Flex: High-Availability Datacenters With Zero Reserved Power

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***Abstract*—Cloud providers, like Amazon and Microsoft, must guarantee high availability for a large fraction of their workloads. For this reason, they build datacenters with redundant infrastructures for power delivery and cooling. Typically, the redundant resources are reserved for use only during infrastructure failure or maintenance events, so that workload performance and availability do not suffer. Unfortunately, the reserved resources also produce lower power utilization and, consequently, require more datacenters to be built. To address these problems, in this paper we propose "zero-reserved-power" datacenters and the Flex system to ensure that workloads still receive their desired performance and availability. Flex leverages the existence of *software-redundant* workloads that can tolerate lower infrastructure availability, while imposing minimal (if any) performance degradation for those that require high infrastructure availability. Flex mainly comprises (1) a new offline workload placement policy that reduces stranded power while ensuring safety during failure or maintenance events, and (2) a distributed system that monitors for failures and quickly reduces the power draw while respecting the workloads' requirements, when it detects a failure. Our evaluation shows that Flex produces less than 5% stranded power and increases the number of deployed servers by up to 33%, which translates to hundreds of millions of dollars in construction cost savings per datacenter site. We end the paper with lessons from our experience bringing Flex to production in Microsoft's datacenters.**

***Index Terms*—Datacenter power management, redundant power, power capping, workload availability.**

I. Introduction

Motivation. As the demand for cloud services (*e.g.*, Infrastructure as a Service or IaaS) keeps growing unabated, cloud providers must build datacenters to keep up. Highly utilizing the infrastructure (*e.g.*, power, space, cooling) of each datacenter is critical to reduce the number of datacenters that must be built and save cost. As power is often the bottleneck resource, large providers use power oversubscription coupled with power capping (via performance throttling) to safely increase utilization by deploying more servers to each datacenter [3], [8], [14], [15], [37]. They carefully select the amount of oversubscription to prevent excessive performance degradation due to capping.

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However, as providers must maintain high infrastructure availability, especially for their IaaS offerings, a large source of inefficiency remains. Specifically, providers provision redundant resources [32], including power and cooling, in datacenters to ensure availability in case of planned maintenance or infrastructure failures (aka unplanned maintenance). These redundant resources are typically "reserved" for use only during relatively rare (planned or unplanned) maintenance. For example, the reserved power is used only when part of the supply of power is lost. Worse, existing power oversubscription approaches ignore these reserves and aim to restrict the peak power utilization so performance does not need to suffer during maintenance. In other words, even during *normal* (non-maintenance) operation, the peak power draw cannot exceed the *failover* power budget.

The reserved resources provide an enormous opportunity for increasing datacenter utilization and reducing costs. For example, in a typical high-availability datacenter, 10%-50% of the power and cooling resources are reserved [20], [32], [36]. Leveraging these resources to deploy more servers would significantly increase power usage, reduce the overall cost per provisioned watt, reduce the number of new datacenters that need to be built, and improve the sustainability of cloud providers. The downside is the potential performance and/or availability impact of having to bring the power draw below the failover budget during maintenance events.

Our work. In this paper, we propose "zero-reserved-power" datacenters and how to manage them so that workloads still receive their desired availability and performance. In more detail, we demonstrate that large cloud providers can allocate *all* reserved resources in highly available datacenters for deploying additional servers, while minimizing the impact of maintenance events. Our work relies on three key observations:

1) Cloud services typically exhibit relatively low power utilization with occasional peaks. Hence, the joint probability of critical infrastructure failure (or planned maintenance) and power peaks is small, even after employing state-of-the-art oversubscription strategies.

2) Providers typically host a mix of workloads with different infrastructure availability requirements in each datacenter, where some *software-redundant* workloads (*e.g.*, Web search, data analytics) can tolerate infrastructure failures due to their built-in redundancy.

3) Workloads that are not inherently redundant (*e.g.*, individual IaaS virtual machines) cannot tolerate infrastructure unavailability. However, some of them (*e.g.*, first-party VMs) can often tolerate slight levels of performance throttling. In fact, the existence of such workloads was the motivation for combining power oversubscription and capping via throttling.

Observation #1 suggests that maintenance events would rarely require corrective actions to bring the power draw down, given that the power utilization of the servers provisioned using the reserved resources would also only spike occasionally. Observation #2 and #3 suggest that some workloads can be shut down (by cutting off their power) and others throttled upon those rare events.

Unfortunately, accomplishing all this is challenging. First, since we allocate the reserve power for servers, the infrastructure must immediately transfer the load under a failed power supply to the remaining supplies, and temporarily support overdraw while corrective actions are being taken to lower the power draw below the failover budget. Second, the provider must place the workloads across the datacenter so as to guarantee safety against failures while minimizing "stranded" power (*i.e.*, power fragmentation). Third, during a maintenance event, the provider must take corrective actions within the short duration over which overdraw can be sustained. Failure to bring the power down within this time will cause a power outage. As the infrastructure does not have information about workload characteristics and requirements, the actions must be performed in software and in the presence of potential server and communication failures. These constraints make managing zero-reserved-power datacenters even more challenging.

To address these challenges, we build the *Flex* system. First, we extend the (highly available) power infrastructure of the most recent generation of Microsoft datacenters to ensure it can draw more power and to create enough time to take corrective actions in software.

Second, we introduce a new offline workload placement policy that reduces stranded power while ensuring safety during maintenance events. The policy leverages mathematical programming and optimization to select an efficient placement for each workload (*e.g.*, the servers for a Web search engine, servers for running IaaS VMs) in a batch of workload deployments. We call this policy *Flex-Offline*.

Third, we build a highly available distributed system that dynamically monitors for infrastructure failures and takes corrective actions to bring the power down below the failover budget within a few seconds. The monitoring relies on a highly available power telemetry pipeline that we also build. The actions, including throttling or shutting down workloads, respect pre-defined workload performance and availability requirements. We call this system *Flex-Online*.

We have deployed Flex-Online in production in multiple datacenters; Flex-Offline will come next. We discuss the lessons from bringing the system to production.

Our evaluation shows that Flex-Offline produces less than 4% median stranded power when we batch Microsoft's workload deployments, whereas simpler policies strand at least

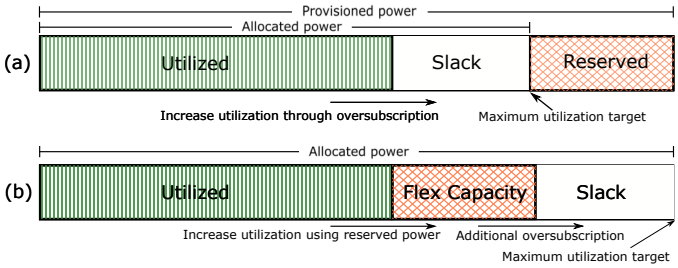


Fig. 1. Difference between traditional oversubscription (a) and Flex (b).

37% more power at the median. Using simulation, emulation, and large-scale experiments, we also show that Flex-Online manages power quickly and effectively, while respecting the workloads' performance and availability requirements. Overall, Flex can increase the server deployments to each datacenter by up to 33%. Depending on the exact building costs per Watt, this increase translates to savings between $211M ($5/W) and $422M ($10/W) for each 128MW site (multiple datacenters). The savings can be passed on to customers via differentiated pricing based on their workloads' requirements.

Related work. Prior work [3], [4], [6], [8], [9], [11], [13]–[18], [22], [28], [31], [34], [37], [39] has focused on power oversubscription and capping under normal (non-maintenance) operation.. These works did not explicitly consider allocating reserved power for additional server deployments. Figure 1 illustrates this difference. Oversubscription leverages underutilization of the allocated power for deploying more servers, while keeping the peak power draw under a budget. In contrast, Flex enables fully allocating the reserved power, while mitigating supply of power disruptions. Allocating reserved power is orthogonal to power oversubscription, *i.e.* allocated power that is underutilized can be oversubscribed.

CapMaestro [15] is the only prior system that uses the reserved power to deploy more servers. However, it does not consider each workload's availability requirements in workload placement or for runtime decisions during a failover. This limits the amount of reserved power that can be used. In contrast, Flex can use the entire reserved power for server deployment and provide each workload's desired availability.

Summary. We make the following main contributions:

- We propose the notion of highly available, zero-reserved-power datacenters and demonstrate that it can be achieved by a combination of infrastructure support and distributed software.
- We design and implement Flex, a system for managing zero-reserved-power datacenters with minimal impact to workloads. Flex comprises an offline component responsible for smartly placing workloads and an online component for dynamically managing power, availability, and performance.
- We thoroughly evaluate Flex, via simulations and experimentation with realistic workloads, to show that it reduces stranded power at the same time as managing power with minimal impact to workloads.
- We made changes to the power infrastructure of Microsoft's datacenters and deployed Flex in production with live loads. We present lessons from this experience.

II. Background and Motivation

A. Distributed redundant power infrastructure

To provide a high-availability infrastructure, cloud providers build datacenters with redundant power devices and lines, such as Uninterruptible Power Supplies (UPSes), Generators, Transformers, and Power Distribution Units (PDUs) [32]. The redundancy may take several forms, *e.g.* single-backup (N+1), full (2N) [25], [30], [36], [37], or distributed (xN/y) [20], each with its own tradeoff in cost, maintainability, and fault tolerance. Based on these tradeoffs, designers often use different redundancy patterns at different levels in the power hierarchy.

For example, Figure 2 shows the power hierarchy for a single datacenter server room with *xN/y* distributed redundancy at the UPS level (x=4, y=3) and 2N redundancy at the PDU level; 2N redundancy is simpler and more maintainable at lower levels of the power hierarchy. A datacenter consists of several such rooms with isolated power distribution hierarchies. In this design, the IT racks are connected to two PDUs (a PDU-pair) in an *active-active* manner such that both PDUs support roughly equal load. The two PDUs are then connected to two different upstream UPSes, as shown in the figure, which ensures each UPS shares roughly a third of its IT load with each of the other three UPSes.

When a UPS becomes out of service (due to planned or unplanned maintenance) or stops providing power (due to concurrent utility and generator failures), the entire load from that UPS is instantaneously transferred to the remaining three UPSes based on the PDU-to-UPS mapping. (This is the key difference between 4N/3 and N+1, in which the power would transfer to a single backup UPS.) To provide high availability in such a scenario, the total load on each of the three UPSes must not exceed their rated power capacity during such failover event. This can be done by limiting the power allocation for each UPS to the following:

$$UPS\_Allocation\_Limit = UPS\_capacity \times \frac{y}{x}$$

This implies $UPS\_capacity \times (1 - \frac{y}{x})$ power is reserved on each UPS and remains unallocated to any servers. This is a massive source of inefficiency. We propose to allocate all this reserved power to additional servers, increasing the number of servers by $\frac{x}{y} - 1$ (*i.e.*, 33% for a 4N/3 design). We refer to the sum of the UPSes' reserve and non-reserve capacities as the "provisioned" power.

For Flex's ability to use all the reserved resources, a distributed redundant architecture is key. N+1 cannot accommodate Flex because the redundant power supply is not active, *i.e.* we cannot allocate servers to use it. 2N is not ideal because a supply failure would require one of the redundant supplies to take on twice its normal load in the worst case.

B. Workload and hardware heterogeneity

Workloads. Large cloud providers offer many services ranging from IaaS, which provides VMs, to Software-as-a-Service (SaaS), which provides end-user services built on the provider's own software stack. IaaS requires high availability from the underlying infrastructure to ensure availability Service-Level Agreements (SLAs) are met for individual (or groups of) VMs. Individual VMs do not embody any redundancy that can be used to tolerate infrastructure failures. In contrast, SaaS is typically a distributed system designed by the provider to tolerate failures, minimizing the reliance on high-availability infrastructure. Specifically, SaaS components are replicated across availability zones (AZs), where each AZ has an independent supply of power. SaaS can tolerate server failures in one AZ by service-healing or scaling-out in another. For this reason, we refer to SaaS as *software-redundant* and all other workloads, including IaaS VMs, as *non-redundant*.

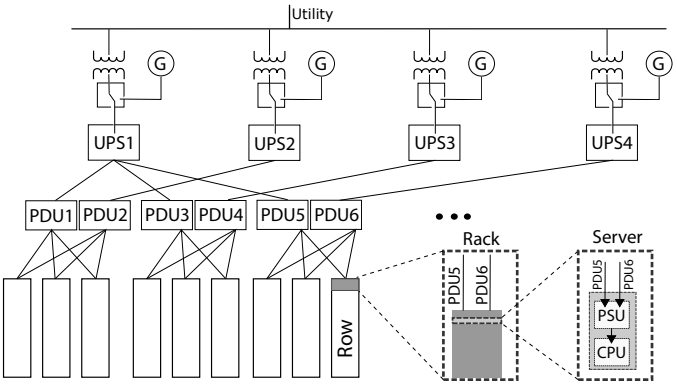


Fig. 2. 4N/3 power hierarchy design. G = generator; UPS = Uninterruptible Power Supply; PDU = Power Delivery Unit; PSU = Power Supply Unit.

SaaS may be implemented on top of IaaS VMs or on bare-metal hardware. For example, Google's search engine runs on its own set of dedicated bare-metal servers. Similarly, Microsoft runs several of its large SaaS offerings (*e.g.*, the Bing search engine and the Exchange messaging service) and other distributed systems (*e.g.*, the Cosmos data processing system [26]) on bare-metal servers that share the same datacenters with its VM service, Microsoft Azure.

From the perspective of Flex datacenters, "workloads" are those services/systems that are large enough (or require special hardware) to have their own rack deployments. To represent and account for the differences between workloads, Flex relies on pre-defined workload performance and availability requirements called "impact functions".

Hardware. Providers deploy a variety of hardware configurations (*e.g.*, compute clusters, GPU clusters, storage clusters) to meet customer demand. Different hardware configurations have varying support for reducing power draw as we require in Flex. For example, server hardware often includes CPU/memory power capping mechanisms, such as Intel's Runtime Average Power Limit (RAPL). RAPL lowers power by throttling CPU frequency (and possibly voltage) and, if necessary, memory accesses. However, other power-hungry hardware (*e.g.*, GPUs, disk arrays) may not have similar capabilities. Moreover, services may not be amenable to throttling.

Thus, we divide the cloud workloads broadly into three categories: *software-redundant, non-redundant but power-capable, and non-redundant and non-cap-able.* Figure 3 shows the

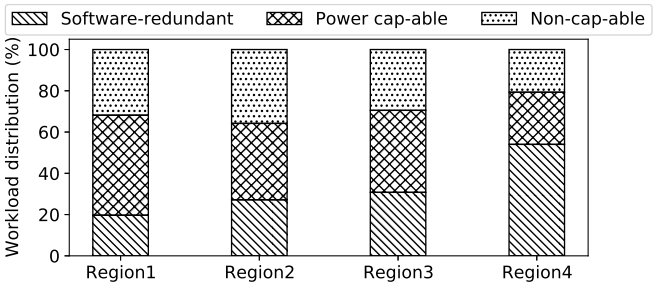


Fig. 3. Workload distribution across 4 Microsoft regions.

distribution of workloads into these categories in 4 Microsoft regions. Clearly, a significant portion of the deployed capacity is either software-redundant or non-redundant but cap-able. Flex relies on this observation to fully allocate the reserved power. We expect that other large cloud providers exhibit similar workload distributions and can leverage Flex to run zero-reserved-power datacenters. However, for datacenters hosting a mix of non-redundant cap-able and non-capable workloads, but no software-redundant workloads (*e.g.*, public VM cloud), Flex still allows using a smaller portion of the reserved power based on the cap-able deployments. Microsoft's first deployments of Flex target this scenario, as we describe in Section VI.

C. Capacity planning and workload deployment

Providers use short-term (few weeks to months) demand forecasting to procure IT resources (*e.g.*, servers). This short-term planning and deployment is typically done in large discrete chunks (*e.g.*, 20 racks of servers) to optimize the supply-chain pipeline, and to provide predictable and sizable capacity growth to the workloads.

Each deployment has power, cooling, networking, and space requirements that must be satisfied. In particular, the networking requirement typically forces each deployment to be treated as an unbreakable unit. As power is typically the bottleneck resource, we focus only on it in this paper. The power requirement (defined per rack) is a conservative estimate of the peak rack power obtained by running existing benchmarks (*e.g.*, SPECPower [12]) at the expected average utilization for a particular workload. This estimate is used to allocate power to the deployment in the datacenter. Any system responsible for workload placement must account for such requirements and optimize placement decisions to minimize the stranded power (fragmentation) due to large deployment sizes.

III. Flex feasibility analysis

Since Flex datacenters might involve throttling and/or shutting down some workloads, we first need to confirm that the expected frequency of these corrective actions would be very low. Corrective actions are necessary when maintenance downtime coincides with a power utilization higher than the failover budget. Thus, we performed a mathematical analysis to estimate the joint probability of these factors and the potential impact on workloads.

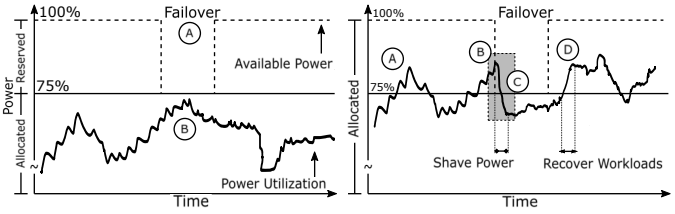


Fig. 4. Power profile for conventional datacenter with reserved power (left) and Flex datacenter with zero reserved power (right).

The analysis models datacenter power utilization (average and variance) and the distributions of power device planned and unplanned downtime, using data from 128 fully allocated (non-Flex) datacenter rooms for September 2020. The data shows peak utilizations ranging from 65% to 80% of the non-reserve provisioned power. Unplanned maintenance that would take out a power supply averages to 1 hour/year, whereas planned maintenance that would do the same averages to 40 hours/year. Since planned maintenance can be scheduled during periods of low utilization, these events are highly unlikely to actually engage Flex-Online. In fact, in our dataset, utilizations are 15%-19% lower at night or on weekends than the peaks during weekdays. These lower utilizations last for 6-12 hours, providing enough time for planned maintenance.

Assuming that only unplanned maintenance can coincide with a high enough utilization, the analysis shows that *99.99% (4 nines) of the time a datacenter room would operate with no need for corrective actions.* Assuming the default behavior where Flex-Online would throttle all servers that are cap-able before shutting down any servers from software-redundant workloads, the analysis also shows that the probability that any such server would have to be shut down is only roughly 0.005%. So, *availability for the servers of software-redundant workloads would be at least 4 nines* (availability for servers of non-redundant workloads is 5 nines, as the datacenters are designed for such high availability and any corrective action would at most involve throttling). Through impact functions (Section IV-D), customers can change this default behavior; *e.g.* a software-redundant workload may offer to be shut down more aggressively for a reduction in price.

These results suggest that Flex will not impose excessive unavailability even for software-redundant services/systems.

IV. Flex System Design

The goal of Flex is to use as much of the reserved power as possible while ensuring *safety* (*i.e.*, prevent cascading failures) and guaranteeing the workloads' *performance and availability SLAs*. The distributed redundant power hierarchy coupled with mixed workload requirements are key enablers of Flex.

A. Overview

In a conventional, non-Flex datacenter with 4N/3 distributed redundancy, only 75% of the total provisioned power is allocated to IT equipment and the rest is reserved. Figure 4(left) illustrates such a datacenter; the horizontal line at 75% marks the failover budget, *i.e.* the amount of provisioned power that can be safely allocated and used. Because of the reserved

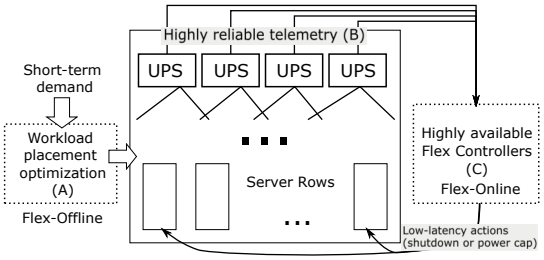


Fig. 5. Flex system overview.

power, during a failover event (A), the total power load on the remaining power devices (*e.g.*, UPSes) remains below their aggregate capacity (B). This scenario does not require corrective actions, but at the cost of the reserved power.

In a Flex datacenter, we instead use the *entire* provisioned power to deploy IT equipment. As we show in Figure 4(right), this could push peaks in power usage beyond the failover budget (A). During normal (non-failure) operation, the aggregate capacity of all power devices is sufficient to withstand this high load. However, when a failure (or planned maintenance) event coincides with a high load (B), the total load on the remaining devices exceeds their capacity. If this overdraw lasts too long, it would lead to a cascading failure where the initial device failure causes another device to shutdown, which in turn causes another one to shutdown and so on.

To prevent cascading failures, we must shave the power usage above the capacity of the remaining devices quickly, within their overload tolerance (C). We propose to do so with a combination of shutting down software-redundant workloads and power capping non-redundant but cap-able workloads. Once the failure is mitigated or maintenance is completed, the power caps can be lifted and the servers can be turned back on (D) to resume operations at full capacity.

Our approach involves several challenges:

- The deployment of IT equipment should ensure that sufficient software-redundant and cap-able workloads are available, even in the worst case (*i.e.*, 100% power utilization), to bring the power draw below the failover budget. The inability to produce such workload diversity can lead to stranding power.
- The device telemetry and the Flex system controller become mission critical and must be highly available to ensure no overload conditions are missed and actions are taken within the tolerance duration (based on the overload trip curves).
- Enforcing power caps or shutting down servers can have a significant impact on the workloads, either in terms of performance and/or availability. While it is critical to ensure safety, it is also important to minimize workload impact and act only on the smallest subset of servers needed to safely bring the power below the failover budget.

Flex tackles these challenges with three components as in Figure 5. First, an offline component (called *Flex-Offline* and labeled A) that takes the short-term capacity demand for different workloads and optimizes the placement of servers (Section IV-B). Second, the highly reliable power telemetry pipeline (B) that provides real-time monitoring of power devices (Section IV-C). Third, the highly available Flex controllers (C) that make and enforce decisions to shutdown or power cap a subset of the deployed servers during failover (Section IV-D). We call the set of controllers *Flex-Online*.

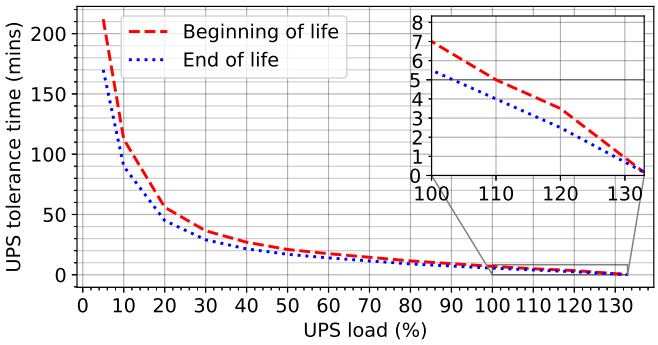


Fig. 6. UPS tolerance as a function of load.

Flex-Online relies on the temporary overload capacity of UPSes and their batteries; other parts of the infrastructure (*e.g.*, switchboards, cables, breakers) typically have higher tolerance. For example, Figure 6 shows our UPSes' tolerance curves for the beginning and end of the battery life, as a function of load. At the worst-case failover load of 133%, the UPS provides 10 seconds of tolerance, followed by an additional 3.5 minutes at 100% load (not shown). This additional ride-through allows the generators to start up and receive the load from the batteries. As a result, we enforce a 10-second limit on the end-to-end latency of *Flex-Online*, including failover detection, telemetry collection and controller actions, to reduce the power below the rated (100%) UPS capacity.

B. Flex-Offline: Workload placement optimization

As we describe in Section II-C, each server deployment request specifies the number of racks, the power allocation per rack, and the workload (*e.g.*, Web search, IaaS VMs). We additionally associate an availability attribute with each deployment that states whether the servers in the deployment can be shut down during failover. Similarly, a capping attribute defines whether the deployment is cap-able or non-cap-able. Finally, for the cap-able deployments, we associate a "flex power" value that defines the lowest power cap that can be installed on these racks. For provider-owned cap-able workloads, we determine the flex power value by running experiments to find the power cap that produces the maximum acceptable performance impact. For external cap-able workloads (*e.g.*, IaaS VMs), we leverage historical power utilization coupled with statistical multiplexing to bound the average power reduction to an acceptable threshold (*e.g.*, 10-15%) at high utilization (*i.e.*, when Flex-Online may actually engage). This requires no knowledge of individual external workloads, just historical rack power profiles. The impact is thus spread across workloads in the affected datacenter room and does not overly penalize any specific customer. Finally, for provider-owned software-redundant workloads, we set the flex power value to 0 as those racks can be shut down if needed.

Our goal is to place all deployments requested in the short-term demand so that the stranded power (due to either small pockets of power or lack of workload diversity) is minimized,

while ensuring enough power can be shaved in the worst case (*i.e.*, 100% utilization) during any maintenance scenario. Thus, we assume that the maximum power that can be shaved from software-redundant racks is the entire allocated power, and for non-redundant but cap-able racks it is the difference between the allocated and the flex power. No power can be recovered from the non-redundant and non-cap-able racks.

Historically, this placement has been done manually to each datacenter room one deployment at a time using simple approaches, like first-fit or round-robin across the UPSes in the room. Simple modifications to these approaches can balance the shave-able and non-shave-able workloads across the UPSes, and ensure that power constraints are met during both normal and failover operation. However, simple approaches could cause high stranded power due to suboptimal placement.

Thus, we propose Flex-Offline as an automated workload placement algorithm based on Integer Linear Programming (ILP) that seeks an optimal placement for all the requests in the short-term demand at the same time. Next, we present a simplified formulation focusing on UPS power during normal and failover operation. For brevity, we omit other constraints (*e.g.*, space, cooling) and other power devices (*e.g.*, PDUs).

Let $\hat{d}$ be a set of deployment requests in the short-term demand, $\hat{u}$ be the set of UPSes, and $\hat{p}$ the set of PDU-pairs. $Map(p \in \hat{p}) \rightarrow (u_1, u_2) \mid u_1, u_2 \in \hat{u}$ models the mapping from the PDU-pair p to the two upstream UPSes. Let Pow_d be the total allocated power to deployment $d \in \hat{d}$. We associate an indicator variable, $P_{d,p}$, representing whether a deployment $d \in \hat{d}$ is placed under the PDU-pair $p \in \hat{p}$.

Each deployment must be placed at most once:

$$\forall d \in \hat{d}, \sum_{p \in \hat{p}} P_{d,p} \leq 1 \tag{1}$$

During normal operation, the total allocated power is constrained by UPS power capacities accounting for distributed redundancy (*i.e.*, distribute half the load across the two UPSes connected to each PDU-pair).

$$\forall u \in \hat{u}, \left[Load_u = \sum_{\substack{d \in \hat{d} \\ p \in \hat{p}}} 0.5 \times P_{d,p} \times Pow_d | u \in Map(p) \right] \leq Capacity_u \tag{2}$$

During failover of UPS f, in addition to its regular load, each UPS u must take its share of f's load. Let $CapPow_d$ be the power for each deployment d after capping or shutting down the servers based on their workloads.

$$CapPow_d = \begin{cases} 0 & d \in \text{Software-redundant} \\ FlexPow_d & d \in \text{Non-redundant, cap-able} \\ Pow_d & d \in \text{Non-redundant, non-cap-able} \end{cases} \tag{3}$$

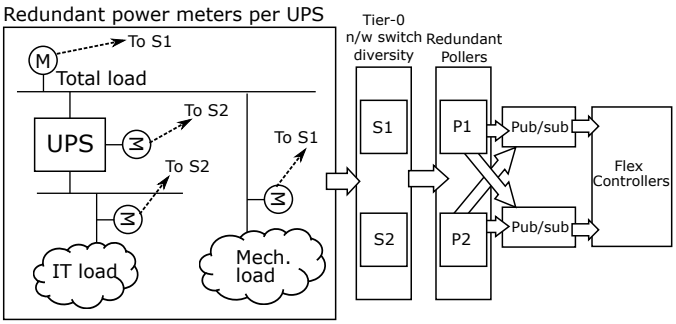


Fig. 7. Highly reliable telemetry pipeline.

The total load on each UPS (u) for any failure (f) after power shaving must be constrained by the UPS capacity.

$$\forall f \in \hat{u}, u \in \hat{u}, f \neq u,$$
$$\left(\sum_{\substack{d \in \hat{d} \\ p \in \hat{p}}} 0.5 \times P_{d,p} \times CapPow_d | u \in Map(p) \right) +$$
$$\left(\sum_{\substack{d \in \hat{d} \\ p \in \hat{p}}} 0.5 \times P_{d,p} \times CapPow_d | u \in Map(p), f \in Map(p) \right) \leq Capacity_u \tag{4}$$

Finally, the objective is to find a workload placement plan to minimize the total stranded power across all the UPS devices.

$$StrandedPow = \sum_{u \in \hat{u}} Capacity_u - Load_u \tag{5}$$

A solution to this ILP problem determines (a) whether to place a deployment in the datacenter, and (b) which PDU-pair p to pick for selected deployment d. Note that cloud providers may have additional soft constraints, such as bounding the impact on external non-redundant workloads (*e.g.*, external VMs), which we omit here, but include in the evaluation.

C. Highly available power telemetry pipeline

Flex's success hinges on a reliable, high-fidelity, and low-latency power telemetry from the power devices. For Flex, the importance of the telemetry pipeline is significantly higher than for usual power oversubscription approaches (*e.g.*, [37]). This is because a device failover in a Flex datacenter would cause instantaneous load transfer and, soon after, cascading failure, if not detected and tackled within the device tolerance duration. In contrast, load spikes during normal operation are usually gradual, especially at the higher layers of the power hierarchy, so slower detection is typically acceptable. Further, in a Flex datacenter, unreliable telemetry could lead to unnecessary throttling or shutting down of servers to ensure safety when data is missing, and cause high workload impact.

Given these factors, we build a highly reliable telemetry pipeline with no single point of failure. Figure 7 shows the pipeline, starting with the meters monitoring the power devices on the left and reaching the Flex controllers on the right. We build in redundancy and diversity in each pipeline stage.

The pipeline comprises meters, network switches, pollers, and publish/subscribe (pub/sub) systems. As we explain in the next section, it is sufficient to monitor only the power of the power devices (UPS in the figure); there is no need to monitor explicitly for device failures. However, relying on a single meter is subject to errors due to meter failure or misreadings. Hence, we use three logical meters that provide the equivalent of the device power (after accounting for losses). For example, in Figure 7, $UPSMeter \sim ITMeter \sim (TotalMeter - MechMeter)$ measure the equivalent of the power drawn by the UPS. This redundancy allows a consensus-based approach that tolerates failure or misreading of one meter.

To prevent a single point of failure at the network switch, we build network diversity by connecting these logical meters to management switches in two datacenter rooms (network paths beyond this are also redundant). Similarly, we deploy independent data pollers (on separate fault domains and physically separated), as well as independent pub/sub systems to which Flex controllers connect.

Our experimental observations show a telemetry pipeline latency of less than 1 second, which is fast enough to meet the 10-second end-to-end limit for Flex.

D. Flex-Online: Runtime decision-making

Controller operation: The Flex controllers are responsible for detecting failover and taking corrective actions. While several failure or maintenance events (*e.g.* UPS, generator, utility transformer, main switch board, busways) could lead to failover from one UPS to the others, the Flex controllers only need to monitor for power overdraw on individual UPS devices (vs for specific failures). This is sufficient because the distributed redundant architecture coupled with workload placement constraints ensure that UPS overdraw occurs only during failover (even at 100% utilization).

Like the telemetry pipeline, the controllers must be highly available. Thus, we run the controllers in a multi-primary configuration with each instance running in a separate fault domain (*e.g.*, different PDU and top-of-the-rack switch). As the power telemetry from the UPSes (∼1.5s frequency) and individual racks (∼2s frequency) may arrive at each controller instance at different times, each instance could take different actions. This could lead to overcorrection as the throttle and shutdown actions are idempotent and are taken independently, but does not compromise safety.

Algorithm 1 shows the policy the controllers execute to select a subset of racks to throttle or shut down when power overdraw is detected at any UPS. The goal is to ensure safety and to minimize the overall impact on the workloads. The policy first picks a candidate workload *w* that is either software-redundant or non-redundant but cap-able (line 6). The *PickRack(w)* function returns a rack from the given workload either randomly or as prioritized by the workload (line 7). It then decides the corresponding action A_r (line 8), computes the estimated recovered power R_r (line 9), and calculates the estimated total impact I_w on the workload due to capping or throttling the selected rack (line 10). To complete the inner loop, the policy accumulates the candidate racks with the corresponding impacts, actions, and estimated recovered powers across workloads (line 11). It finally selects the single rack from the candidates with minimum impact (line 13) and updates the estimated UPS power based on the rack's portion of load on each UPS (line 15). This continues until the estimated power for all UPS devices is lowered below their limits. The policy returns the set of actions to be taken.

Algorithm 1 Online decision policy based on impact functions

1: $Actions \leftarrow \{\ \}$
2: $P_u \leftarrow \{UPSPowerSnapshot_u\}$
3: $P_r \leftarrow \{RackPowerSnapshot_r\}$
4: **while** $any(P_u > Limit_u - \textit{buffer})$ **do**
5: $\quad \mathrm{C} \leftarrow \{\ \}$
6: $\quad$ **for** $w \in workloads$ **do**
7: $\quad\quad r \leftarrow$ *PickRack(w)*
8: $\quad\quad A_r \leftarrow \begin{cases} Shutdown & w \in \text{Software-redundant} \\ Throttle & w \in \text{Non-redundant, cap-able} \end{cases}$
9: $\quad\quad R_r \leftarrow \begin{cases} P_r & w \in \text{Software-redundant} \\ P_r - FlexPow_r & w \in \text{Non-redundant, cap-able} \end{cases}$
10: $\quad\quad I_w \leftarrow Impact(w, Actions \cup (r, I_w, A_r, R_r))$
11: $\quad\quad \mathrm{C} \leftarrow \mathrm{C} \cup (r, I_w, A_r, R_r)$
12: $\quad$ **end for**
13: $\quad a \leftarrow argmin_{c \in C}\{I_c\}$
14: $\quad Actions \leftarrow Actions \cup a$
15: $\quad P_u \leftarrow P_u - R_a^u$
16: **end while**
17: **return** $Actions$

As the policy needs to estimate the amount of power that can be recovered from the candidate racks, the Flex controllers need to continuously monitor all racks in the datacenter. A recent snapshot or an estimate based on time series models can be used (line 3). To ensure safety, we add a small buffer to account for mis-estimation (line 4).

Flex-Online enforces the corrective actions by limiting the selected non-redundant cap-able racks to their corresponding flex power value (*e.g.*, using RAPL) or by shutting down software-redundant racks. To prevent instability due to auto-recovery or scaling-out, Flex-Online sends a notification about the power emergency to the software-redundant workloads, which in turn recover or scale out in a different AZ.

Once the actions are enforced, the controllers must continue to monitor the power draw as any changes in the workload characteristics could again increase the power over the device limits and additional actions may be needed. Conversely, if the power draw falls significantly, some power caps may be lifted or servers restored to reduce the impact (not shown here).

The policy also needs to estimate an action's impact on the workload to pick a candidate (line 10). We allow each workload to define the perceived performance or availability impact as a function of the percentage of its affected (either shut down or throttled) racks. For this, we use impact functions.

Impact functions: Figure 8 shows a few example functions. Each workload defines the impact from 0 to 1 (Y-axis), given

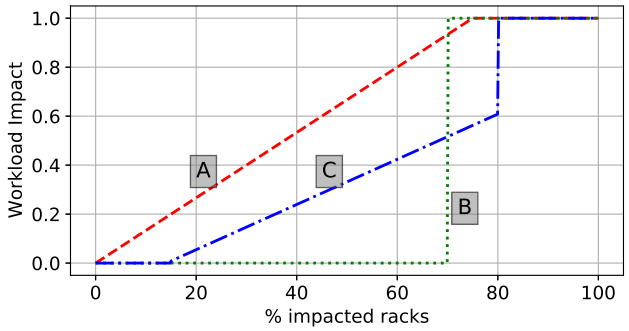


Fig. 8. Impact functions for different workloads.

the percentage of the racks of the workload that have been impacted (X-axis). $y = 0$ means that throttling or shutting down a percentage of racks would have no perceivable impact on the workload performance or availability, whereas $y = 1$ means that a percentage of racks is critical and should not be touched (unless this would be absolutely vital for safety). $0 < y < 1$ means that a percentage of racks can be throttled or shut down with incremental impact on the workload. Note that $y = 1$ does not mean a complete halt to forward progress, as workloads can implement business continuation processes and failover to another datacenter. All software-redundant workloads typically plan for such a scenario.

In Figure 8, functions A, B, and C illustrate potential impact functions for three large-scale services operated by Microsoft. Function (A) represents a typical non-redundant but cap-able workload (*e.g.*, VM service) with incremental impact of throttling any rack, and a set of critical management racks that must be protected. In contrast, function (B) is a software-redundant stateless workload where shutting down a large percentage of racks has no impact as the load is migrated seamlessly to the remaining racks or another datacenter. Finally, function (C) is a software-redundant stateful workload partitioned across racks with a growth buffer (which can be shut down with no impact), a set of racks performing useful work (incremental impact from shutting down), and a set of critical management racks that must be protected.

In the absence of impact functions for any software-redundant workloads, Flex-Online only acts on them if necessary, after non-redundant cap-able workloads have been throttled.

Summary. The deployment time workload placement optimizations (Flex-Offline) coupled with the runtime Flex controllers (Flex-Online) allow us to use the reserved power and safely lower power during failover scenarios, while providing the desired performance and availability to the workloads.

V. Evaluation

A. Workload placement with Flex-Offline

We evaluate Flex-Offline using simulations of short-term demand based on Microsoft's historical production workload deployments. We also simulate our datacenter server room size and power delivery infrastructure.

Methodology. Our workload placement simulator faithfully models a 4N/3 distributed redundant power hierarchy (Figure 2) in a 9.6MW room. The simulator models the placement of each deployment of racks to a specific row in the room. It validates the space, cooling, and power constraints, including normal and failover limits for all power devices, and rejects deployments that cannot be placed without violating constraints.

We drive the simulator with a trace containing short-term demand deployment requests. Each request specifies the number of racks (*e.g.*, 10, 20), provisioned power per rack (*e.g.*, 14.4kW, 17.2kW), flags indicating software redundancy and capping capability coupled with the flex power value.

We evaluate the placement policies using a trace representing the typical deployments at Microsoft. For example, a typical deployment size is 20 racks, but there are also a few smaller deployments of 10 and 5 racks. For the workload distribution, we use an average 13% software-redundant, 56% non-redundant but cap-able, and the rest 31% non-redundant and non-capable workloads (Figure 3). For the flex power values, we use 75-85% of the corresponding allocated rack power. We generate the trace with 15% more power demand than the provisioned power, which gives flexibility to the placement policies. The undeployable requests can be routed to other rooms for placement. Finally, to study the impact of the order of deployment requests, we shuffle the trace to create 10 variations in total. With these data, the simulator solves the Flex-Offline ILP problem using the Gurobi [24] solver.

Evaluation metrics. We evaluate the effectiveness of Flex-Offline using the following metrics:

- *Stranded power* is the unusable, unallocated power due to fragmentation (Equation 5 in Section IV-B). We seek placements that reduce this metric, so lower values are better.
- *Throttling imbalance* indicates the fairness of throttling impact for all non-redundant, cap-able workloads across any UPS failure. We seek to reduce this metric by selecting placements that balance the power that is recoverable via throttling as evenly as possible across all possible UPS maintenance events. Better balance means that no workload will be unduly penalized, regardless of the event. We calculate this metric as follows. For a given UPS maintenance (f), we determine the worst-case power to be recovered from each of the other UPSes through throttling (as a fraction, r_u^f, of provisioned power) after shutting down software-redundant workloads. We then calculate the throttling imbalance as $\forall_u^f(max(r_u^f)) - \forall_u^f(min(r_u^f))$. A value of 0 means perfect balance, so lower values are better.

Placement policies. We evaluate the following policies:

- *Random* randomly places a single deployment at a time. This is the simplest policy but is also clearly naive.
- *Balanced Round-Robin* places deployments from each category (software-redundant, non-redundant cap-able, or non-redundant non-cap-able) across the PDU pairs in a round-robin manner. The goal is to roughly balance the demand from each category under each UPS. This simple policy can be implemented as a set of guidelines to datacenter administrators.
- *Flex-Offline* optimizes the placement for all deployment requests in the short-term demand horizon. Depending on the length of the horizon (*i.e.*, batch size), we consider three variations: Flex-Offline-Short, which batches demand worth about

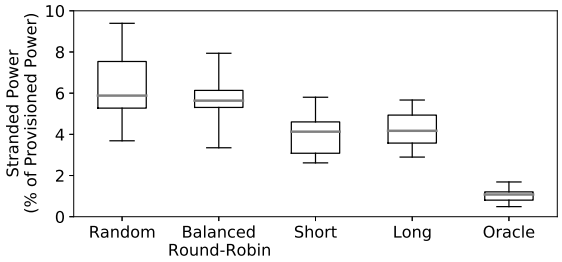


Fig. 9. Impact of placement policy on stranded power.

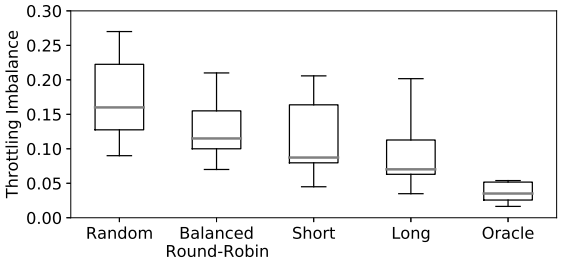


Fig. 10. Impact of placement policy on throttling imbalance.

33% of the total power capacity; Flex-Offline-Long, which batches about 66% of the total capacity; and Flex-Offline-Oracle, which groups the entire demand trace in a single batch. The length of the horizon depends on the certainty of the demand forecast and typically ranges between Flex-Offline-Short and -Long policies in production.

There are variations of these policies that we purposely do not consider. First, batching is only helpful for Flex-Offline and does not improve Random or Balanced Round-Robin. Second, we do not consider first-fit placement, the most common policy in real datacenters, because it does the opposite of what Flex needs by concentrating instead of spreading load across PDU pairs. Finally, we do not consider a simple round-robin policy because it is strictly worse for Flex than Balanced Round-Robin.

Results. Figure 9 shows the stranded power as a percentage of the total provisioned power in a datacenter room. For each policy, we show a box delimited by the 25^{th} and 75^{th} percentile stranded powers across the 10 deployment traces; the horizontal line crossing each box is the median value. The whiskers extend from the minimum to the maximum stranded power across the traces.

The figure shows that all policies produce stranded power that is less than 10% of the total provisioned power. Although the Random policy is more flexible, it also exhibits higher median stranded power. Balanced round-robin improves both the median and the variation across traces.

All Flex-Offline policies perform better, as they consider more deployments at a time and search for the optimal solution within their respective horizons. Flex-Offline-Short provides a 27% reduction in median stranded power compared to Balanced round-robin. Flex-Offline-Long shows the same median as Flex-Offline-Short but with a narrower range. Finally, Flex-Offline-Oracle shows that less than 2% stranded power can be achieved for even longer-term horizons with little variation (the reason Flex-Offline-Oracle varies at all is that we stop the ILP solver after 5 minutes, when solution improvements are already small but non-zero). We are working to improve our demand forecasting pipeline and lengthen the horizon.

Figure 10 shows the policies' throttling imbalance. Balanced round-robin outperforms Random as it explicitly tries to balance the workload categories across PDUs and UPSes. The Flex-Offline policies provide further improvements with increase in the horizon. Flex-Offline-Long shows only slightly higher median throttling imbalance than Flex-Offline-Oracle.

Impact of deployment sizes. The results above use Microsoft's deployment size distribution, which is dominated by 20-rack deployments. Other providers or large Internet services may have mostly smaller deployments for incremental growth. Thus, we study the impact of Flex-Offline for such smaller deployments. Specifically, we used the same traces but limited the largest deployments to smaller sizes. For example, when studying 10 racks as the largest deployment, we broke any 20-rack deployments in the traces into two deployments of 10 racks each. As one would expect, smaller deployments tend to reduce stranded power and throttling imbalance. For example, when the maximum deployment is 10 racks, Flex-Offline-Short exhibits roughly half the median stranded power and throttling imbalance of when the maximum is 20 racks.

Impact of software-redundant workloads. We also study how much software-redundant workload we need to use all the reserve power. Again assuming the original traces and 31% non-redundant and non-cap-able workloads, we find that Flex needs no more than 10% software-redundant workloads to significantly reduce stranded power. In more detail, at 0% software-redundant workload, the median stranded power with Flex-Offline-Long is 15% because allocating more could leave the datacenter without enough cap-able power to shave upon a maintenance event. When we increase the software-redundant workload to 5% and 10%, median stranding goes down quickly to 4% and 3%, respectively. Larger fractions stay within plus or minus 1% of this median.

Summary. Flex-Offline improves both stranded power and throttling imbalance through a combination of batching and optimizing the solution in the demand horizon via ILP. The benefits are robust across a range of deployment sizes and workload distributions. As Flex-Offline-Oracle provides the optimal solution due to complete visibility into future demand, we plan to study how a *certain* short-term demand can be combined with *uncertain* long-term demand forecast to further increase the practical horizon for placement and thereby reduce the stranded power and the throttling imbalance.

B. Runtime decisions with Flex-Online

In this section, we evaluate Flex-Online using simulation of several impact scenarios. We evaluate its performance using real large-scale experiments in the next section.

Methodology. We evaluate Flex-Online and its corrective actions (Algorithm 1) given some example impact functions. First, we use Flex-Offline-Short to place the deployments from our original trace in a datacenter room. Next, we use the historical rack power draws of these workloads in our

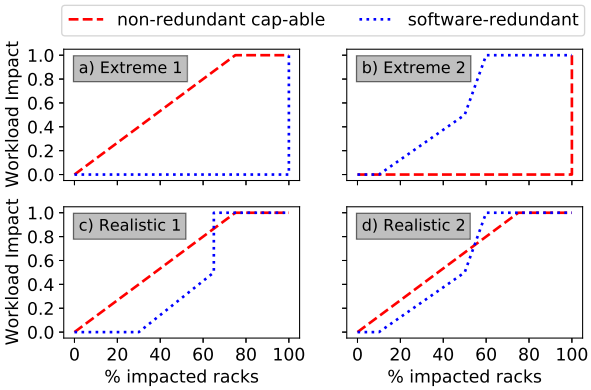


Fig. 11. Impact functions for workloads.

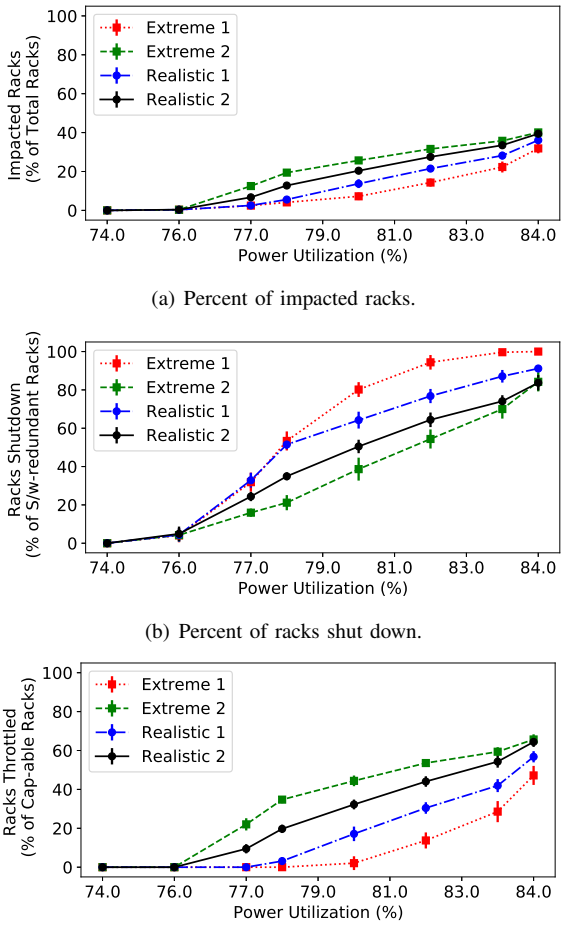
datacenters to model their rack power distributions. Using these distributions, we pick a power draw for each rack and derive the UPS loads accordingly. We use these snapshots as inputs to the controllers (Algorithm 1, lines 2 and 3).

Figure 11 shows the sample impact function scenarios we study. For clarity, we show only one function for each workload category per scenario, assuming that all software-redundant workloads have the same performance/availability needs and all non-redundant cap-able workloads have the same needs as well. Our implementation imposes no such restrictions. Figure 11(a) and (b) show two extreme scenarios, where the first represents no impact from shutting down the software-redundant workloads, and the second represents no impact from throttling the non-redundant cap-able workloads. In contrast, Figure 11(c) and (d) are realistic scenarios representing workloads running in our datacenters.

Evaluation metrics. We simulate the failure of each UPS and report the average percentage of impacted racks, racks shut down, and racks throttled across all UPS failures.

Results. Figure 12 compares the impact of the corrective actions in each scenario (Y-axis), as a function of the room's real-time power utilization at the time of UPS failover (X-axis). For each curve and power utilization, the marker point represents the mean value and whisker represents the standard deviation across all UPS failures. We focus on a narrow range of utilizations on the X-axis, as no actions are needed at utilizations lower than 74% and sustained utilizations higher than 85% at the UPS-level are impractical (though Flex-Offline guarantees safety even at 100% utilization). Figure 12(a) shows the impacted racks, as a percent of the total number of racks; Figure 12(b) shows the racks that were shut down, as a percentage of the total number of racks that can be shut down; and Figure 12(c) shows the racks throttled, as a percent of the total number of throttle-able racks.

The figure shows that up to 30-40% of racks may be impacted by a UPS failure, but this only happens under very high utilizations. Scenario Extreme-1 impacts the fewest racks because it is also the most aggressive at shutting racks down (shut down is the action that recovers the most power). At the same time, it throttles the fewest racks. The reason is that its impact functions promote shutting down of software-redundant racks, while preferring to not throttle any non-redundant cap-able ones. At the other extreme, scenario Extreme-2 first throttles all the candidate non-redundant cap-able racks before shutting down any software-redundant racks.



(a) Percent of impacted racks.

(b) Percent of racks shut down.

(c) Percent of racks throttled.

Fig. 12. Flex-Online runtime decisions during a failover event.

The remaining scenarios behave between these extremes. Realistic-1 specifies a lower performance impact for shutting down than throttling and, therefore, results in shutting down more and throttling fewer racks, in comparison to Realistic-2.

Summary. Thanks to our impact functions, Flex-Online is successful at prioritizing its corrective actions according to the workloads' performance and availability needs during maintenance events. Moreover, the ability to aggressively shut down software-redundant racks enables Flex-Online to reduce the impact on non-redundant workloads like IaaS VMs.

C. End-to-end Flex-Online performance

As the joint probability of failover and peak utilization is extremely low in production (Section III) and forcing a failure event can cause undesirable performance impact, here we present the end-to-end operation of Flex-Online on an emulated environment with 360 servers. We discuss the learnings from our production deployments in the next section.

Methodology. We emulate a datacenter room consisting of four UPSes, with the distributed redundant hierarchy shown in Figure 2, each with a capacity of 1.2MW for a total capacity

of 4.8MW with no reserved power. The room has 36 rows, with space for 10 racks per row. We generate a trace of short-term demand with the same distribution of workload categories as in Section V-A, but with one workload per category. We then use the Flex-Offline-Short policy to determine workload placement. We emulate each rack placed in the room with a single server and run synthetic benchmarks to emulate workload execution. We scale the server power utilization to a rack by a pre-defined scale factor based on the server peak power and the rack provisioned power. We use a flex power value of 85% of the provisioned rack power for non-redundant, cap-able workloads. We run benchmarks we use internally to evaluate our software stack. Specifically, we run TeraSort [23] to represent the software-redundant workload and a latency-sensitive TPC-E-like [7] benchmark to represent both the non-redundant cap-able and non-cap-able workloads. Each workload instance runs independently in its own VM. We configure the benchmark parameters, including number of instances running on each server, to emulate an aggregate utilization of 80% of the provisioned power at the UPS level.

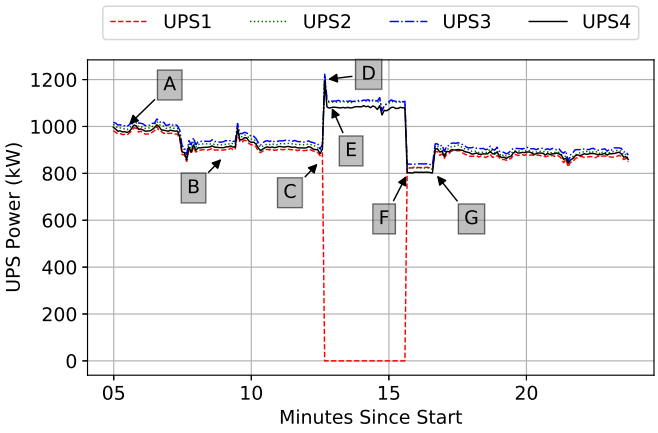
Results. We divide the experiment into four stages: setup, normal operation, failover, and recovery. Figures 13(a) and 13(b) show the emulated UPS and rack power during the experiment, respectively. In the setup stage (A), servers spawn benchmarks according to their assigned workload mapping. During normal operation (B), the power utilization of all UPSes stabilizes at about 80% of the provisioned power. We simulate a UPS failure after twelve minutes (C) and observe the load transferred to the remaining three UPSes. This causes a power spike above the 1.2MW capacity for those UPSes (D).

The Flex-Online controller detects this power overdraw and uses the impact function from Figure 11(c), coupled with the rack power snapshot based on the real-time power utilization to make throttling and shutting down decisions. The controller policy decides to shut down 64% of the racks of the software-redundant workload, and throttle 51% of the non-redundant, cap-able racks to shave the needed power. Total corrective action enforcement takes about 2 seconds (E). Racks running non-redundant, non-capable workloads remain untouched.

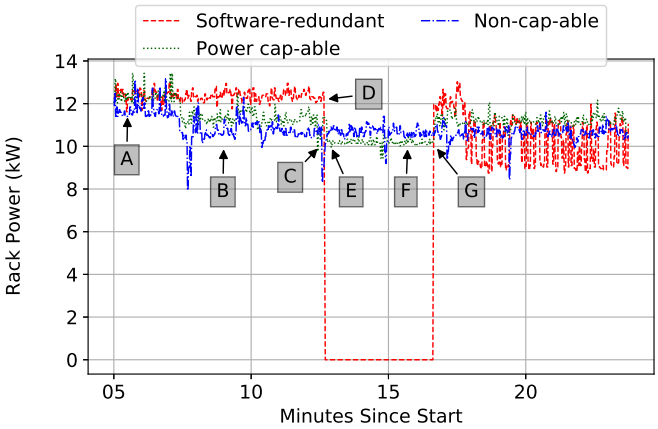
After some time, we restore the failed UPS (F), which results in load sharing among all four UPSes and a drop in UPS power. The Flex-Online controller detects this recovery, and releases the throttle on the racks running the non-redundant cap-able workload and restarts the racks for the software-redundant workloads (G) to resume normal operation.

As the amount of throttling is limited by the pre-defined flex power values, the impact of throttling on non-redundant, cap-able workloads is small. The overall 95^{th}-percentile latency of the TPC-E-like benchmark running on the throttled racks increased only by 4.7% compared to the non-throttled ones. The worst-case increase (during the highest rack power draw) was 14%. These losses only occur during extremely rare events, and can be further reduced with a stricter impact function for this workload. A small loss in rare cases is a good tradeoff given the benefits of allocating all reserved resources.

Summary. This large-scale experiment shows the dynamic behavior of Flex-Online. As expected, it is capable of quickly reacting to a UPS failure and taking corrective actions. In fact, the latency of Flex-Online in production has been similar to what we see in this emulation (Section VI).



(a) UPS Power



(b) Rack Power

Fig. 13. UPS and rack power during Flex-Online emulation.

VI. Lessons from Production Deployment

We are deploying Flex to production at Microsoft in stages. So far, we have deployed Flex in several datacenters that allocate a portion (42% instead of 100%) of the reserved power for additional servers. For this portion, there is no need to shut down any workloads during a maintenance event, so we only use throttling. In this section, we discuss the lessons from these deployments and the production requirements for using the entire reserved power.

Infrastructure upgrades: There are two main reasons the systems we have deployed so far use only a portion of the reserved power in legacy datacenters. First, the continuous load capacity of upstream devices (*e.g.*, medium-voltage transformers, feeders, and generators) does not support the entire load. Second, when all the reserved power is allocated (maximum potential overload of 33%), the overload capacity of the UPS batteries during failover is insufficient to sustain the load long enough to detect a failure and enable the Flex controllers to lower the power draw. As a result, Microsoft

is building its new datacenters with higher rated upstream devices and larger UPS batteries, which will allow Flex to use all reserved resources at a small additional cost ($\sim$3%).

Implications on cooling infrastructure: Flex must consider the available cooling capacity to safely deploy servers using the reserved power. Thus, in production, we include rack cooling requirements, measured in cubic feet per minute per watt (CFM/W), as constraints in our offline workload placement optimization. In our experience, these constraints have not been the bottleneck even with increased server density for two reasons: (1) there has been a significant drop in server CFM/W requirements as server airflow and heatsink designs improve, and (2) datacenters are designed to support much higher cooling needs for backward compatibility.

Further, just as redundant power, Flex can leverage the redundancy in cooling for deploying additional servers. Upon the loss of this redundant cooling, unlike losing redundant power, several minutes are available for mitigation as datacenter temperature rise is gradual. Hence, other mitigations, such as workload migration to another cooling domain, can be used before enacting strict Flex capping/shutdown actions. Thus, we envision no extra cooling infrastructure cost to support additional servers with Flex even at zero reserved power.

Power meter fidelity: As we state in Section IV-C, reliable telemetry is critical for Flex-Online. However, some power devices like UPSes are not designed for such high-fidelity external monitoring. For example, in our experience, repeated polling of the UPS meters would often return the same value for up to 5 seconds, due to meter inaccuracy. As a result, we had to deploy additional UPS output meters to compensate. Further, there are multiple systems in the datacenter that monitor these and other devices. As these meters only provide pull-based readings, contention between various systems could cause a drop in fidelity. We solved this problem with dedicated Flex meters and careful coordination between these systems, reducing polling intervals from $\sim$3 to $\sim$1 seconds.

Firmware and network status: We use out-of-band mechanisms supported by the rack manager (RM) and the baseboard management controller (BMC) [21] to throttle or shutdown servers. It is critical to keep the firmware on the RMs and BMCs up-to-date, especially when deploying new servers or when existing servers are serviced or replaced due to failures. In addition, to ensure that the actions take effect, the RMs and BMCs must be reachable during a maintenance event. To ensure both of these, we built a separate background service that monitors both firmware status and network reachability for all RMs. It is also responsible for periodically injecting failures and taking fake actions to ensure no firmware regressions, software bugs, or other issues cause actions to fail during an actual maintenance event. If such issues occur, the service warns operators and engineers to take immediate remedial actions, *e.g.* redeployment of firmware or bug fixes.

Performance characteristics: The two key metrics we consider in production are the "data latency", *i.e.* the time to detect a failure, and the latency to take corrective actions. So far, we have observed the 99.9^{th} percentile data latency in production to be under 1.5 seconds, including the windowing delay to consolidate the several physical data points for a given logical meter. Further, we observe the latency to take throttling or shutdown actions to be around 2 seconds at 99.9^{th} percentile for a $\sim$10MW room in the DC. The end-to-end latency (3.5 seconds) is well below the limits imposed by the power devices towards their end-of-life ($\sim$10 seconds).

Financial incentives for lower availability workloads: To use the entire reserved power, it is critical to deploy enough workloads that are amenable to lower infrastructure availability. Microsoft has many such workloads. Unfortunately, not all existing workloads have been built with this capability (and some, like individual IaaS VMs, are inherently not redundant). Still, it is possible to redesign some of them with greater software redundancy and fault-tolerance. We are currently developing new charge models that incentivize workloads with relaxed performance and availability requirements.

VII. Related work

To our knowledge, this work is the first to propose datacenters that use their entire reserved power for server deployments, guarantee safety during failover using offline workload placement, and provide workloads with their desired availability. Nevertheless, works on power oversubscription, workload awareness, and energy storage are related.

Power oversubscription. Many works have addressed power oversubscription, typically with power capping for preventing circuit breaker trips [2]–[4], [8], [11], [14], [15], [28], [30], [31], [34], [35]. Some authors underprovision the infrastructure and either discharge batteries [4], [34] and/or throttle workloads [19] when needed, again during normal operation. Some recent papers [11], [14], [30], [37] treat workloads differently based on their priority, interactivity, or availability requirements for higher oversubscription or lower performance impact. These works focused on power management during normal (non-maintenance, non-failover) operation without regard for fully utilizing reserved resources and the associated challenges. Flex focuses on allocating all reserved resources for additional servers and managing maintenance events, so it is orthogonal and can be combined with these prior works.

CapMaestro [15] combines oversubscription with the power redundancy provided by 2N-redundant datacenters to deploy more servers. It uses priorities to selectively throttle workloads, but does not consider their availability requirements during placement or failover. This approach ensures safety but limits the amount of reserved power that can be used. In contrast, our infrastructure- and availability-aware workload placement, and the highly-available power telemetry allow Flex to use the entire reserved power and still guarantee safety. Oversubscription can be used in addition to Flex to further increase server density, if the observed utilization is low.

Workload priority awareness. Some prior oversubscription works recognize the potential performance degradation of power capping and include some notion of workload priority [11], [14], [15], [29], [30], [37]. For example, IBM's CapMaestro [15] shifts power to servers running high-priority

workloads by throttling servers running low-priority ones harder even across PDUs. Li *et al.* provide quality of service for tasks running on the same server [14]. In contrast, Flex implements a much more detailed and descriptive approach to workload awareness. With impact functions, it accounts for explicit descriptions of workload performance and availability impact, in both placement and runtime decision-making.

Energy storage and flexible power infrastructure. Researchers have considered repurposing energy storage devices (ESD) to shave power peaks [1], [5], [10], [33], [38]. Most of them focus on distributed ESDs that attach to either servers or racks. These approaches are vulnerable to long-lasting or unbalanced peaks, which may deplete all or some of the ESDs quickly. In Flex datacenters, we keep centralized ESDs and use them as backup until software can react.

Finally, Power Routing [27] adds more connections from racks and rows to other PDUs so that they form shuffled distribution topologies. The design lowers the need for reserved capacity, but does not eliminate it. Moreover, for the common dual-corded power supply architecture, costly infrastructure upgrades must be made to enable such richer physical connectivity.

VIII. Conclusions

We introduced zero-reserved-power datacenters and the Flex system to manage them. Flex leverages the lower infrastructure availability requirements of software-redundant workloads and combines static workload placement with dynamic power management to safely allocate the reserved power. Using simulation and large-scale experiments, we showed that Flex significantly reduces stranded power while quickly and effectively managing workload availability and performance. Flex decreases construction costs significantly, producing savings of hundreds of millions of dollars from each datacenter site. Our experience deploying Flex in production at Microsoft drew many lessons that should benefit any other provider.

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