Can OS Specialization give new life to old carbon in the cloud?

Han Dong
Boston University
Boston, USA
handong@bu.edu

Sanjay Arora
Red Hat Inc
New York, USA
saarora@redhat.com

Orran Krieger
Boston University
Boston, USA
okrieg@bu.edu

Jonathan Appavoo
Boston University
Boston, USA
jappavoo@bu.edu

ABSTRACT

Is there "fat" (overheads) in cloud computing infrastructure software that can be trimmed? Would doing so help ameliorate the need for frequent hardware refreshes and extend the life of existing hardware? In this paper, we demonstrate that, indeed, there is "fat" that can be trimmed by using specialized OS-based software stacks. Doing so can allow decade-old computers to be used for critical cloud infrastructure services, potentially yielding 3x improvements in efficiency compared to standard software stacks on newer hardware. The implications of these results raise the possibility of exploiting OS optimizations to reduce server hardware obsolescence. Further, it suggests the importance of addressing the key portability challenges of specialized OS stacks.

CCS CONCEPTS

• **Hardware** → **Power and energy**; • **Computer systems organization**;

KEYWORDS

sustainability, operating systems, measurement

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1 INTRODUCTION

In this paper, we discuss the opportunity to breathe new life into old hardware by using specialized software for data center-scale applications. Doing so can potentially reduce cloud computing providers' embodied and operational carbon footprints. However, to realize this potential, we must address some challenges and open problems.

We present data suggesting that using specialized software stacks for dedicated services can enable performance improvements and energy savings by over 3X on older hardware. These improvements make it viable to use older hardware for performance critical services and help reduce hardware obsolescence by prolonging the life of purchase hardware within data centers. A data center operator can then squeeze more value out of their investments by judiciously using their modern higher-performance hardware.

1.1 Background

A hallmark of modern cloud computing are the fleets of servers that run core infrastructure services such as in-memory caches and databases [17]. While not glamorous, these services are critical in ensuring that hot data used on every web request resides in memory and thus can be efficiently accessed and computed on.

For example, serving a single page involves many internal transactions accessing static and dynamic data such as images, text, and generating personalized content like stats, feeds, and ads. To ensure a fast response, this initial request is split into many smaller parallel transactions to multiple distributed servers. Each transaction must then complete promptly to meet the provider's service-level agreement (SLA), an example is that 99% of requests are satisfied within X milliseconds or microseconds. To meet these stringent latency requirements, the aforementioned in-memory services are often scaled horizontally in dedicated nodes, and run on hundreds of clusters representing hundreds of thousands of cores and growing [46, 49].

Ultimately, to meet these SLA targets while keeping the development and maintenance burden of these web pages reasonable, developers rely on generic reusable software components, which in turn run on the generic, widely used operating systems (OSes), such as Linux, that they know and are familiar with. While it is easy and natural to deploy on Linux, there is also a broad understanding in the systems community that *specialization* improves overall *efficiency*. Prior research has demonstrated that when running

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a single primary application, a specialized OS tailored to the application's needs, can yield orders of magnitude better performance [4, 8, 10, 15, 22, 24–26, 29–34, 36, 38–40, 43, 48, 51], however, we find there has been limited works to explore their performance and power efficiency [37]/carbon tradeoffs.

Therefore in this paper, we present preliminary results from a novel comparative performance and carbon study of two distinct OSes, Linux and a specialized library OS stack, EbbRT [43], on different hardware generations. We demonstrate that a baremetal EbbRT deployed on older process node technology (Q3'14) can yield significant performance and energy wins over newer hardware (Q2'21) running Linux. Further, our results also suggest that with the ever-increasing demands for cloud services, specialized OS stacks can help abate the demand to replace/upgrade older hardware.

Obviously, the use of specialized OSes need not be restricted to older hardware given prior work demonstrating how newer hardware features are used for significant performance gains [10, 15, 16, 25, 32, 36, 51]. However, in this work we restrict EbbRT to run on older hardware in order to: 1) motivate its adoption to address server hardware obsolescence while improving both performance and power/carbon efficiency, 2) highlight the portability challenges to using library OSes such as EbbRT as it would've required significant engineering effort (i.e. developing and maintaining device drivers) to work with new hardware, 3) and help pave a way forward of how one can marry the portability of Linux with the advantages of these specialized stacks in §4.

The remainder of this paper is organized as follows. In §2, we present results from our study on three generations of Intel server-class nodes. We then discuss the results with respect to carbon emissions in §3. In §4, we conclude with a discussion of potential implications and future work that our results suggest.

2 STUDY

2.1 Software Stacks

Our study aims to expose the performance and energy consumption of generic versus specialized software stacks. Each stack is composed of an OS and a primary application. We use two applications that prior work has used to evaluate in-memory services: 1) memcached [8, 14, 16, 32, 38, 43] and a transactional database, silo [10, 36].

2.1.1 ***OSes.*** We explore the impact of software stack specialization by comparing a commodity OS, Linux, commonly used by cloud providers and a research library OS, EbbRT, designed for event-driven network-oriented applications. These OSes represent two extremes in design: Linux is a general-purpose OS with tens of millions of lines of code supporting a wide range of hardware and applications, and EbbRT is a specialized OS with about 20K lines of code that supports a single application on a specific hardware platform.

Linux uses the default Ubuntu 22 images available on CloudLab [13], which runs the Linux 5.15 kernel. To ensure a fair comparison between the OSes, we optimize Linux by using the `performance` governor[1], fixing packet receive interrupts to specific cores, and enabling large-page support. We measure CPU package power and instruction counts using Linux *perf* [18], which employs Intel RAPL [9] for energy measurements, and has been independently validated by other researchers [11, 27, 50].

EbbRT is a library OS/unikernel that was developed almost a decade ago, whose advantages with respect to KVM virtualized performance (over 2X compared to Linux) was previously published [43]. Shortly after, we developed an EbbRT device driver for the Intel 10 GbE NIC from scratch [12], which permits EbbRT to run non-virtualized on bare-metal hardware with this older NIC. Like other specialized OSs [4, 8, 10, 30, 32, 34, 36, 38, 48, 51], EbbRT features a small optimized code base with custom event-driven interfaces and components designed to eliminate the overheads associated with a general-purpose OSes. Optimized applications are written to these interfaces, compiled with the kernel code, and executed within the single supervisor-privileged domain.

Unfortunately, these specialized OSes have seen little adoption due to the difficulty of maintaining and forward porting them to new hardware and software. To our knowledge, beyond UniKraft[28], there are few, if any, non-active research uni-kernels. Given our goal of evaluating, in the extreme, what benefits OS specialization can have concerning breathing new life into older hardware, we use bare-metal EbbRT, which aggressively uses multi-threading, large-pages, and has a version of both memcached and silo ported to it.

2.1.2 ***Applications.*** We use two standard applications to evaluate our OS stacks.

memcached: This widely used OS-demanding caching application benefits from specialization techniques like kernel bypass to improve performance [8, 14, 16, 32, 38, 43]. In our study, we use the Ubuntu-provided memcached-1.6.26 for the Linux stack, while EbbRT uses a re-implemented version tailored to its native interfaces, supporting the standard memcached binary protocol.

[1]We also experimented with Linux's dynamic `ondemand` governor, which showed reduced overall performance compared to `performance` mode. For example, in memcached on Linux-Node3, `ondemand` reached only 37% of the peak throughput of `performance`. However, at lighter RPS rates, `ondemand` used up to 43% less power than `performance`. Ultimately, EbbRT consumed the least power overall, 2.3 times less than `ondemand` for the same RPS rates.

Name	CPU	Node	Release	Threads	TDP (W)	Idle (W)	NIC	DDR4 RAM	SSD
Client	Intel Xeon Silver 4314	10 nm	Q2'21	32	135	45	Mellanox 40GbE	128GB	960 GB
Node1	Intel E5-2630 v3	22 nm	Q3'14	2 x 16	2 x 85	16	Intel 82599ES 10GbE	128GB	480 GB
Node2	Intel Xeon Silver 4114	14 nm	Q3'17	2 x 20	2 x 135	47	Intel X710 10GbE	192GB	480 GB
Node3	Intel Xeon Silver 4314	10 nm	Q2'21	2 x 32	2 x 135	89	Mellanox 40GbE	256GB	960 GB

Table 1: Different hardware used in experiments. We used Linux perf [18] to measure its idle power consumption. We have also validated the idle power number on LibOS for Node1. Note that Node1, Node2, Node3 all have 2 packages in one node.

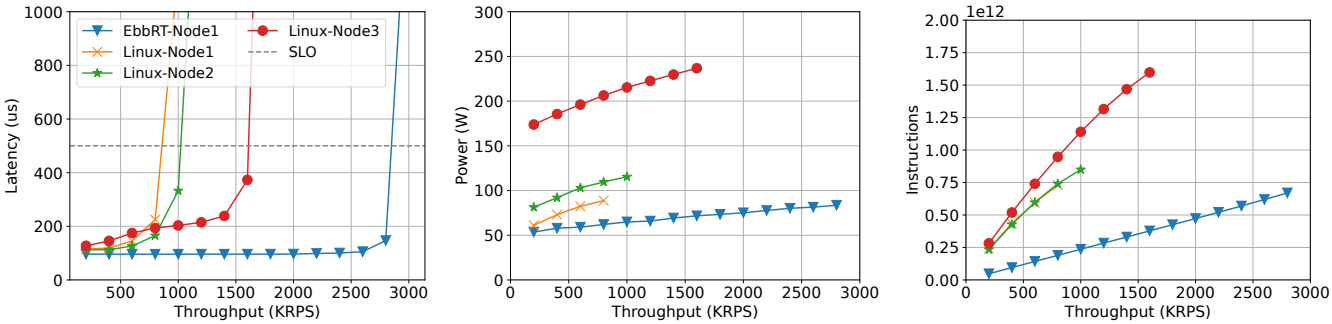


Figure 1: Memcached latency, power, and instruction count measures at different RPS rates.

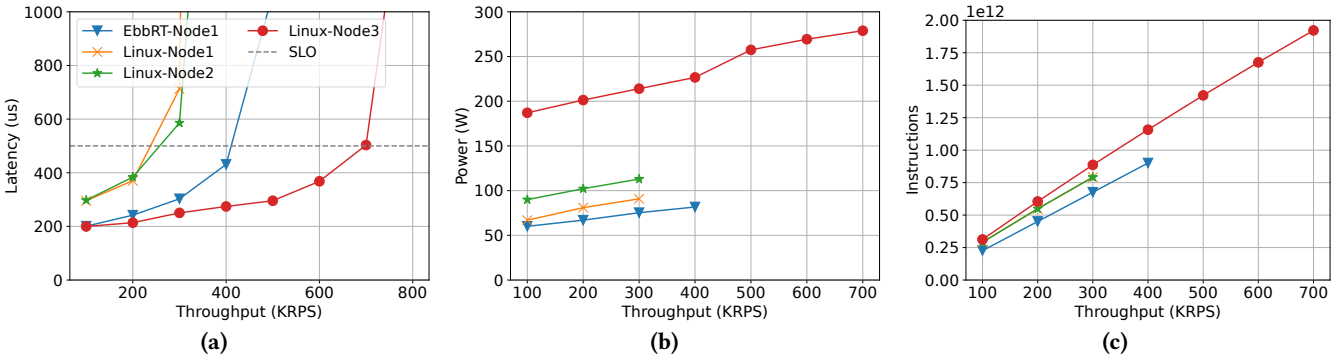


Figure 2: Silo latency, power, and instruction count measures at different RPS rates.

silo: Cloud services also use systems that support complex operations on stored data, such as in-memory relational databases (SQL and No-SQL) [3]. These databases impose significantly more CPU and memory load per operation than memcached. Silo [47] is designed to represent this type of application. We built, from source, a version of silo [35] with a web front-end for both OSes. Each incoming web request triggers a set of TPC-C transactions on its in-memory database component.

2.2 Hardware

Details of the hardware nodes used in the study are in Table 1. We set up a cluster of these nodes using CloudLab [13]. The core goal is to compare EbbRT booted on the oldest CPU technology, Node1 (2014), to Linux on all three CPU generations: Node1 (2014), Node2 (2017), and Node3 (2021).

2.3 Methodology

To generate load on the memcached and silo servers, we use the mutilate [21] tool in order to create load across a total of 1280 connections - this is coordinated by using four of the Client node type shown in table 1. The load is based on the representative ETC workload from Facebook [5]. We use a standard SLA (as used by others [8, 16, 32, 36, 43]) of 99% latency under 500 μs for both applications and we increase the amount of requests-per-second (RPS) at mean rates until the server node is saturated where it can no longer meet the SLA. We run each mean RPS rate for a total of 30 seconds in order to measure the server node's power, instruction count, and the reported 99% latency at the corresponding RPS rate. Experiments were repeated up to four times, with worst-case standard deviations of 2.49% from the mean.

2.4 Performance Results

Fig. 1 and fig. 2 illustrates the overall data from our study. For each application, we present performance as the load is increased (fig. 1a and fig. 2a), along with its measured power consumption (fig. 1b and fig. 2b,) and instruction counts (fig. 1c and fig. 2c)[2].

By enabling both OS stacks to use all available cores on a hardware node, we can observe how the stacks compare in terms of their ability to satisfy a particular load (e.g. throughput in KRPS). The memcached results indicate that `EbbRT-Node1` can satisfy requested loads with considerably fewer instructions: almost 5X reduction when compared to `Linux-Node1`. This reduction reveals both the "fat" (overheads) of the general-purpose OS and the ability of the specialized OS to trim it.

We note that given the OS-centric nature of memcached, the instruction counts in fig. 1c reveals more insight into the ability of EbbRT to squeeze more out of the hardware. While it is unsurprising that `Linux-Node2`, and `Linux-Node3` require more instructions given the higher thread count of their CPUs, `EbbRT-Node1` can still achieve a higher peak throughput (1.75X over `Linux-Node3`) while using the fewer threads available on `Node1`. Furthermore, contrasting the shape of the curves, one can see that EbbRT's instruction count scales linearly with the load. This indicates its ability to use the threads of the `Node1` more efficiently. In contrast, the non-linearity of the Linux curves shows poorer scalability and suggests multi-core overheads. Prior works in optimizing memcached [8, 16, 32, 36, 43] have also remarked on these scalability issues.

Given that silo is a more compute-intensive application and that both OS stacks are constructed with the same application source, it is harder to see the instruction count differences in fig. 2c. The raw data reveals that at a query rate of 100 KRPS on `Node1`, EbbRT requires 22% fewer instructions compared to Linux. While not as dramatic a difference, eliminating this overhead helped contribute to the specialized OS being able to squeeze out a 2X improvement in the peak throughput compared to `Linux-Node1` and `Linux-Node2`. Lastly, we note that the increased number of CPUs and faster clock speeds of `Node3` eventually enable Linux to achieve the highest peak throughput for silo in our study (1.75X better than EbbRT-Node1). The following sections examines the carbon implications of these trade-offs in more detail.

3 CARBON ANALYSIS

In the prior section, we observed that a specialized software stack can support critical work with fewer instructions, resulting in greater efficiency, higher performance, and lower energy consumption when run on older hardware (a 22nm-2014 CPU, DRAM, and NIC conforming to a networking standard defined in 2002 [1]). This data also exposes a form of software-driven hardware obsolescence that increases e-waste and carbon. To extrapolate on this observation, we conduct an analysis below which considers both the embodied and operational carbon of our study.

[2]Note for figures (b) and (c), we filter out RPS values that violate the SLA objective.

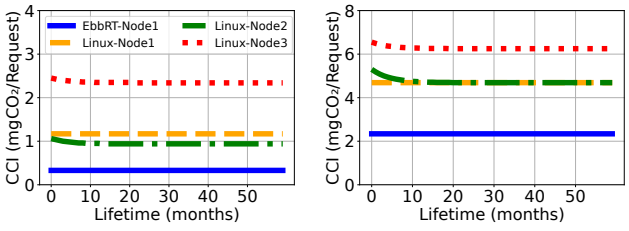
	CO2 (kg)			
	CPU	DRAM	SSD	Total
Node1	14.2	86.9	17.3	118.4
Node2	13.1	122.5	17.3	152.9
Node3	15.1	172.5	34.3	221.9

Table 2: Embodied carbon calculations.

3.1 Computational Carbon Intensity (CCI)

For this analysis, we use the Computational Carbon Intensity (CCI) metric [45] as it helps calculate the lifetime CO_2 released per unit of work. Further, CCI captures both embodied and operational carbon while rewarding the reuse of existing hardware. Roughly, CCI is defined as: $\frac{\sum_{lifetime}(C_M+C_C+C_N)}{\sum_{lifetime} ops}$

C_M is the embodied carbon and we use information provided by ACT [19], to calculate it for the three servers used in our study in table 2[3]. C_C is operational carbon and it is calculated as $CI_{grid} * E$ where CI_{grid} is the carbon intensity of the electrical grid and E is energy consumption of the server. We calculated a CI_{grid} of 277.3 gCO_2/kWh using a New England resource mix [20]. C_N is networking carbon and is calculated as $CI_{grid} * f_{net} * EI_{net}$, where f_{net} is the server's NIC speed and EI_{net} is energy intensity of networking; we use a published value of 2.7 μJoules/Byte [6]. We consider the lifetime ops of each server as the peak rates shown in fig. 1a, fig. 2a sustained across multiple years. CCI does not consider multiple lifetimes (i.e. repairs/maintenance) as it can be difficult to get this visibility in old hardware.



(a) memcached **(b) silo**

Figure 3: CCI for both workloads. Lower is better.

[3]We expect the embodied carbon trend to continue to increase as a modern server, such as those deployed in the Aurora supercomputing cluster (10nm CPU, deployed 2023) [2], contains an embodied carbon of 732 kg.

3.2 Analysis

Fig. 3 shows the computed CCI for memcached and silo across both OSes. Similar to [45], we assume C_M (embodied carbon) of the oldest server, `Node1`, is 0. Further, a refurbished server such as `Node1` [42] can also be purchased for 4X cheaper compared to `Node3` [44].

In both memcached and silo, `EbbRT-Node1` achieved the lowest CCI and is typically 2-6X lower compared to Linux. We find that the peak RPS-per-Watt of `EbbRT-Node1` contributed greatly to its lower CCI as well as the carbon savings from the use of older hardware components (i.e. CPU, NIC, etc). Further, by sticking with `EbbRT-Node1`, a provider not only abates the need to upgrade a memcached server until the request peak rate increases above 2800 KRPS (1.75X beyond `Linux-Node3`), but it also can exploit the low CCI to process each request more efficiently. For silo, though `EbbRT-Node1` cannot reach the peak RPS of `Linux-Node3`, its CCI efficiency indicates a provider could choose to scale horizontally by purchasing from the refurbished market another `Node1` hardware instead.

It has been noted that the load on web service's fluctuate significantly due to its diurnal patterns [5, 23]; with datacenter service's often running at low utilization to respond to bursty behavior [7]. From a carbon perspective, this can significantly change the trade-offs concerning hardware refresh that specialized OSes can help unlock. `Node1` (2014) has both a lower idle power consumption and thermal design power (TDP)[4] when compared to `Node2` (2017) and `Node3` (2021). For memcached at peak load, `Linux-Node3` induced only a 1.33X increase in power when compared to `Linux-Node1`, at lighter loads (200 KRPS) we find this actually increased to over 2.84X. In contrast, using `EbbRT-Node1` yields a reduction of 12% power compared to `Linux-Node1` at light loads. Therefore over a server's lifetime, we find that the combination of a specialized stack running on older hardware serves as better units for horizontal scaling while reducing both embodied and operational carbon costs.

4 FUTURE DIRECTIONS

Our study illustrates how optimizing the OS can help address the three **R**'s of sustainability for cloud providers [19]: 1) **R**educe the demand for new hardware systems, 2) **R**euse older systems for a broader set of roles, and 3) have a path to utilizing **R**ecycled hardware for modern use cases. However, there are still some open questions and challenges that must be addressed.

As mentioned, although there have been significant effort for over a decade to build specialized OSes; there has been little real-world deployments of these systems due to their portability limitations. To reap the potential benefits that our study suggests, the challenges of porting specialized OSes deserve more attention. From literature, we find a key optimization approach taken by these systems is to bypass traditional kernel paths and co-optimize directly with the hardware (i.e. NICs) itself; either through in-house implementations [15, 34, 43] or the use of third-party libraries such as DPDK [8, 10, 24, 25, 32, 36, 51]. Unfortunately, this limits its portability as these systems typically require a rewrite or modification of the original application to take advantage of systems optimizations. Ideally, one would like to marry the portability and richness of Linux with specialized OS stacks.

Junction [15] is an example of recent library OS work that makes kernel-bypass practical by adding compatibility to run unmodified Linux applications. However, it relies on advanced hardware features of new data center CPUs and NICs (as well as a custom mlnx5 driver). Another approach is to take incremental steps instead where any unmodified application, running on Linux, can be the starting point and incremental application and OS co-optimization can be induced to move its performance and power profile towards specialized OSes. Expanding on this, UniKernel Linux (UKL) [41], introduces a set of Linux kernel configurations that permits primary application to be compiled into the kernel. When the primary application is launched, it executes at the same hardware privilege as the kernel. As such the application can directly call internal kernel routines to optimize its behavior. This raises the interesting possibility of developing a novel hybrid OS runtime.

We can consider a port of the scalable components of one of the many available specialized OSes [4, 8, 10, 22, 25, 26, 29, 31–34, 36, 38, 43, 48, 51] that is linked with the primary application but also designed, and implemented, to judiciously use internal Linux routines to inherit Linux's hardware compatibility. When the primary application is started, it bootstraps the specialized OS components. It relies on these for core functionality such as high performance scalable memory allocation and event scheduling. However, rather than including its own NIC driver, the specialized OS exploits the standardized NAPI interfaces to use the NIC drivers present in Linux. A similar approach can be take for other devices such as GPUs, SSD, and other hardware. In this approach an application can incrementally exploit the optimized code paths of the specialized OS and the specialized OS can also exploit Linux's battle-tested codebase and large hardware compatibility list to support a broad range of use-cases.

[4]TDP is a Intel provided metric that represents the average power the processor dissipates under some predefined high-complexity workload.

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