Abstract

It requires significant energy to manufacture and deploy computational devices. Traditional discussions of the energy-efficiency of compute measure operational energy, i.e. how many FLOPS in a 50 MW datacenter. However, if we consider the true lifetime energy use of modern devices, the majority actually comes not from runtime use but from manufacture and deployment. In this paper, then, we suggest that perhaps the most climate-impactful action we can take is to extend the service lifetime of existing compute.

We design two new metrics to measure how to balance continued service of older devices with the superlinear runtime improvements of newer machines. The first looks at carbon per raw compute, amortized across the operation and manufacture of devices. The second considers use of components beyond compute, such as batteries or radios in smartphone platforms. We use these metrics to redefine device service lifetime in terms of carbon efficiency. We then realize a real-world “junkyard datacenter” made up of Nexus 4 and Nexus 5 phones, which are nearly a decade past their official end-of-life dates. This new-old datacenter is able to nearly match and occasionally exceed modern cloud compute offerings.

1. Introduction

Datacenters worldwide consume large amounts of energy (250–500 TWh in 2018), which is estimated at 1% of world-wide electricity use [29]. They are projected to become even more power-hungry (840–3640 TWh in 2030 [8]). Increased efficiency and grid decarbonization can go a long way towards reducing the carbon footprint of compute, but an even larger problem remains: the huge carbon cost of manufacturing. ICT devices take a lot of energy to manufacture, and we go through them quickly. The end result is that a significant portion of the lifetime carbon footprint of ICT devices comes from manufacturing—as much as 17% for HPC devices and 90% for consumer electronics such as laptops and phones [16, 18, 23].

Unfortunately, there are not currently simple pathways for reusing old devices. While reselling is a possibility, this is in practice difficult, since a single broken component (e.g., a cracked screen) can make an otherwise fully-functional device worthless. Furthermore, recycling options for E-waste are extremely limited, and oftentimes reduce to simply shipping old devices overseas for someone else to deal with [11, 21]. In a nod to this growing problem, the 2021 Olympic Games featured medals sourced from discarded electronics [32].

We propose an alternative: Extend the lifetime of consumer devices by reusing them as general-purpose compute nodes.

Consumer electronics are becoming increasingly powerful and the compute requirements of cloud services increasingly diverse. The performance of recent smartphones rivals that of an Intel Core-i3 processor [3]. Meanwhile, cloud services such as EC2, which provide small-scale cloud capabilities with as little as 2 cores and 0.5 GiB of memory, are becoming increasingly widespread. The specifications provided by these services are well-within the capabilities of reused consumer devices. We capture these trends in Figure 1.

In this work, we explore several possible ways to architect
a reused datacenter. We build and benchmark a small-scale proof-of-concept implementation, and use these results to characterize the expected performance and carbon intensity of a hypothetical full-scale version.

Our main contributions are: (1) We define two new metrics for evaluating our proposed solutions: Computational Carbon Intensity and Reuse Factor (Section 3). (2) We perform a design space exploration of the possible ways to architect such a reused datacenter (Section 4). (3) We build and benchmark a working prototype constructed from reused devices (Sections 5 and 6).

2. Background

2.1. E-waste’s long shadow

The manufacturing of electronic devices is an energy-intensive process that often dominates their lifetime carbon footprint [18]. This is especially true when devices are discarded frequently. In the United States alone, 150 million smartphones are discarded each year. This amounts to approximately one phone discarded per person every two years [13].

The immense carbon footprint is not the only negative outcome of the manufacturing process. The mining of rare earth metals, e.g. gold, copper, and cadmium, which are integral to the manufacturing of smartphones and other ICT devices has been associated with local environmental destruction [1] and human rights violations [40]. A prominent example is the sourcing of conflict minerals in the Democratic Republic of Congo, which funds ongoing conflicts in the region [12].

Beyond this, the disposal of ICT devices has a negative local impact on people and the environment [11, 21]. The inclusion of precious metals in ICs makes recycling them worthwhile, but the presence of toxic chemicals means that the recycling process is energy-intensive and hazardous [25]. Wealthy countries in North America and the EU outsource these hazards. They ship large amounts of E-waste to developing nations such as China and India.

In a 2018 study, researchers attached geo trackers to devices that were dropped off at official US E-waste recycling facilities and found that approximately 35% of them were shipped overseas [26]. 93% of the exported devices were eventually received in China. Just three towns in China are estimated to process 11.5% of the world’s E-waste [14]. Extensive studies of one of these towns revealed dangerous levels of pollutants in the surrounding environment [28] and elevated levels of heavy metal poisoning among residents. Elevated levels were especially prevalent in children born in the area [41].

Given this recycling paradigm, it might actually a good thing that between 60-70% of smartphones are neither thrown out nor recycled [9, 27]. Instead they sit in drawers, which creates a huge stockpile of computational potential. If even 10% of the devices decommissioned in the last five years were available for reuse, we would have 75 million new, “free” compute nodes available. Reusing them significantly lowers their overall carbon footprint and the computational carbon intensity, as described in the following.

2.2. The limits of efficiency

While efficiency metrics are useful for many applications, they do not capture the true environmental (and human) cost of compute. Greater energy efficiency does not necessarily imply a lower carbon footprint, especially if that efficiency is achieved via fast equipment turnover.

Take for instance Power Usage Effectiveness (PUE), a commonly used metric for datacenter efficiency. PUE is defined as the ratio of the total energy consumption of the datacenter to the energy consumption of ICT devices only, with 1 being an ideal value. While PUE might reflect the operational efficiency of the datacenter’s computational devices and cooling system, it does not reflect the huge amount of energy that went into manufacturing the facility and the equipment housed within.

To understand why this is important, consider a toy example with two datacenters, A and B. For the same computational output, datacenter B consumes 10% more energy than A, such that $PUE_B = 1.1 \times PUE_A$. However, datacenter A achieves its greater efficiency by upgrading its servers at a rate that is 2× faster than datacenter B, such that its ICT manufacturing costs are 2× that of A. Let us then assume that manufacturing is responsible for 20% of the carbon emissions associated with both datacenters and that operational energy accounts for the other 80%. Then, the carbon footprint of datacenter B can be related to that of datacenter A as follows:

$$CO_2e_B = (0.8 \times 1.1 + 0.2 \times 0.5) \times CO_2e_A$$
$$CO_2e_B = 0.98 \times CO_2e_A$$

thus, despite having a higher PUE, datacenter B can have a slightly lower carbon footprint.

3. Carbon Metrics

To quantify the true environmental cost of proposed solutions, we need to define a new metric. Ideally, this metric should:

1. Reward operational energy efficiency.
2. Reward manufacturing efficiency.
3. Reward the reuse of already-manufactured devices.
4. Reflect computational work achieved per unit carbon.

Existing efficiency metrics, such as PUE, often fulfill point #1 but fail to capture points #2-4, while carbon footprint alone does not satisfy point #4.

3.1. Computational Carbon Intensity

We define Computational Carbon Intensity (CCI) as the CO$_2$-equivalent released per unit of computation work. We calculate this metric across the entire lifespan of our devices to get their amortized carbon intensity. The general formula is as follows:

$$CCI = \frac{PUE \times CO_2e}{W}$$

where $PUE$ is the Power Usage Effectiveness, $CO_2e$ is the carbon footprint per joule of work, and $W$ is the computational work accomplished.
The numerator can be further broken up into the carbon associated with manufacturing, compute, and networking:

\[
CCI = \frac{\sum_{\text{lifetime}} \text{CO}_2 e}{\sum_{\text{lifetime}} \text{flop}}
\]

\[C_M = \sum_{\text{lifetime}} \text{CI}_{\text{grid}} \ast E\]

\[C_N = \sum_{\text{lifetime}} \text{CI}_{\text{grid}} \ast f_{\text{net}} \ast E_{\text{net}}\]

CCI satisfies point #1, as it accounts for operational energy consumption per instruction in the numerator’s \(C_C\) term. It satisfies point #2 via the inclusion of \(C_M\). Since the total carbon cost is amortized per instruction, point #4 is also satisfied. To satisfy point #3, we stipulate that when reusing a device, the carbon cost of manufacturing is considered already ‘paid’, that is \(C_M = 0\).

3.2. Reuse Factor

CCI tells most of the story but not all of it. It misses whether or not we are using our reused devices to their full potential. For that, we need the reuse factor.

Smartphones contain many components that could be useful in a datacenter: CPUs, GPU(s), diverse networking hardware, and batteries. Not all of these components have the same carbon footprint, either, as seen in Figure 2. We therefore weigh each component by its carbon footprint to get an estimate of how well we are reusing the devices in our cluster:

\[
RF = \frac{\sum_{\text{reused}} C_{M(i)}}{C_M}
\]

A full lifecycle assessment is beyond the scope of this work, but we can get reasonable estimates by extrapolating from the available data. Our estimates are based on the results of Erdal et al. [18], which are also summarized in Figure 2.

IC production is responsible for 77% of the carbon emissions related to smartphone manufacturing. The PCB is 4.9%. The battery is responsible for 3.3%.

We further break down the numbers for ICs and PCB to get estimates for the relative contributions of CPUs, GPUs, and networking ICs. We make the naïve assumption that the CPU is responsible for 50% of the IC and PCB manufacturing cost, the GPU 25%, and networking devices 10%, with the remaining 15% taken up by components that we do not consider (e.g. the microphone and speaker). Note that these assumptions are almost certainly inaccurate, but for the purpose of comparison it is sufficient to get ballpark estimates. The reuse factor should be treated as a proxy for reuse.

4. Designing a Junkyard Datacenter

We aim to extend the lifetimes of old smartphones by reusing them to perform useful computation. This section articulates the design tradeoffs and proposes options for a smartphone datacenter architecture. The major considerations include:

1. Cooling: We want to eliminate the need for external cooling, which is energy-intensive. Smartphones are built with strict guidelines on power consumption to avoid overheating, which largely eliminates the needs for any additional thermal management.

2. Cluster Management: Our goal is to build a server that can provide FaaS capabilities. This will require cluster

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2And the uncertainty involved in any such calculation is extremely high; see, for instance, the ±100% uncertainty reported by Dell in their carbon footprint report for the PowerEdge 460 server [16].
management, and we need to ensure that we do not end up with unexpected, infrastructure-related bottlenecks.

3. Networking: Here we consider communication both among devices and between the cluster and the outside world. Communication is a major component of energy use, so it is important that we optimize this facet. These considerations are interrelated, and the choice of hardware can affect the design of the software and its capabilities.

4.1. Hardware Selection

This section describes the tradeoffs innate in hardware selection for a smartphone datacenter, including the choice of peripherals and the selection of the smartphones themselves.

4.1.1. Networking Networking can be accomplished via the phones directly, by augmenting some of all of them with SIM cards, or via an outside network. The former is preferably in terms of energy, since WiFi modems are relatively high-energy. The latter is both simpler to architect and higher bandwidth.

4.1.2. Cooling In modern datacenters, cooling accounts for 40% of operational energy consumption [19]. Smartphones are designed so as to not burn your hand when you use them, meaning that they have a strict upper limit on their thermal dissipation. As a result, a well-behaved smartphone should never overheat due to its own operation.

However, if the device is damaged it might exhibit irregular heating patterns. This effect can be seen in Figure 3. In a deployment setting, this overheating could become a significant problem. While healthy smartphones are able to regulate their internal temperature, high ambient temperatures may still cause overheating. For instance, leaving one of our Nexus 4 phones outside in the sunlight on a hot summer’s day caused the device to crash. Of the approximately thirty smartphones we have collected, only two have been observed exhibiting this thermal mismanagement. In a deployment setting, phones should be periodically screened for this behavior, and misbehaving phones removed or physically isolated from the others.

4.1.3. Smartphone selection In addition to filtering out deficient phones, we consider whether or not it is worthwhile to prioritize certain types of phones. Options include:

1. Full uniformity, all devices are the same make and model. This is the simplest solution in terms of management, but makes the collection of decommissioned devices more difficult, and risks limiting those devices that can be reused.

2. Mixed hardware, treated equally. Devices are of various makes and models, but are all treated “equally” in terms of scheduling. This has the best tradeoff in terms of simplicity and applicability to a wide range of devices, but might not make good use of all available capabilities. For instance, a device with a powerful GPU might be passed over for a machine learning task.

3. Mixed hardware, treated differently. Devices are of various makes and models. The scheduler is aware of their capabilities and distributes tasks accordingly. This is the best case scenario for performance and reuse factor but would involve more complicated cluster management.

4.2. Appropriate Workloads

Not all workloads are appropriate for a smartphone-based datacenter. Mobile SoCs are optimized for short, high-intensity bursts, so the cluster will likely perform better on jobs with short runtimes. Further, to ensure that phones do not overheat, enough time should be left between jobs to allow devices to cool off.

4.3. Cluster Management & Networking

There are multiple ways to manage communications between devices in a smartphone cluster. We present three possibilities below, which are also summarized in Figure 4.

Orientation A: SIM connected, leader election – Figure 4a. All devices contain a SIM card, which lets them connect to the wide-area network and each other. There is no fixed leader; a leader is periodically chosen via election.

Orientation B: WiFi, leader election – Figure 4b. A WiFi network is present in the deployment area. The devices communicate with each other and the outside world via Wi-Fi. There is no fixed leader; a leader is periodically chosen via election.

Orientation C: Hot spot, fixed leader – Figure 4c. One device (perhaps a more powerful device, or a device with better networking capabilities) is chosen as the leader, and contains a SIM card. This device is responsible for communications with the outside world. It also creates a WiFi hot spot for communication within the cluster.

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6 W on average [4], compared the phones’ 0.5-3 W.
5. Microbenchmarking Results

We use the 2012 Nexus 4 and 2013 Nexus 5 smartphones as our benchmarking and development phones. Table 2 summarizes their capabilities, and our microbenchmarking results.

5.1. Embodied Carbon

Ercan et al. calculate $C_M$ for the Sony Xperia Z5 to be 48 kgCO$_2$e. We use the simplistic assumption that this result scales according to the weight of the device. The Z5 weighs 154 g, the Nexus 4 139 g, and the Nexus 5 130 g. This gives an estimate of 43.32 kgCO$_2$e for the Nexus 4 and $C_M = 40.5$ kgCO$_2$e for the Nexus 5.

5.2. CPU Benchmarking

We perform a CPU stress test on our Nexus 4 and 5 smartphones to characterize their energy consumption at different utilizations. A summary of the results are presented in Figure 5. Figure 6 provides a power trace for both devices under a four core, 100% CPU stress test.

5.2.1. Experimental Setup

To reduce peripheral power consumption, we turn off WiFi and Bluetooth, and turn the screen brightness as far down as possible. We run the Linux `yes` command $n$ times, where $n$ is the number of cores we wish to stress, and use `cpulimit` to restrict the CPU usage of each `yes` process. At the same time, the power draw of the device is measured via `powerstat`. Note that this is not meant to provide an accurate measure of the device’s energy consumption under more realistic workloads, but rather to provide a comparison point for different utilization regimes and between the two devices.

5.2.2. Active States

In all cases, as CPU utilization increases, power increases at a less than linear rate. This is consistent with the results reported by Zhang et al. [42], and indicates that the phones are most efficient when operated at a higher CPU utilization. The energy consumption of the Nexus 5 is lower than that of the Nexus 4 for almost all regimes.

5.2.3. Idle States

Comparing our results to Zhang et al. indicates that during these experiments, the Nexus 4 did not enter a true idle state. This is unsurprising since the use of `powerstat` to take our measurements means that the CPU is never fully idle. However, our results—of an approximately 1 W idle power consumption—is consistent with their reported value for a phone that is not actively computing but has not entered an idle state either.

Newer smartphones (2012 and later) are designed with multiple idle states, each offering a different trade-off of power draw to the latency needed to fire back up. For the Nexus 4, these idle states range from “Wait for interrupt” with 0.433 W and 1 $\mu$s latency to “Power collapse” at 0.2 W and 2,000 $\mu$s latency [42]. For the purpose of cluster computing, however, we assume that the devices will almost-never enter a true idle state, and consider the unoccupied but not idle state as baseline.

5.3. Example Applications

We compare the Nexus 4 and Nexus 5 against each other and against a modern laptop for a set of benchmarks, described in detail later in Table 3.

The Nexus 4 was 10.7-13.9× slower than the laptop, and the Nexus 5 was 5.9-8.5× slower. In all cases, the slowdown

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4A Lenovo ThinkPad X1 Carbon Gen 8 with an Intel(R) Core(TM) i7-10610U CPU @ 1.80 GHz and 16GB RAM.
| CPU                  | Memory | Cores | $P_{\text{active}}$ | $P_{\text{idle}}$ | WiFi       | 3G  | 4G  |
|---------------------|--------|-------|---------------------|-------------------|------------|-----|-----|
| Nexus 4             | Quad-core 1.5 GHz Krait | 2GiB  | 4                   | 2.8 W            | 0.9 W      | 5 µJ/byte | 8 µJ/byte | N/A |
| Nexus 5             | Quad-core 2.3 GHz Krait | 2GiB  | 4                   | 2.5 W            | 0.6 W      | 5 µJ/byte | 8 µJ/byte | 11 µJ/byte |

Table 2: Hardware specifications and microbenchmarking results for the Nexus 4 and 5. *Sourced from [7]

Figure 6: Power usage during CPU stress test. The newer Nexus 5’s power draw spikes higher but then settles at a lower rate than the older Nexus 4’s.

rate increases with the length of the job. This indicates that the phones are best suited for relatively short tasks. This supports the hypothesis that mobile devices are better suited to tasks with shorter runtimes. It is also consistent with the results presented in Figure 6—both devices enter their highest power, and therefore most performant state immediately, then drop off to lower power states over time.

While the steady state power draw of both devices peaked at around the same value, the shorter runtimes of the Nexus 5 meant that its overall energy consumption was much lower across all three benchmarks. Overall, the Nexus 5 is both faster and more energy efficient than the Nexus 4.

5.4. Networking

Both the Nexus 4 and 5 are 3G and WiFi enabled, with the Nexus 5 additionally having 4G capabilities. Both devices are also able to act as WiFi hotspots. Both of these actions will affect the active power, $P_{\text{active}}$, of these devices.

Using the network: [7] characterizes the energy consumption of the Nexus 5 for 3G, 4G, and WiFi. We use their reported values for 3G and WiFi to parameterize our CCI calculations, assuming a bitrate of 100 kbps. We further assume that these values are the same for the Nexus 4.5

Hotspotting: We measure the power draw associated with using the Nexus 5 as a WiFi hotspot. When the hotspot is active, but no devices are connected, the phone’s baseline power is 0.93 W—approximately 1.5 times that of its typical 0.6 W baseline power.

5.5. Projected Lifespan

Lifetime projections are notoriously challenging, and data on these projections seem to sadly be trending towards less and less public dissemination. Nonetheless, we attempt an estimate of the lifetime of each of the major elements of our old-phones-as-compute platform.

SoC: Qualitatively, SoCs seem least likely to be the source of device failure. They are typically the longest-lived part of the device. A recent survey of lifetime for desktop and server-class computing components came to the same conclusion, and chose not to consider embedded SoC lifetime in their analysis [22]. Bak and Baeg find that even under heavy radiation, the Snapdragon 880 SoC had a mean-time to system-level failure of 44 years [10].

Battery: Phone batteries become unusable after about 2,500 cycles [5]. This is quick enough for it to become significant. Consider a Nexus 5 with a 20% utilization rate. The mean power draw of the device would be 0.98 W, giving a daily energy consumption of 84.67 kJ. The 2,300 mAh (31.4 kJ) battery included in the Nexus 5 would then require 2.72 charges per day if cycled completely. After 919 days, or just under 3 years, the battery would be unusable. Furthermore, this assumes no battery degradation; in reality the battery capacity declines by approximately 20% every 500 charges. Taking this decline into account yields a more accurate 618 days, or 1.7 years. After this, the battery would have to be replaced.

The Nexus 5’s battery has an embodied carbon of 1.22 kgCO₂e. Thus, we add 1.22 kgCO₂e to $C_M$ every 1.7 years to account for replacing the battery. The Nexus 4’s 2100 mAh battery yields an embodied carbon of 1.11 kgCO₂e and projected lifespan of 1.5 years.

I/O: We assume that networking peripherals will have a similar lifespan to the CPU, and that they will not be a limiting factor to our cluster’s lifespan.

The USB/charging port is more vulnerable to failures, however, since it is exposed to the environment and experiences regular wear and tear. Charging port failures are a common cause of smartphone failure, with the micro-USB port being especially vulnerable. We assume that devices in our cluster will be plugged in at all times, however, with power toggling accomplished via smartplugs. In this way, the charging port does not experience continuous wear.

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5In reality, there is almost certainly some small difference between the two, but the network component of $P_{\text{active}}$ is small enough that this is a reasonable assumption to make when comparing CCIs.

6Calculated using results from [30], also consistent with the value in [18].
Figure 7: Results for three example applications. In all cases, the runtime, and therefore the overall energy consumption, of the Nexus 4 was higher than that of the Nexus 5.

| Description         | On Laptop | Nexus 4 | Nexus 5 |
|---------------------|-----------|---------|---------|
|                     |           | Runtime | Slowdown | Energy   | Runtime | Slowdown | Energy   |
| fib                 |           | 0.20 s  | 2.14 s   | 10.7x    | 3.39 J   | 1.17 s   | 5.85x    | 2.46 J   |
| knn                 |           | 0.69 s  | 8.56 s   | 12.4x    | 16.04 J  | 4.56 s   | 7.6x     | 8.23 J   |
| mean                |           | 15.35 s | 213.16 s | 14.21x   | 375.54 J | 130.9 s  | 8.72x    | 242.94 J |

Table 3: Results from running our example applications on the Nexus 4 and 5, and a laptop

Other peripherals: We do not consider the failure rates of other peripherals (e.g., the screen, camera, microphone, speaker, and headphone jack) since they are unnecessary for our purposes. Some of these—in particular the screen—tend to be the first points of failure in a consumer setting.

6. Proof of Concept

We build out a proof-of-concept cluster consisting of five decommissioned smartphones (four Nexus 4s and one Nexus 5), which we purchased from eBay. For simplicity, we set up the cluster as per Orientation D (local WiFi network, fixed leader). We assign the Nexus 5 as the leader and refer to the other devices as workers.

The leader provides a single point of entry to the cluster. It maintains a list of all currently active workers and their status, which includes battery level, storage use, and CPU utilization. The workers communicate this information to the manager via regular heartbeats. Outside users submit jobs to the leader. Each submitted job consists of a zip file of the code to be executed, which is distributed to an available worker.

We replace the phones’ native Android with Ubuntu Touch’s Nexus 4 and 5 distributions [6], which are built on versions 3.4.0 of the Linux kernel. To set up the OS for development, we reconfigure the file system to be writable, and repartition the disk to allocate 6 GB to system folders (this leaves 10 GB for user data). We otherwise leave the OS unaltered.

We define the response time of our proof-of-concept cluster to be the time elapsed between job submission to the manager, and the return of a completed result to the end user. We use this metric to compare its responsiveness to that of AWS Lambda, a commercial FaaS provider.

We use the fib benchmark (described in Table 3) as our test function for these experiments.

We modify the cluster code slightly to fix which phone is assigned the job. We use a laptop as the end user and use the bash time command to measure the total time elapsed between submitting the job to the manager, and the receipt of the result. We also benchmark the time elapsed for the phone to perform the computation alone, and for it to set up and take down the environment for the computation.7

We run the same experiment on AWS by copying our fib code into a Python Lambda function that we trigger via a REST API. We present the response time as reported by CloudWatch.

Figure 8 summarizes the results. For the fib job, our cluster’s response time is $1.5 - 1.9 \times$ faster than AWS Lambda, depending on the device that is assigned the job. The majority of this time is spent computing the result, with cluster management and environment setup and take down adding an additional 0.44 – 0.76 seconds.

7. Characterizing Carbon

We use the results from our microbenchmarks to realistically parameterize CCI calculations following the methodology described previously for individual devices and for several possible cluster configurations.7

7For our implementation, this means unzipping the received code, creating and deleting temporary folders, and packaging the result.
| Device             | World Energy Mix | California Energy Mix |
|--------------------|------------------|-----------------------|
|                   | 1-year CCI       | 3-year CCI            |
|                   | 5-year CCI       | 1-year CCI            |
|                   | 3-year CCI       | 5-year CCI            |
| PowerEdge 460     | 2.270            | 1.771                 |
|                   | 1.361            | 0.863                 |
|                   | 1.173            | 0.674                 |
| Nexus 4           | 0.273            | 0.135                 |
|                   | 0.275            | 0.137                 |
|                   | 0.270            | 0.130                 |
| Nexus 5           | 0.162            | 0.083                 |
|                   | 0.154            | 0.076                 |
|                   | 0.153            | 0.074                 |

Table 4: Per-device CCI results, in mgCO$_2$/gflop.

Figure 8: Cluster response time for the fib benchmark compared to that of AWS Lambda (dotted line). All results are mean over 10 iterations.

Figure 9: Lifetime CCI results, in units of mgCO$_2$/gflop. For all devices, longer lifetimes yield lower CCIs.

For each computational device:

$$C_C = \text{CI}_{\text{grid}} \times \sum_{\text{lifetime}} u \times P_{\text{active}} + (1 - u) \times P_{\text{idle}}$$

(7)

Where $u$ is the fraction of time the device spends actively computing. The carbon intensity of the grid ($\text{CI}_{\text{grid}}$) is a measure of the amount of CO$_2$ released per kWh of energy provided, and varies depending on the source of that energy. Select values are presented in Table 6. Unless otherwise stated, we assume a California energy mix.

Networking ($C_N$): We calculate the carbon footprint of networking as described in Equation (4):

$$C_N = \sum_{\text{lifetime}} \text{CI}_{\text{grid}} \times f_{\text{net}} \times E_{\text{net}}$$

$E_{\text{net}}$ varies for 3G, 4G, and WiFi. The true value of $f_{\text{net}}$ will vary depending on workload and cluster management. For single-device CCI calculations, we assume an average rate of 10 kb/s across all devices.

Results: CCI results for a single reused Nexus 4 and 5 compared to a PowerEdge 460 server are given in Figure 9. The
Figure 10: Energy mix has a significant impact on CCI, especially for higher-power devices. The discrepancy between the Nexus 4 and 5 is more pronounced for more carbon intensive energy mixes.

Figure 11: Effect of declining efficiency on the CCI of a single Nexus 5 device. The black curve at the bottom is the Nexus 5 baseline, and the black curve at the top is the PowerEdge 460 baseline. Dashed curves represent the CCI of a Nexus 5 with increasing $P_{\text{active}}$ of 10-50% per year, compounded monthly. These numbers are contrived but serve to illustrate the potential impact of increasing $P_{\text{active}}$. In reality, we have not observed an increase in the energy consumption of our older phones. Nonetheless, this analysis serves to illustrate that even if our devices were to become significantly less energy efficient, they would still beat out a traditional server.

We also calculate the single-device CCI for our Nexus smartphones at different CPU utilizations (Figure 12) and with varying energy mixes (Figure 10). The results confirm that keeping the phone at a higher CPU utilization increases its carbon efficiency (in line with well-known computational sprinting principles [35]) and that renewable energy mixes yield a lower CCI overall.

7.2. Cluster-level CCI

We now combine the results from our microbenchmarking and per-device CCI calculations to get an estimate for the cluster-level CCI of each of the suggested orientations presented in Figure 4. We assume that our ten phones consist of nine Nexus 4s and one Nexus 5 and that the latter acts as the leader in the case of a fixed leader orientation.

7.3. CCI under declining efficiency

We can take into account the effect of declining computational efficiency by making $P_{\text{active}}$, $P_{\text{idle}}$, and/or flops a function of time. We imagine such a scenario in Figure 11, which presents the per-device CCI for a Nexus 5 smartphone over time. Realistically, this trajectory is unlikely, especially since we are periodically switching out the battery. However, these results serve to illustrate that, even with higher-than-expected energy consumption, smartphones still have significantly lower CCIs than traditional servers.

7.4. Embodied carbon

We define the embodied carbon of each smartphone as described Section 3. In addition to the smartphones, some of our possible orientations also include a WiFi network in the deployment area, so for these we have to take into account the carbon cost of that network. Raghavan and Ma estimate the embodied energy of a WiFi router to be 1 GJ, or 278 kWh [36]. Assuming a world energy mix and therefore a carbon intensity of $0.602 \text{ kgCO}_2\text{e/kWh}$, during the manufacturing process, this would equate to $C_M = 167.36 \text{ kgCO}_2\text{e}$.

7.5. Networking

Networking presents the largest difference between our clusters. In the case of hotspotted leaders, we need to take into account the effect that hotspotting has on their baseline power consumption. Furthermore, WiFi, 3G, and 4G involve differing energy intensities. When a Nexus 5 acts as a hotspot, all reused devices have a significantly lower carbon footprint per instruction than the server.
We explored the feasibility of reusing decommissioned smart-phones as general-purpose compute nodes. The computational power of these devices is on-par or greater than that demanded by modern cloud microservices. Extending the lifetime of these devices reduces the overall computational carbon footprint. We demonstrate that 9-year-old smartphones can be reused for present-day general computational tasks, and that a cluster of such devices can provide FaaS capabilities.

The largest barrier to a widespread deployment are questions related to scalability and fault tolerance. For smartphones to succeed as cloud computing nodes, more work needs to be done to reimagine the mobile compute platform as retirees in datacenters. In particular, we think that the following are particularly valuable areas for future work:

1. **Addressing the OS.** In our proof of concept, we replace the Android OS with Ubuntu Touch, which streamlined development.\(^8\) However, support for Ubuntu Touch is limited, with only 64 devices supported [6]. Furthermore, adding support for a new device involves added development work. An ideal solution would likely involve a slightly-modified Android runtime.

2. **Intelligent scheduling.** We treat all devices the same, however the capabilities of smartphones varies widely, even among devices released in the same year. This should be taken into account via intelligent scheduling of tasks to best make use of the most powerful resources.

3. **Testing at scale.** Our work—and previous work in the area [15]—is based on a very small-scale, proof-of-concept cluster. This ignores the problems that will almost certainly arise at scale.

There is also the question of adoption. For smartphone-based cloud computing to succeed, it must be worthwhile for cloud providers. While a dollar-cost analysis is beyond the scope of this work, previous work estimates the total cost of ownership (TCO) of such a system to be less than an equivalently-performant HPC device [39].

### 8.2. The Importance of Reuse

Given the large embodied carbon of ICT devices, it is worthwhile to reuse them.

While they will still eventually be discarded, lifetime extension through reuse helps to displace the carbon that would otherwise be associated with the manufacture of a new device. Assuming it takes 50 smartphones to achieve the same compute capacity as a PowerEdge 460 server (a conservative estimate), and that we are able to reuse 1% of the 750 million smartphones discarded in the US over the last five years to replace PowerEdge servers—We could save 192 million kgCO\(_2\)e in displaced carbon, the equivalent of driving the circumference of the earth 18,760 times.

While this example is contrived, it does illustrate the huge amount of computational potential and sunk carbon currently sitting in drawers and landfills the world over.

### 8.3. Carbon Metrics

Our work highlights the need for a more holistic analyses of environmental impact of computing. With the huge carbon

\(^8\)It is worth noting that a parallel effort of ours attempted to repurpose phones using stock Android. However, we ran into many of the same challenges as Klugman et al. [24], which led us to abandon this approach.
cost of manufacturing, and the difficulties of responsible re-
cycling, the energy efficiency of a device may be the least
significant component of its environmental and human impact.

This is especially the case when electricity is sourced from
lower-carbon sources. With the US setting a target of full grid
decarbonization by 2030 [20], embodied carbon will become
even more significant.

We apply CCI to our smartphone-based designs, but believe
it is more widely applicable to computing systems in general.

9. Related Work

Related work in this area can be broken into two general
groups: Work to characterize the carbon footprint of ICT
devices and infrastructure and proposals for reusing hardware.

9.1. Characterizing the Carbon Footprint of ICT

There are several models that aim to measure the carbon foot-
print of technology. Erçan et al. perform a detailed life cycle
assessment of a smartphone and find that as much as 84% of
the carbon emissions associated with the device are released
during manufacturing [18]. As we focus on smartphones, we
are able to leverage these more detailed methodologies to
calculate the embodied carbon of our proposed clusters.

Olivetti et al. present PAIA, a general-purpose algorithm
for calculating the carbon footprint of ICT devices [33]. Com-
panies such as Dell have used this methodology to calculate
the carbon footprint of their products [16]. While [18] charac-
terizes the carbon footprint of a single device in detail, PAIA
is meant to provide a streamlined and general-purpose tool
for businesses. In both cases, the results reflect the carbon
footprint of the device in aggregate, and not amortized per unit
of computation.

Zooming out even more, Raghavan and Ma characterize the
embodied energy (emergy) of the internet [36]. In follow-on
work, Pragman and Raghavan argue for the importance of
including embodied (manufacturing-related) energy in discus-
sions of sustainable computing more generally [34]. With this
work, we attempt to take a step towards fulfilling this mandate
by providing architects and systems engineers the tools to
quantitatively express embodied energy in datacenter design.

9.2. Consumer Electronics as Compute Nodes

The interplay and lines between specialized and general pur-
pose or consumer and industrial computer hardware has a
long and fuzzy history. Within this past, phones specifically
continue to capture interest and attention as their primary ap-
lication so intensely drives performance-per-Watt as well as
unique, optimized compute engines.

For one example, Rajovic et al. propose the use of mobile
SoCs for high-performance computing (HPC) [37]. Their
analysis finds that mobile SoCs are both sufficiently perfor-
manent for many applications and are more energy-efficient than
traditional HPC chips. In follow-on work, they build out a
real-world mobile SOC-based cluster [38]. Their implementa-
tion is based on the use of new and isolated mobile SoCs,
however, not the reuse of existing devices.

In contrast, Shahrad and Wentzlaff propose a server built
from decommissioned mobile phones [39]. While the work
considers e-waste reduction as motivation, it does not look
into quantifying the carbon impact. As a design proposal, this
work also does not include an implementation or empirical
evaluation.

Another work by Büsching et al. does include an implemen-
tation [15]. They connect six Android phones over WiFi and
evaluate the resulting cluster’s performance via the LINPACK
benchmark. Their implementation targets parallel computing
and does not include an associated cluster management system.
They also do not explore applications beyond LINPACK.

9.2.1. Other Efforts for Phone Use & Re-Use. Instead of
raw compute, Phonelab sought to provide a wide-area platform
for testing applications [31]. Phonelab did the heavy-lifting
of recruiting a large mobile user base willing to run diverse,
experimental software on phones carried with them day-to-day.
While less of a compute cluster and more of a human factors
cluster, Phonelab provides a wealth of insight into managing
a large fleet of heterogeneous phone-class compute nodes.

An orthogonal line of work is the use of smartphones as
gate devices. Why build new, special-purpose sensor nodes
when phones have storage, sensing, power, and communica-
tion capability built-in? Klugman et al. relay their experience
deploying a smartphone monitoring system for monitoring the
health of power grids [24]. Zink et al. compare the carbon
footprint of refurbishing old smartphones versus repurposing
them as parking meters, and find that the latter has a smaller
carbon footprint [43].

In neither case was repurposing the phone as technically
simple as promised, however. Mobile phone operating systems
are optimized for interactive use, and when human interaction
is completely removed, a very long tail of deployment-ending
issues crop up. With phones in datacenters, however, we can
 – as we do in this work – replace the standard mobile phone
operating system with a more traditional technology stack.
As these phones are largely plugged in and powered, we can
trade away some of the energy-optimality of phone OSes for
the robustness and reliability of more traditional datacenter
runtimes. Bridging this gap remains a non-trivial engineering
challenge but also a very exciting avenue for future work.

10. Conclusion

Millions of used smartphones languish in junk drawers and
landfills. Recycling these devices is an energy-intensive and
imperfect process that typically only recovers trace minerals.
Instead of discarding or recycling, we should promote the
reuse of computationally-capable hardware. Decade-old de-
vice are capable of running a non-trivial subset of modern
workloads. We should take advantage of the sunk cost, and
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