchy can be confusing (especially with DRAM domains appearing nested under the package domain) powercap remains user-friendly and scriptable. It supports fine-grained access control via file permissions and offers good adaptability to hardware changes, provided the measurement tool doesn't rely on hard-coded domain structures.

- The **perf-events** subsystem provides a higher-level Linux interface for accessing RAPL energy counters as counting events. It supports overflow correction and requires less hardware-specific knowledge than MSR. Each RAPL domain must be opened per CPU socket using `perf_event_open`, and values are polled from userspace. While it lacks a hierarchical structure like powercap and may be harder to use in certain languages or scripts, it remains adaptable and robust across different architectures. Fine-grained access control is possible via kernel capabilities or `perf_event_paranoid` settings.

- **eBPF** enables running custom programs in the Linux kernel, and in this context, it is used to directly read RAPL energy counters from within kernel space, potentially reducing measurement overhead by avoiding user-kernel context switches. The implementation attaches an eBPF program to a CPU clock event, using `perf_event_open` to access energy counters and buffering results for userspace polling (is visualized in figure 2.2a).While offering the same overflow protection as regular `perf-events`, this approach is significantly more complex, prone to low-level errors (especially in C), and requires elevated privileges (`CAP_BPF` or `root`). It also lacks portability, as it demands manual adaptation to kernel features and domain counts, limiting its maintainability across systems.



(A) RAPL perf-event eBPF mechanism

mechanism	technical difficulty	required knowledge	safeguards	privileges	resiliency
MSR	medium	CPU knowledge	none	SYS_RAWIO cap. + msr module	poor
perf-events + eBPF	high (long, complicated code)	limited	overflows unlikely, many other possible mistakes	PERFMON and BPF capabilities	manual tweaks necessary for adaptation
perf-events	low	limited	good, overflows unlikely	PERFMON capability	good
powercap	low	limited	beware of overflows	read access to one dir	good, very flexible

(B) RAPL measurement mechanisms comparison

FIGURE 2.2: RAPL measurements: eBPF and comparison[25]

In their research, Raffin et al conclude that all four mechanisms have small or negligible impact on the running time of their benchmarks. They formulate the following recommendations for future energy monitoring implementations:

- Measuring frequencies should be adapted to the state of the node, preventing high measurement overhead, due to a reduction in time spent in low-power states. Under heavy load, a highfrequencay can be used in order to capture more information.
- `perf-events` is the overall recommeded measurement method with good efficiency, latency and overflow protection. Powercap is less efficient, but provides a simpler sysfs API.
- Even though `perf-events` and eBPF-measurement method seems to be the most energy-efficient, it is not recommended in light of its complexity. For the same reason, the MSR method is not recommeded, as it raises complexity while counter-intuitively being slower than `perf-events`

RAPL MSRs can be read on some cloud computing resources (e.g. some Amazon EC2-instances), although the hypervisor traps the MSR reads, which can add to the polling delay. in EC2, the performance overhead also significantly increases to <2.5% (as compared to <1% on standalone systems)[23].

2.3.3.2 RAPL Validation

Since its inception, RAPL has been subject of various validation studies, with the general concensus that it's accuracy could be considered "good enough"[25]. Notable works are Hackenberg et al, that in 2013 found RAPL accurate but missing timestamps[29], and in 2015 noticed a major improvement to RAPL accuracy, after Intel switched from a modeling approach to actual measurements for their Haswell architecture[28]. Desrochers et al concluded in a 2016 RAPL DRAM validation study[14] that DRAM power measurement was reasonably accurate, especially on server-grade CPUs. They also found measurement quality to drop when measuring and idling system. Later, Alt et al[30] tested DRAM accuracy of heterogeneous memory systems of the more recent Ice Lake-SP architecture and concluded that DRAM estimates behaved differently than on older architectures. They noted that the RAPL

overestimates DRAM energy consumption by a constant offset, which they attribute to the off-DIMM voltage regulators of the memory system.

A critical point in the RAPL validation was the introduction of the Alder Lake architecture, marking Intel's first heterogeneous processor, combining two different core architectures from the Core and Atom families (commonly referred to as P-Cores and E-cores) to improve performance and energy efficiency. While this heterogenity can improve performance and energy efficiency, it also increases complexity of scheduling decisions and power saving mechanisms, adding to the already complex architecture, featuring per-core Dynamic Voltage and frequency Scaling (DVFS), Idle states and Power Limiting / Thermal Protection.

Schöne et al[27] found RAPL in the Alder Lake architecture to be generally consistent with external measurements, but exhibiting lower accuracy in low power scenarios. The following figure 2.3 shows these inaccuracies, albeit tested on a conusmer-grade Intel Core i9-12900K processor measured at the base frequency of 0.8GHz.

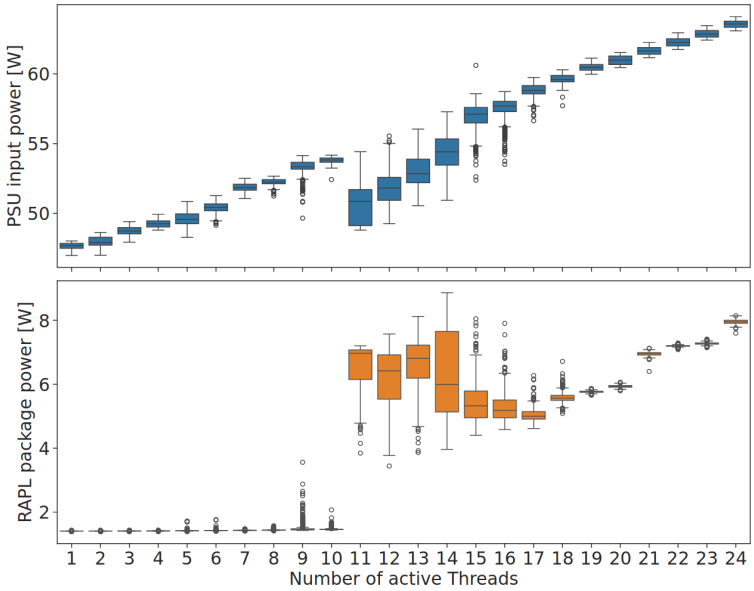


FIGURE 2.3: RAPL and reference power consumption sampled at 100 ms / 50 ms intervals respectively. Double precision matrix multiplication kernel at 0.8GHz running for 60s each at increasing number of active threads[27].

2.3.3.3 RAPL Limitations and issues

Several limitations of RAPL were noticed in various research works. Since RAPL is continually improved by Intel as new Processors are released, some of these issues have since been improved or entirely solved.

- **Register overflow:** The 32-bit register can experience an overflow error[25, 31]. This can be mitigated by sampling more frequently than the register takes to overflow. This interval can be calculated using the following equation:

$$t_{\text{overflow}} = \frac{2^{32} \cdot E_u}{P} \tag{2.1}$$

Here, E_u is the energy unit used (61μJ for haswell), and P is the power consumption. On a Haswell processor consuming 84W, an overflow would occur every 52 minutes. Intel acknowledges this in the official documentation, stating that the register has a *wraparound time of around 60 seconds when power consumption is high*[26] This is solvable with a simple correction, provided that the measurement interfals are small enough: For two successive measurements m_{prev} and m_{current}, the actual measured difference is given by

$$\Delta m = \begin{cases} m_{\text{current}} - m_{\text{prev}} + C & \text{if } m_{\text{current}} < m_{\text{prev}} \\ m_{\text{current}} - m_{\text{prev}} & \text{otherwise} \end{cases} \tag{2.2}$$

where C is a correction constant that depends on the chosen mechanism:

mechanism	**constant C**
MSR	`u32::MAX` i.e. $2^{32} - 1$
perf-events	`u64::MAX` i.e. $2^{64} - 1$
perf-events with eBPF	`u64::MAX` i.e. $2^{64} - 1$
powercap	value give by the file `max_energy_uj` in the sysfs folder for the RAPL domain

TABLE 2.2: RAPL overflow correction constant

- **DRAM Accuracy:** DRAM Accuracy can only reliably be used for the Haswell architecture[14, 30, 31], and may still exibit a constant power offset (like attributed to the voltage regulator power loss of the memory system).

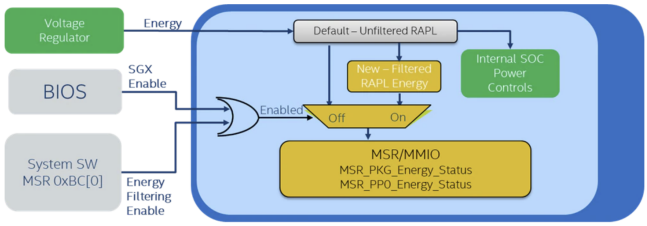
- **Unpredictable Timings:** While the Intel documentation states that the RAPL time unit is 0.976ms, the actual intervals may vary. This is an issue since the measurements do not come with timestamps, making precise measurements difficult[31]. Several coping mechanisms have been used to mitigate this, notably *busypolling* (busypolling the counter for updates, significantly compromizing overhead in terms of time and energy[32]), *supersampling* (lowering the sampling interval, increasing overhead and occasionaly creating duplicates that need to be filtered[31]), or *high frequency sampling* (*lowering* the sampling rate when the resulting data is still sufficient[33]). Another solution is to use a *low sampling frequency* to smoothe out the relative error due to spikes, with the only drawback of loss of temporal precision. At sampling rates slower than 50Hz, the relative error is less than 0.5% [23].

- **Non-atomic register updates:** RAPL register updates are nont atomic[31], meaning that the different RAPL values show a delay between individual updates. This may introduce errors when sampling multiple counters at a high sampling rate, making it possible to read both fresh and stale values of different counters.

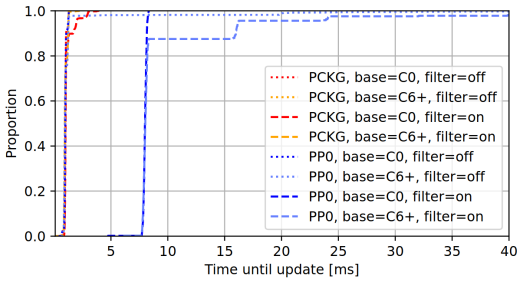
- **Lower idle power accuracy:** When measuring an idling server, RAPL tends to be less accurate[14, 27].

- **Side-channel attacks:** While the update rate of RAPL is usually 1ms, it can get as low as 50 μs for the PP0 domain (processor cores) on desktop processors[27]. This can be used to retrieve processed data in a side channel attack (coined "Platypus")[27, 34].

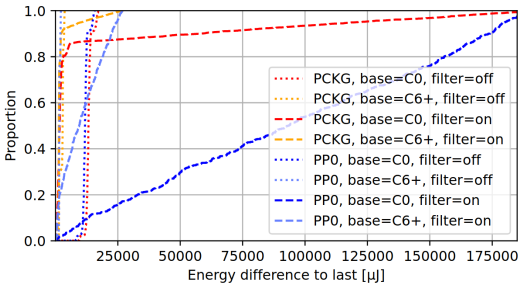
To mitigate this issue while retaining RAPL functionality, Intel implements a filtering technique via the `ENERGY_FILTERING_ENABLE`[35, Table 2-2] entry, or when *Software Guard Extension (SGX)* is activated in the BIOS. This filter adds random noise to the reported values (vizualized in Figure 2.4a). This can be seen For the PP0 domain, this raises the temporal granularity to about 8ms. While this does not affect the average power consumption, point measurement power consumption can be affected. Figure 2.4 shows the effect of the filter, clearly indicating the loss granularity resulting from the activation of the filter. In a 2022 article, Tamara[36] found a surprising higher mean with the filter activated and deemed filtered RAPL energy data unusable. In a more elaborate experiment in 2024, Schöne et al did not encounter these inaccuracies anymore.



(A) RAPL energy filtering[37]



(B) Distribution of time between updates: With an enabled filter, the PP0 domain only provides updates every 8 ms, otherwise RAPL values are updated every 1 ms. If the load is too low, some updates might be skipped, e.g., the next update for PP0 and an enabled filter is at 16 ms.



(C) The minimal increase of a measurement is 1 energy unit of 61.035 μJ. Enabling the filter leads to a significant influence on measurements for the PP0 domain and a measurable influence on PCKG measurements.

FIGURE 2.4: Observable loss of granularity caused by the activation of `ENERGY_FILTERING_ENABLE`[27]

2.3.3.4 RAPL conclusions

The energy measurement accuracy of RAPl has significantly improved since its inception and provides a generally accepted way to measure system energy consumption. It is well-validated and accepted as the most accurate fine-granular energy measurement tool. Some known limitations have historically created inaccuracies in developed measurement tools, but corrections of these limitations exist.

2.3.4 Graphical Processing Units (GPU)

In recent years, the utilization of GPUs in cloud computing environments has grown significantly, driven primarily by the increasing demand for high-performance computations in machine learning, artificial intelligence, and large-scale data processing [38]. Kubernetes now includes mechanisms for GPU provisioning, enabling containerized workloads to leverage GPU acceleration [39].

Although GPUs remain less common than traditional CPU-based workloads in typical Kubernetes clusters, their adoption is rapidly accelerating. Industry reports indicate that GPU usage in Kubernetes has seen a growth rate of nearly 58% year-over-year, outpacing general cloud computing growth rates [40]. This increase is largely attributed to ML workloads and real-time processing tasks that benefit from the parallel processing capabilities of GPUs [41]. Furthermore, hyperscalers have integrated GPU support directly into their managed Kubernetes services, reflecting the growing demand for GPU-powered workloads in containerized environments.

Despite this growth, GPU deployments are still not as pervasive as CPU-based workloads in Kubernetes-managed clusters. The primary focus of this thesis is on the measurement and analysis of energy consumption in more common, CPU- and memory-centric Kubernetes workloads. Nevertheless, due to the rising significance of GPUs, their energy measurement techniques and potential integration within Kubernetes environments are briefly examined.

Ultimately, the inclusion of GPU energy measurements remains outside the primary scope of this thesis but is acknowledged as an important area for future research. This structured exploration serves to highlight current limitations and opportunities for enhancing energy efficiency in Kubernetes-managed GPU workloads.

2.3.4.1 GPU virtualization technologies

Full GPU Virtualization Full GPU virtualization provides isolated instances of a single physical GPU to multiple virtual machines. This is achieved using technologies such as NVIDIA's *vGPU* or AMD's *MxGPU (Multiuser GPU)*. These technologies allow a VM to see a complete GPU, while the underlying hypervisor manages resource partitioning and scheduling [42, 43] eigher though the use of partitioning or time-slicing. In a Kubernetes environment, full GPU virtualization is commonly utilized through:

- **vGPU on VMware or OpenStack:** Kubernetes clusters running on VMware vSphere or OpenStack can request vGPU instances as if they were physical GPUs. These instances are shared among containers while maintaining memory and compute isolation.
- **Device Plugin Integration:** NVIDIA, AMD and Intel provide a Device Plugin for Kubernetes, enabling seamless GPU discovery and allocation across pods [39].

Multi-Instance GPU (MIG) Introduced with the NVIDIA A100 architecture, Multi-Instance GPU (MIG) allows a single GPU to be partitioned into up to seven independent instances, each with its own dedicated compute, memory, and cache resources [44]. Unlike traditional vGPU, MIG provides true hardware-level isolation, preventing noisy-neighbor effects and enabling finer resource allocation. MIG instances are exposed to Kubernetes as individual GPUs. For example, a single A100 GPU partitioned into seven MIG instances appears as seven separate GPU resources, each assignable to different containers. MIG-aware device plugins ensure proper scheduling and isolation. Hence, MIG technology is particularly useful for multi-tenant environments and supports finer granularity in resource allocation compared to traditional vGPU models.

GPU Passthrough GPU passthrough allows a physical GPU to be exclusively assigned to a single VM or container. Unlike virtualization, where resources are shared, passthrough dedicates the full GPU to one environment, offering near-native performance [45]. GPU passthrough is configured at the hypervisor level (e.g., KVM or VMware ESXi) and can be exposed to Kubernetes nodes. Pods scheduled on nodes with GPU passthrough access gain complete control of the GPU, enabling direct memory access and high-performance computation.

GPU virtualization technologies enable efficient multi-tenant use of GPU resources, enhancing performance and cost-effectiveness in cloud-native environments. For the purposes of energy measurement, understanding these virtualization layers is essential for accurate per-container energy attribution.

2.3.4.2 GPU nvidia-NVML energy measurements and validation

Modern GPUs are equipped with **built-in power sensors** that enable real-time energy measurement. For instance, Nvidia GPUs expose power metrics through the *Nvidia System Management Interface (nvidia-smi)*, which reports instantaneous power draw, temperature, and memory usage [46]. This interface allows for programmatic access to GPU power consumption, making it a common choice for monitoring and energy profiling in both standalone and containerized environments [44].

In 2024, Yang et al. conducted a comprehensive study on the accuracy and reliability of NVIDIA's built-in power sensors, examining over 70 different models[47]. He concludes that previous research placed excessive trust in nvidia-NVML, overlooking the importance of measurement methodology. The study revealed several critical findings:

- **Sampling Limitations:** Nvidia NVML gives the option to specify a sampling frequency in units of milliseconds. However, on certain models, such as the A100 and H100, power is sampled only around 25% of the time, introducing potential inaccuracies in total energy consumption estimations.
- **Transient Response Issues:** While measured power reacted instantly to a suddenly applied workload, nvidia-NVML would report values with a delay of several hunderd milliseconds on some devices. Also, a slower rise (with linear growth) was discovered, taking over a second to catch up to correct power figures in some instances. Generally, server-grade GPUs were shown to provide more instantaneous power measurements.
- **Measurement Inaccuracies:** The average error rate in reported power draw was found to be approximately 5%, deviating from NVIDIA's claimed fixed error margin of 5W. This error would remain consistent when the GPU reached a constant power draw.
- **Averaging Effects:** Reported power consumption values are averaged over time, masking short-term fluctuations and potentially underreporting peak consumption.

To address these limitations, the study proposed best practices such as running multiple or longer iterations of workloads to average out sampling errors, introducing

controlled phase shifts to capture different execution states, and applying data corrections to account for transient lags [47]. These adjustments reduced measurement errors by up to 65%, demonstrating the importance of refining raw sensor data for more accurate energy profiling.

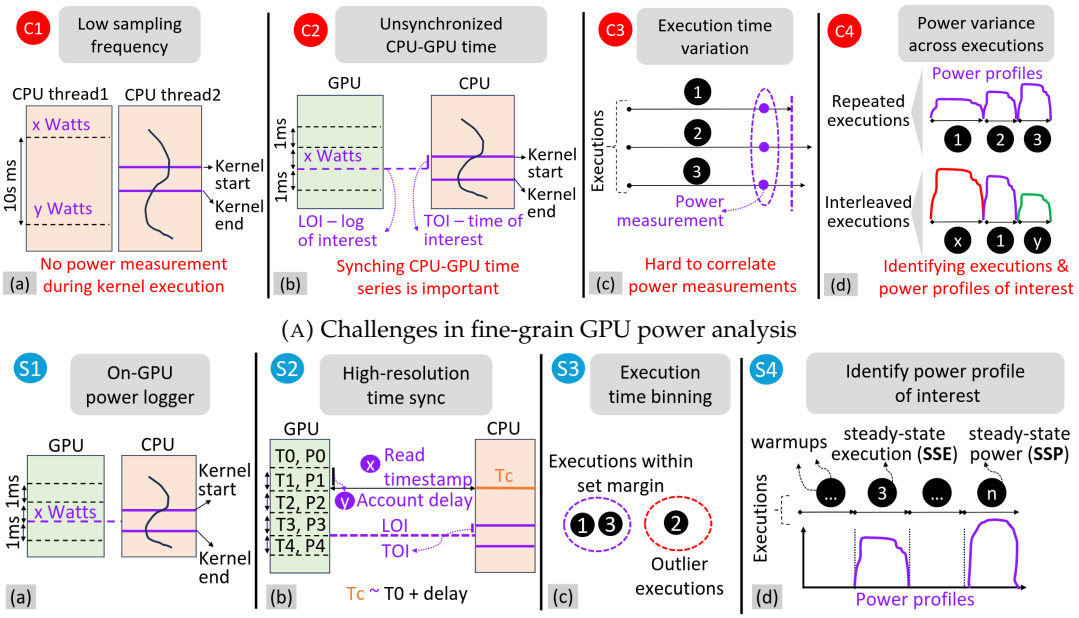
2.3.4.3 Related Research

While most reaseach has used nvidia-NVML to measure GPU power consumption, some research was done on alternative measurement tools, ususally to address similar issues as were stated by Yang et al in the previous section. Specifically, the following three tools focussed were proposed to provide higher sampling rates to enable finer-grained power analysis.

AccellWattch In 2021, Pan et al proposed *AccelWattch*[48], a configurable GPU power model that provides both a higher accuracy cycle-level power model, and a way to measure constant and static power, utilizing any pure-software software performance mode,nvidia-NVML, or a combination of the two. Notably, their model is DVFS-, power-gating- and divergence-aware. The resulting power model was validated against measured ground truth using an Nvidia Volta GV100, yielding a MAPE error between $7.5 - 9.2 \pm 2.1\% - 3.1\%$, depending on the AccelWattch variant. The Volta model was later validated against Pascal TITAN X and Turing RTX 2060-architectures without retraining, achieving $11 \pm 3.8\% and 13 \pm 4.7\%$ MAPE, respectively. The authors conclude that AccelWattch can reliably predict power consumption of these specific GPU architectures. In the context of Kubernetes energy consumption, AccelWattch contributes a fine-grained temporal granularity

FinGraV In 2024, Singhania et al propose *FinGraV*[49] (abbreviated from **Fin**e-**Gra**in **V**isibility), a fine-grained power measurements tool capable of sub-millisecond power profiling for GPU executions on an AMD MI300X GPU. They identify these main challenges of high-resolution GPU power analysis (see figure 2.5a):

- **Low sampling frequency:** Standard GPU power loggers operate at intervals too coarse (tens of milliseconds) to capture the sub-millisecond executions of modern kernels.
- **CPU-GPU time Synchronization:** Synchronizing power measurements with kernel start and end times is problematic due to the asynchronous nature of CPU-GPU communication.
- **Execution time variation:** Minor variations in memory allocation or access patterns lead to inconsistent kernel execution times, complicating time-based power profiling.
- **Power variance across executions:** Repeated executions of the same kernel, or interleaved executions with other kernels, manifest in fluctuating power consumption, challenging consistent profiling.



(A) Challenges in fine-grain GPU power analysis

(B) FinGraV strategies to adress challenges

FIGURE 2.5: FinGraV GPU power measurement challenges and strategies[49]

To overcome these challenges, FinGraV introduces several strategies (see figure 2.5b).

- **On-GPU Power Logger:** FinGraV leverages a high-resolution (1 ms) power logger, capturing the average of multiple instantaneous power readings.
- **High-Resolution Time Synchronization:** GPU timestamps are read from the CPU side before kernel execution, and synchronization is maintained throughout execution to correlate power samples with kernel events.
- **Execution Time Binning:** Kernel executions are grouped into "bins" based on empirical runtime ranges, enabling tighter power profiling while discarding outlier runs.
- **Power Profile Differentiation:** FinGraV distinguishes between Steady-State Execution (SSE) and Steady-State Power (SSP) profiles. SSP represents the stabilized power consumption after initial transients, providing the most accurate depiction of kernel power consumption.

The application of FinGraV to bencharmks reveals several critical obervations: Kernel executions differ significantly between initial runs and steady-state, with deviations up to 80%. Memory-bound kernels and compute-light kernels are found to be highly sensitive to the preceding kernel, impacting their power profile. Furthermore, the authors expose discrepancies in GPU power scaling relative to computational load, particularly for compute-light kernels.

FinGraV introduces promising concepts that could, in theory, enable more granular and accurate GPU power analysis in container-based GPU workloads. Its methodological approach addresses key challenges in sub-millisecond power measurement. However, its current implementation is tightly coupled with the AMD MI300X GPU,

relying on hardware-specific logging capabilities that are not universally available. While the underlying concepts may be extendable to other GPUs, achieving this is far from trivial, requiring significant adaptation and low-level access to power metrics that are often proprietary or limited by driver capabilities.

Consequently, FinGraV highlights both the challenges and potential solutions for fine-grained GPU power analysis but falls short of providing a general-purpose framework that could be easily integrated into Kubernetes energy measurement tools. It also underscores the broader issue that GPU energy consumption analysis remains relatively immature, with only vendor-specific tools like nvidia-NVML offering practical—albeit coarse—power metrics. This illustrates that while the methodology is theoretically sound, practical implementation across diverse GPU architectures remains a significant challenge.

PowerSensor3 *PowerSensor3*[50] is an open-source hardware tool introduced in 2025, designed to provide high-resolution power measurements for GPUs, SoC boards, PCIe devices, SSDs, and FPGAs. Unlike software-based power models or vendor-specific tools such as NVIDIA's NVML, PowerSensor3 achieves significantly higher accuracy and granularity through direct voltage and current measurements at a sampling rate of up to 20 kHz. This fine temporal resolution allows it to capture transient power behaviors that are typically missed by software-based methods, which are constrained by lower sampling frequencies and indirect estimations. As expected for a purpose-built hardware solution, PowerSensor3 outperforms NVML in both precision and the ability to detect rapid changes in power consumption.

A particularly valuable feature of PowerSensor3 is its capability to monitor not only GPUs but also other critical components such as SoC boards, PCIe-connected accelerators, and storage devices like SSDs. For Kubernetes-based energy efficiency analysis, this would provide unprecedented visibility into the power usage of individual containers, extending monitoring beyond the CPU and GPU to the broader spectrum of peripherals that contribute to overall energy consumption. Such granularity could enhance resource scheduling and energy optimization in containerized environments.

However, while its technical benefits are evident, the practical deployment of dedicated hardware sensors like PowerSensor3 at scale remains both complex and expensive. Integrating such devices across large Kubernetes clusters would require substantial investment in hardware and reconfiguration of infrastructure, making wide adoption unlikely outside of specialized research environments. Consequently, PowerSensor3 and other hardware-dependent methods are not considered in the scope of this thesis. Furthermore, the very recent introduction of PowerSensor3 in 2025 highlights the ongoing challenges of accurate energy monitoring through software alone, reflecting the current gap in reliable, scalable, software-based power measurement solutions.

2.3.4.4 GPU Limitations in Kubernetes Context

The analysis of GPU power consumption has revealed promising research efforts aimed at achieving fine-grained power visibility and energy optimization. Tools such as FinGraV and PowerSensor3 demonstrate that significant strides are being

made in capturing detailed power metrics with high temporal resolution and sub-component granularity. FinGraV addresses the complexities of short-lived GPU kernel executions through innovative profiling methodologies, while PowerSensor3 delivers hardware-level accuracy for GPUs, SoC boards, and various PCIe-connected peripherals. These solutions underscore the potential for more refined power monitoring in high-performance GPU workloads.

However, the current state of GPU energy consumption measurement presents significant challenges for scalable, container-based energy tracking in Kubernetes environments. Research tools like FinGraV and PowerSensor3, while technically robust, are either hardware-dependent or too tightly coupled to specific architectures—such as AMD's MI300X in the case of FinGraV. Hardware-based solutions like PowerSensor3, though highly accurate, are impractical for widespread deployment due to cost and scalability concerns. Meanwhile, software-based vendor solutions such as NVIDIA's NVML are far more accessible, but suffer from limitations in temporal granularity and measurement accuracy. These tools offer convenient integration and broad support across data center infrastructures but struggle with capturing rapid transients in power consumption, which are crucial for real-time container energy attribution.

In the context of this thesis, GPU energy consumption is acknowledged as an important yet currently impractical aspect of container energy measurement. The relative immaturity of fine-grained, scalable monitoring solutions for GPUs, combined with the relatively small role of GPUs in Kubernetes clusters, justifies this exclusion. Although the utilization of GPU accelerators in Kubernetes environments is expected to grow, current measurement methods do not yet support the level of precision and scalability required for effective implementation. As such, this thesis will focus on more readily measurable server components, with the understanding that future advancements in GPU power analysis may enable their integration into Kubernetes-based energy efficiency strategies.

2.4 Server Power models

In the absence of actual power data, power consumption models can be formulated that essentially map variables (such as CPU, Memory utilization) related to a server's state to its power consumption. Due to the strong correlation between CPU uzilization and server power, a great number of models use CPU metrics as the only indicator of server power. Fan et al[51] proposed a linear interpolation between idle power and full power, which they further refine into a non-linear form, with a parameter γ to be fitted to minimize mean square error. Similar research was done to further reduce error by introducting more complex non-linear models, such as Hsu and Poole[52], who studied the SPECpower_ssj2008-dataset of systems released between December 2007 and August 2010, and suggested the adaptation of two non-linear terms:

$$P_{\text{server}} = \alpha_0 + \alpha_1 u_{\text{cpu}} + \alpha_2 \left(u_{\text{cpu}}\right)^{\gamma_0} + \alpha_3 \left(1 - u_{\text{cpu}}\right)^{\gamma_1} \tag{2.3}$$

While models like these might work well when custom-fitted to specific, multi-purpose servers, they have since been surpassed by the more common approach of modelling server power is to consider it an assembly of its components, such as

Song et al[53] propose as:

$$P_{\text{server}} = P_{\text{cpu}} + P_{\text{memory}} + P_{\text{disk}} + P_{\text{NIC}} + C \tag{2.4}$$

, where C denotes the server's base power, which includes the power consumption of other components (regarded as static). This approach can easily be extended to include various other components such as GPUs, FPGAs or other connected components.

....

In a systematic review cloud servers power models, Lin et al[13] state that the common way

2.5 Power data collection

see Lin et al for overview -> instruments / dedicated aquisition system / software monitoring and calculation / simulation

2.5.1 CPU

2.5.2 Memory

2.5.3 Storage

2.5.4 Networking

2.6 Container energy estimation based on hardware power estimation

2.7 Tools

2.7.1 RAPL-based tools

- [23] An experimental comparison of software-based power meters (focus on CPU / GPU)
- [50] fast accurate opensource: PowerSensor3 enables real-time power measurements of SoC boards and PCIe cards, including GPUs, FPGAs, NICs, SSDs, and domain-specific AI and ML accelerators
- [16] Rapid and accurate energy models through calibration with IPMI and RAPL
- [54] Scaphandre. Does not handle overflows correctly (https://github.com/hubblo-org/scaphandre/issues/280)
- [55] Smartwatts: Self-Calibrating Software-Defined Power Meter for containers
- [56] JoularJX: jaba-based agent for power monitoring at the code level
- [57]: KEPLER

- [58]: "AI power meter": Library to measure energy usage of machine learning programs, uses RAPL for CPU and nvidia-smi for GPU
- [59] CodeCarbon: Python package, estimates GPU + CPU + RAM: uses pynvml, ram RATIO (3W for 8G) and RAPL. According to Raffin2024, this tool does not account for the MSR overflow: https://github.com/mlco2/codecarbon/issues/322 -> apparently fixed now
- [60]: powertop
- [61]: Green metrics tool: measuring energy and CO2 consumption of software through a software life cycle anslysis (SLCA): Metric providers: RAPL, IPMI, PSU, Docker, Temperature, CPU, ... (sone external devices)

  according to raffin2024: simplified versions of scaphandre and codecarbon hhve 3%, 0.5% overhead at 10Hz according to [23], the full versions have between 2 and 7% at 1Hz.

  [62]: PowerAPI: Python framework for building software-defined power

2.8 "data fusion of power data and cpu metrics

- Estimating the consumption of a single function has been proven to be possible in 2012: M. Hähnel, B. Döbel, M. Völp, and H. Härtig, “Measuring energy consumption for short code paths using RAPL,”, [32]

Chapter 3

Analysis of Energy Consumption Tools

3.1 Introduction

Purpose of tool analysis and its role in your hybrid model.

Explain categories:

General Server Monitoring

Container-Level Monitoring

3.2 General Server Monitoring Tools

PowerSensor3, Powertop, Green Metrics Tool, Kavanagh 2019.

Focus on system-wide measurement.

Capabilities and limitations.

3.3 Container-Level Monitoring Tools

KEPLER, Scaphandre, Smartwatts, JoularJX, AI Power Meter, CodeCarbon.

Granularity down to the container level.

Discuss their internal mechanisms (e.g., eBPF, RAPL, NVML).

Advantages and drawbacks.

3.4 Comparison of Tools

Detailed matrix comparing:

Measurement methodology.

Component focus (CPU, RAM, GPU, Disk, Network).

Real-time capabilities.

Kubernetes compatibility.

3.5 Conclusion and Selection for VT2 Research

Justify which tools will be part of your VT2 methodology.

Discuss limitations of the discarded tools.

Appendix A

Appendix Title

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