BlinkFS: A Distributed File System for Intermittent Power

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Abstract

Operating off intermittent power is beneficial for data centers in a variety of scenarios. For instance, data centers may use real-time electricity markets to buy more power when it is cheap, or leverage more clean, but intermittent, energy sources. As another example, extended blackouts may require capping power at low levels for long periods to extend UPS lifetime. However, regulating power consumption is challenging for clusters that store persistent state, since power fluctuations impact both I/O performance and data availability. To address the problem, we design and implement BlinkFS, which combines blinking with a power-balanced data layout and popularity-based replication/reclamation to optimize I/O throughput and latency as power varies. Our experiments show that BlinkFS outperforms existing energy-proportional approaches, particularly at low steady power levels or high levels of intermittency. For example, we show that BlinkFS improves completion time for MapReduce-style jobs by 42% at 50% full power compared to an existing energy-proportional DFS. Further, at 20% full power, BlinkFS still finishes jobs, while existing approaches stall due to inaccessible data.

1 Introduction

The growth of cloud-based services continues to fuel a rapid expansion in the size and number of data centers. The trend only exacerbates the environmental and cost concerns already associated with data center power consumption, which a recent report estimates at 1.7-2.2% of U.S. consumption [14]. Excessive consumption has serious environmental ramifications as well, since 83% of U.S. electricity derives from burning fossil fuels [15]. Energy costs are also on a long-term upward trend, due to a combination of government regulations to limit carbon emissions, a steady rise in global energy demand, and the increasing complexity of locating and extracting new fossil fuel reserves. Even using today's "cheap" power, a data center's energy-related costs represent a significant fraction ($\sim$31% [4]) of its total cost of ownership. Prior research assumes that data centers have an unlimited supply of power, and focuses largely on optimizing applications to use less energy without impacting performance. By comparison, there has been little research on optimizing application performance for intermittent power that fluctuates over time. However, operating off intermittent power is beneficial in a variety of scenarios.

Market-based Electricity Pricing. Electricity prices vary continuously based on supply and demand. Many utilities now offer customers access to market-based rates that vary every five minutes to an hour [1]. As a result, the power data centers are able to purchase for a fixed price varies considerably over time. Figure 1 shows how much power a fixed budget of $55/hour bought in the New England hourly wholesale market in 2011. In this case, maintaining a fixed per-hour budget, rather than a fixed per-hour power consumption, results in 16% more power for the same price. The example demonstrates that data centers that execute delay-tolerant workloads, e.g., batch jobs, could reduce their electricity bill by varying their power consumption based on its price.

Unexpected Blackouts or Brownouts. Data centers often use UPSs for backup power during unexpected blackouts. An extended blackout may force a data center to limit power consumption at a low level to arbitrarily extend UPS lifetime. While low power levels may impact performance and violate SLAs, it may be critical for certain applications to maintain some, even low, level of availability, e.g., disaster response applications. As we discuss, maintaining availability at low power levels is challenging if applications access distributed state. Further, in many developing countries, the electric grid is unstable with voltage rising and falling unexpectedly based on changing demands. These "brownouts" may also affect the power available to data centers over time.

Increasing Renewable Integration. Recent price trends and environmental concerns have led data centers to experiment with clean energy sources, including wind [3] and solar [17]. Wind and solar power are inherently intermittent. Since long-term battery-based storage is prohibitively expensive, increasing renewable integration requires closely matching power consumption to generation. Data centers are particularly well-positioned to benefit from renewables, since unlike household and industrial loads, delay-tolerant batch workloads may permit performance degradation due to varying power.

We recently proposed a blinking abstraction [19] to regulate a server cluster's energy footprint in response to power variations. The abstraction rapidly, e.g., once a minute, "blinks" servers between a high-power active state and a low-power inactive state. In prior work, we demonstrate how to enable blinking for memcached, a

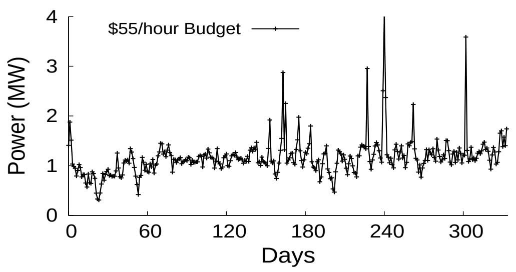


Figure 1: Electricity prices vary hourly in wholesale markets, resulting in the power available for a fixed budget varying considerably over time.

stateless distributed memory cache [19]. However, we intend blinking to be a general abstraction for leveraging intermittent power in a wide range of applications. In this paper, we use blinking to design a distributed file system (DFS) optimized for intermittent power, called BlinkFS. As we discuss, intermittent power raises interesting DFS design questions, since periods of scarce power may render data inaccessible, while periods of plentiful power may require costly data layout adjustments to scale up I/O throughput. BlinkFS has numerous advantages for intermittent power over co-opting prior energy-efficient storage systems, e.g., [8, 13, 16, 18, 22, 23].

Low Amortized Overhead. Blinking every node at regular intervals prevents costly and abrupt data migrations—common to many systems—whenever power decreases, to concentrate data on a small set of active nodes, or increases, to spread data out and increase I/O throughput. Instead, blinking ensures each node is active, and its data accessible, for some time each blink interval, at the expense of a modest overhead to transition nodes between the active and inactive state.

Bounded Replica Inconsistency. Deactivating nodes for long periods requires write off-loading to temporarily cache writes destined for either inactive or overloaded nodes [7]. The technique requires excessive writes whenever nodes activate or deactivate (to migrate or apply any off-loaded writes), while compromising reliability if off-loaded writes are lost due to node failure. In contrast, BlinkFS ensures all replicas are consistent within one blink interval of a write, regardless of the power level.

No Capacity Limitations. Since migrating to a new data layout is expensive, one goal of BlinkFS is to decouple I/O performance at each power level from the specific data layout: the same layout should provide good performance at all power levels. To ensure such a data layout, Rabbit [8] severely limits the capacity of nodes storing secondary, tertiary, etc. replicas. Blinking enables a power-independent data layout without such limitations.

Always-accessible Data. Prior systems render data completely inaccessible if there is not enough power to store all data on the set of active nodes. In contrast, BlinkFS ensures data is always accessible, with latency bounded by the blink interval, even at low power levels.

Since each node's data is inaccessible for some period each blink interval, BlinkFS's goal is to gain the advantages above without significantly degrading latency. In achieving this goal, we make the following contributions.

Blinking-aware File System Design. We detail BlinkFS's design and its advantages over co-opting existing energy-proportional systems for intermittent power. The design leverages a few always-active proxies to absorb reads and writes and mask blinking's complexity.

Latency Reduction Techniques. We discuss techniques for mitigating blinking's latency penalty. Our approach combines staggered node active intervals with a power-balanced data layout to ensure replicas are active for the maximum duration each blink interval. BlinkFS uses popularity-based replication/reclamation to further decrease latency for frequently-accessed blocks.

Implementation and Evaluation. We implement BlinkFS on a small-scale prototype using 10 Mac minis connected to a programmable power supply that drives variable power traces. We benchmark performance and overheads at different (fixed and oscillating) power levels. We then compare BlinkFS with prior approaches in two intermittent power scenarios using three applications: a MapReduce-style batch system, the MemcacheDB key-value store, and file system traces from a search engine. As an example of our results, BlinkFS improves MapReduce job completion time by 42% at 50% power compared to an existing energy-proportional DFS. At 20% power, BlinkFS still finishes jobs, while existing approaches stall due to inaccessible data.

2 Background

Reducing data center power consumption is an active research area. Much prior work focuses on *energy-proportional* systems, where power usage scales linearly with workload demands [12]. The goal of energy-proportional systems is to not impact performance: if demands increase, these systems increase power consumption to maintain performance. Energy-proportional distributed applications vary power consumption by activating and deactivating nodes as workload demands change. One approach for addressing intermittent power is to co-opt existing energy-proportional approaches, but vary the number of active nodes *in response to changes in available power rather than workload demands*. Unfortunately, the approach does not work well with intermittent power, since power variations may be significant, frequent, and unpredictable. While energy-proportional systems optimize energy consumption to satisfy workload demands, designing for intermittent power requires systems to optimize performance as power varies. Below, we summarize how intermittent power affects energy-proportional storage systems, and then discuss two specific approaches.

2.1 Energy-Proportional DFSs

DFSs, such as the Google File System (GFS) [11] or the Hadoop Distributed File System (HDFS) [20], distribute file system data across multiple nodes. Designing energy-proportional DFSs is challenging, since naïvely deactivating nodes to reduce energy usage has the potential to render data inaccessible [16]. One way to prevent data on inactive nodes from becoming inaccessible is by storing replicas on active nodes. Replication is already used to increase read throughput and reliability in DFSs, and is effective if the fraction of inactive nodes is small.

For example, with HDFS's random placement policy for replicas, the probability that any block is inaccessible is $\frac{m!(n-k)!}{n!(m-k)!}$ for n nodes, m inactive nodes, and k replicas per block. Figure 2 plots the fraction of inaccessible data as a function of the fraction of inactive nodes, and shows that nearly all data is accessible for small numbers of inactive nodes. However, the fraction of inaccessible data rises dramatically once half the nodes are inactive, even for aggressive replication factors, such as k=7. Further, even a few inactive nodes, where the expected percentage of inaccessible data is small, may pose problems, e.g., by stalling batch jobs dependent on inaccessible data.

A popular approach for designing energy-efficient storage systems is to use *concentrated data layouts*, which deactivate nodes without causing data to become unavailable. These layouts generally store primary replicas on one subset of nodes, secondary replicas on another mutually-exclusive subset, tertiary replicas on yet another subset, etc., to safely deactivate non-primary nodes [8, 16]. Unfortunately, these layouts cause problems if available power varies frequently. Below, we highlight two problems with the approach

Inaccessible Data. If there is not enough power available to activate the nodes necessary to store all data, then some data will become inaccessible at low power levels. As we mention in §1, sustained low power periods may occur during extended blackout or brownout scenarios. Thus, gracefully degrading throughput and latency down to extremely low power levels is important. With concentrated data layouts, as data size increases, the number of nodes, and hence minimum power level, required to store all data and keep it accessible also increases.

Write Off-loading Overhead. Energy-proportional systems leverage write off-loading to temporarily cache writes on currently active nodes, since clients cannot apply writes to inactive nodes, e.g., [8, 7, 22]. Write off-loading is also useful for deferring writes to overloaded nodes, which are common when only a small number of active nodes store all data. While a small number of active primary nodes decreases the minimum power level

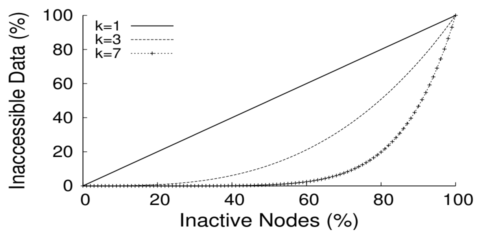


Figure 2: Inaccessible data rises with the fraction of inactive nodes using a random replica placement policy.

necessary to keep data accessible, it overloads primaries by forcing them to process all writes. The approach also imposes abrupt overheads when activating or deactivating nodes, either to apply off-loaded writes to newly active nodes or overloaded primary nodes, respectively.

Further, intermittent sources, e.g., wind power, that exhibit abrupt power variations require near-immediate node deactivations and may not permit the completion of such high overhead operations. While battery-based energy storage may mitigate the impact of sudden power variations, it is expensive to install and maintain [10]. Further, deferring writes to replicas on inactive nodes degrades reliability in the event of node failure. Failure's consequences become worse during low power periods, by both increasing the number of off-loaded writes stored on active nodes, as well as the time that replicas on inactive nodes must remain in an inconsistent state.

Below, we outline two approaches to energy-proportional DFSs that use concentrated data layouts and vary power by activating and deactivating nodes. We highlight the additional problems these DFSs encounter if power variations are significant and frequent.

2.2 Migration-based Approach

We classify any approach that varies power consumption by migrating data to concentrate it on a set of active nodes, and then deactivating the remaining nodes, as a *migration-based approach*. With this approach, power variations trigger changes to number of nodes storing either the most popular data or primary, secondary, tertiary, etc. replicas. In either case, data layout changes require migrations to spread data out to provide higher I/O throughput (as nodes become active) or to concentrate data and keep it accessible (as nodes become inactive). Thus, mitigating migration overheads is a focus of prior work on energy-efficient storage [13, 18, 23].

To highlight the problems with this approach, consider the simple example in Figure 3(a), where there is enough power to operate four nodes storing a data set's primary replicas and the data fills two nodes' storage capacity. A sudden and unexpected drop in power by 2X, leaving only two active nodes, may not afford enough time for the necessary migrations, leaving some data inaccessible. Even with sufficient time for migration, an additional 2X

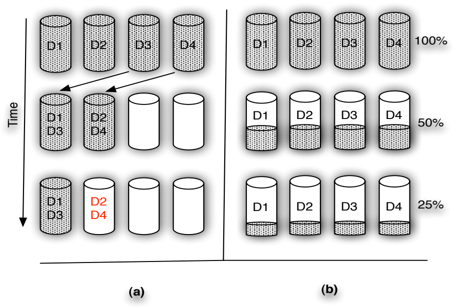


Figure 3: Simple example using a migration-based approach (a) and blinking (b) to deal with power variations.

power drop, leaving only one active node, forces at least 50% of the data to become inaccessible.

We focus on regulating power consumption within a single data center. Another way to handle power variations is to migrate applications and their data to remote data centers with ample or cheap power [9]. The technique is infeasible for large storage systems. Even assuming dedicated high-bandwidth network links, we view frequent transfers of large, e.g., multi-petabyte, storage volumes as impractical.

2.3 Equal-Work Approach

Amur et al. propose an energy-proportional DFS, called Rabbit, that eliminates migration-related thrashing using an *equal-work* data layout [8]. The layout uses progressively larger replica sets, e.g., more nodes store $(n+1)$-ary replicas than n-ary replicas. Specifically, the layout orders nodes $1 \dots i$ and stores $b_i = \frac{B}{i}$ blocks on the ith node, where $i > p$ and p nodes store primary replicas (assuming a data size of B). The layout ensures that any $1 \dots k$ active nodes (for $k < i$ total nodes) are capable of servicing $\frac{B}{k}$ blocks, since $\frac{B}{i} < \frac{B}{k}$. Since the approach is able to spread load equally across any subset of nodes in the ideal case of reading all data, it ensures energy-proportionality with no migrations.

Amur et al. provide details of the approach in prior work [8], including its performance for workloads that diverge from the ideal. Rabbit's primary constraint is its storage capacity limitations as $i \rightarrow \infty$, since $\frac{B}{i}$ defines the capacity constraint for node i. Thus, for N homogeneous nodes capable of each storing M blocks, the nodes' aggregate storage capacity is MN, while Rabbit's storage capacity is $pM + \sum_{i=p+1}^{N} \frac{pM}{i} = O(logN)$. As an example, for N=500 nodes and M=2^{14}=16384 64MB blocks, the aggregate storage capacity across all nodes is MN=500 terabytes, while Rabbit's capacity is less than 15 terabytes, or 3% of total capacity, when p=2.

The relationships above show that the fraction of unused capacity increases linearly with N. Thus, the total storage capacity is capable of accommodating significantly more replicas than Rabbit uses as N increases. To reduce capacity limitations, Rabbit is able to individually apply the layout to multiple distinct data sets, by using a different $1 \dots i$ node ordering for each data set. However, multiplexing the approach between data sets trades-off desirable energy-efficient properties, e.g., few nodes storing primary replicas and ideal energy-proportionality. Thus, Rabbit's design presents issues for large clusters of nodes with similar storage capacities.

3 The Blinking Abstraction

The systems in the previous section use *activation* policies that vary power consumption only by varying the number of active nodes. The blinking abstraction supports other types of *blinking policies*, including *synchronous* policies that transition nodes between the active and inactive state in tandem, *asynchronous* policies that stagger node active intervals over time, and various *asymmetric* policies that blink nodes at different rates based on application-specific performance metrics. Below, we provide a brief summary of blinking. A more detailed description is available in prior work [19].

Blinking enables an external controller to remotely set a blink interval t and an active interval t_{active} on each node, such that for every interval t the node is active for time t_{active} and inactive for time $t - t_{\text{active}}$. ACPI's S3 (Suspend-to-RAM) state is a good choice for the inactive state, since it combines the capability for fast millisecond-scale transitions with low power consumption (<5% peak power). In contrast, techniques that target individual components, such as DVFS in processors, are much less effective at satisfying steep drops in available power, since they are often unable to reduce consumption below 50% peak power [21]. To control inter-node blinking patterns, the abstraction also enables a controller to specify when a blink interval starts, as well as when within a blink interval the active interval starts.

3.1 Advantages for DFSs

To see the advantages of blinking for DFSs, recall the previous section's example (Figure 3(b)), where there is initially enough power to operate four nodes that each provide storage for a fraction of the data. If the available power decreases by 2X, with blinking we have the option of keeping all four nodes active for time $t_{\text{active}} = \frac{t}{2}$ every blink interval t. In this case, instead of migrating data and concentrating it on two active nodes, we are able to keep the same data layout as before without changing our aggregate I/O throughput over each blink interval, assuming each node has the same I/O throughput when active. Thus, at any fixed power level, blinking is able to provide the same I/O throughput, assuming negligible transition overheads, as an activation approach.

However, blinking has a distinct advantage over a migration-based approach if the available power changes, since it is possible to alter node active intervals nearly instantly to match the available power without the overhead of migration. Additionally, in contrast to Rabbit, the blinking approach does not require severe capacity limitations on nodes to maintain throughput. A blinking approach is also beneficial at low power levels if not enough nodes are active to store all data, since data is accessible for some period each blink interval.

3.2 Reliability Concerns

We are not aware of any work that addresses the reliability impact of frequently transitioning a platform's electric components between ACPI's S0 and S3 state. Anecdotally, we have blinked our prototype tens of thousands of times over the past year without any failures. Prior work on energy-proportional storage has likely not considered blinking due to the reliability concerns of frequently transitioning magnetic disks to and from their low-power standby state. For instance, prior work estimates a disk reaches its rated limit (estimated at $50,000$ start/stop cycles) in 5 years when transitioning only 28 times per day [23]. Since our prototype blinks nodes once a minute, it would reach the same limit in only 35 days. Flash-based Solid State Drives (SSDs) are reducing the reliance on magnetic disks, and do not have the reliability concerns associated with rapid blinking. SSDs are becoming increasingly popular, since they support higher I/O rates and are more energy-efficient than disks for a range of seek- and scan-intensive workloads [5, 21].

We also view blinking as potentially useful for nodes with magnetic disks that co-locate computation and data, since a node's mechanical components, e.g., disks and exhaust fans, typically comprise only a small percentage of overall power consumption [5]. For example, prior work estimates that consumer disks use roughly 10W when active and 5W when idle [5], while other non-mechanical components may consume more than 150W. As a result, introducing a new low-power state, similar to ACPI's S3 state, that decouples the power state of the mechanical components from the platform's power state would still permit blinking a node's high-power electric components. Since today's nodes do not have this power state, our prototype uses SSDs. Disk arrays, or nodes with many disks that consume a large fraction of platform power, may require further optimizations—outside the scope of this paper—to make blinking feasible.

4 BlinkFS Design

Figure 4 depicts BlinkFS's architecture, which resembles other recent DFSs, including GFS [11], HDFS [20], Rabbit [8], etc., that use a *master meta-data server* to coordinate access to each node's data via a *block server*. The master also maintains the file system namespace, tree-based directory structure, file name $\rightarrow$ blocks mapping, and block $\rightarrow$ node mapping, as well as enforces the access control and block placement/replication policy. As in prior systems, files consist of multiple fixed-size blocks replicated on zero or more nodes. To mitigate the impact of node failure, the master may recover from meta-data information stored at one or more BlinkFS proxies, described below, or maintain an up-to-date copy of its meta-data on one or more backup nodes.

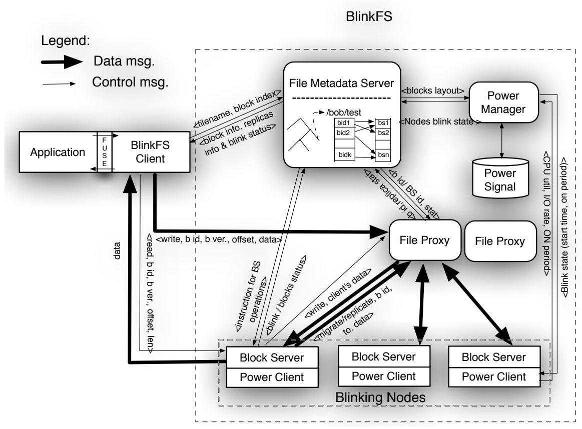


Figure 4: BlinkFS Architecture

BlinkFS also includes a *power manager* that monitors available power, as well as any energy stored in batteries, using hardware sensors. The power manager implements a blinking policy that continuously alters per-node blinking patterns to match power consumption with available power. Specifically, the power manager communicates with a *power client* on each node to set the blink interval duration t, as well as its start time and active interval (t_{active}). The power client also acts as an interface for accessing other node resource utilization statistics, including CPU utilization, I/O accesses, etc. The power manager informs the master of the current blinking policy, i.e., when and how long each node is active every blink interval. To access the file system, higher-level applications interact with BlinkFS *clients* through well-known file system APIs. Our prototype implements the file system calls in the POSIX API.

We do not assume that BlinkFS clients are always active, since clients may run on blinking nodes themselves, e.g., in clusters that co-locate computation and DFS storage. Thus, to enable clients to read or write blocks on inactive nodes, BlinkFS utilizes one or more always-active *proxies* to intercept read and write requests if a client and block server are not concurrently active, and issue them to the appropriate node when it next becomes active. Each proxy maintains a copy (loaded on startup by querying the master) of the meta-data information necessary to access a specific group of files (each file is handled by a single proxy), and ensures replica consistency every blink interval. The proxy propagates any file system operations that change meta-data information to the master before committing the changes. The power manager also maintains an up-to-date view of each node's power state, since each power client sends it a status message when transitioning to or from the inactive state. The messages also serve as heartbeats: if the power manager does not receive any status messages from a power client within a pre-set time interval, e.g., 5 minutes, it checks if the co-located block server has failed; if so, it informs the master to initiate the appropriate recovery actions.

Similar to a set of always-active nodes storing primary replicas, proxies consume power that increases the minimum threshold required to operate the cluster. However, proxies only serve as intermediaries, and do not store data. As a result, the data set size does not dictate the number of proxies. Instead, proxies limit I/O throughput by redirecting communication between many clients and block servers through a single point. However, as we discuss below, mostly-active clients may bypass proxies when accessing data. Further, proxies are most useful at low power levels, where available power, rather than proxy performance, limits I/O throughput. Below we discuss the details of how BlinkFS's components facilitate reading and writing files, and then present techniques for mitigating BlinkFS's high latency penalty.

4.1 Reading and Writing Files

BlinkFS proxies mask the complexity of interacting with blinking nodes from applications. The master and each client use a well-known hash function to map a file's absolute path to a specific proxy. To read or write a file, clients typically issue requests to the proxy directly. We also discuss optimizations that enable a client to bypass a proxy if it is active at the same time as a block server.

Handling Reads. The meta-data necessary to read a file includes its block IDs and their version numbers, as well as the (IP) address and blinking information of the block servers storing replicas of the file's blocks. The proxy holds read requests until a node storing the block becomes active, issues the request to the block server, receives the data, and then proxies it to the client. If multiple block servers storing the block's replicas are active, the proxy issues the request to the node with the longest remaining active interval, assuming the remaining active time exceeds a minimum threshold necessary to read and transmit the block. Using a proxy to transfer data is necessary when executing both clients and block servers on blinking nodes, since the client may not be active at the same time as the block server storing the requested data.

To optimize reads, mostly-active clients may directly request from the proxy the block information—IDs and version numbers—and blinking policy for each block server holding a replica, and then access block servers directly when they become active. The optimization significantly reduces the proxy load for read-intensive workloads. To ensure the proxy applies all previous client writes to a block before any subsequent reads, the proxy includes a version number for each block, incremented on every update, in its response to the client. If the version number for the block stored at the block server differs, then the proxy holds pending writes that it has not yet applied. In this case, the read stalls until the proxy applies the writes and the version numbers match. Note that a read may span multiple blocks across multiple nodes.

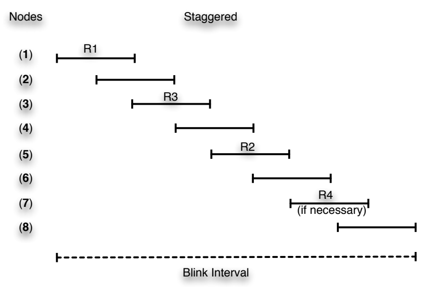
Handling Writes. The proxy performs a similar sequence for writes. All writes flow through a file's proxy, which serializes concurrent writes and ensures all block replicas are consistent each blink interval. The proxy may also return to the client before applying the write to every block replica, since subsequent reads either flow through the proxy or match version numbers at the block server, as described above. The proxy maintains an in-memory write-ahead log to track pending off-loaded writes from clients. Since the log is small, the proxy is able to store in-memory backups on one or more nodes (updated on each write before returning to the client), which it recovers from in case of failure. When the client issues the write, the proxy first records the request in its log and returns to the client; the proxy then propagates the write to all replicas as the block servers become active; finally, when all replicas successfully apply the write, the proxy removes the request from its log.

Since all block servers are active for a period each blink interval, all replicas are consistent within one blink interval from when the write is issued, and the maximum time a write remains pending in the proxy's log is one blink interval. Of course, the proxy does have a fixed-size log for pending writes. After filling the log, further write requests stall until the proxy propagates at least one of its queued writes to each replica. As with reads, clients could also interact directly with block servers, as long as the client and block server are both active at the same time. In this case, the proxy uses a similar lease mechanism as GFS to handle concurrent writes.

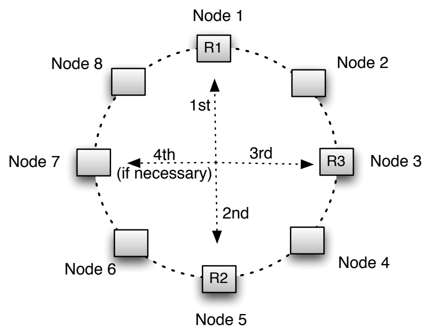
4.2 Reducing the Latency Penalty

While migration-based activation approaches incur high overheads when power levels change, they ensure data is accessible, i.e., stored on an active node, as long as there is enough power to activate the nodes necessary to store all data. In contrast, naïve blinking incurs a high latency penalty, since each node is inactive for some time each blink interval. BlinkFS combines three techniques to reduce its latency penalty: an asynchronous staggered blinking policy, a power-balanced data layout, and popularity-aware replication and reclamation.

Asynchronous Staggered Blinking. Staggered blinking's goal is to minimize the overlap in node active inter-



(a) Staggered Blinking



(b) Power-balanced Data Layout

Figure 5: Combining staggered blinking (a) with a power-balanced data layout (b) maximizes block availability.

vals by staggering start times equally across each blink interval. Figure 5(a) depicts an example of staggered blinking. To perform well at both high and low power levels, the policy assigns equal-sized active intervals to all nodes, and varies the size of this active interval to adjust to changes in available power. Thus, at any power level all nodes are active for the same amount of time. By contrast, while a synchronous policy, where all nodes activate in tandem (akin to co-scheduling), may exhibit slightly lower latencies at high power levels (especially for read requests issued during an active interval that span multiple blocks stored on multiple nodes), it performs much worse at moderate-to-low power since it does not take advantage of replication to reduce latency.

Formally, for available power $p_{\text{available}}$, total power p_{total} necessary to activate all nodes, total power p_{inactive} required to keep all nodes in the inactive state, blink interval duration t, and N nodes, the duration of each node's active interval is $t_{\text{active}} = t * \frac{p_{\text{available}} - p_{\text{inactive}}}{p_{\text{total}} - p_{\text{inactive}}}$, and the blink start time (within each interval) for the ith node (where i=0 . . . $N-1$) is b_{start}=$(t - t_{\text{active}}) * \frac{i}{N-1}$. As we discuss next, combining staggered blinking with a data layout that carefully spreads replicas across nodes maximizes the time that at least one replica of a block is stored on an active node each blink interval. Importantly, the approach maximizes this time at *all* power levels.

Power-balanced Data Layout. A power-balanced data layout spreads replicas for each block across nodes, such that any set of nodes storing the block's replicas have minimum overlapping active intervals using the staggered blinking policy above. To place replicas in such a layout, we order all N nodes in a circular chain from $0 \ldots N-1$ and choose a random node to store the first replica of each block. We then place the second replica on the node opposite the first replica in the circle, the third replica on one of the nodes half-way between the first and second replicas, the fourth replica on the other node between the first and second replicas, etc. Similarly, to delete replicas, we reverse the process. Figure 5(b) depicts an example of the layout for the three replicas using staggered blinking from Figure 5(a).

The layout policy above is optimal, i.e., maximizes the time each block is available on an active node each blink interval, if the number of replicas is a power of two. Maintaining an optimal placement for any number of replicas requires migrating all replicas each time we add or remove a single one. The layout performs well as the number of replicas for each block vary, and does not require expensive migrations each time the number of replicas for a block changes. Note that for blocks with highly stable access patterns, where the number of replicas rarely changes, we evenly distribute replicas around the chain. Our layout is more resilient to failures than concentrated data layouts, since it spreads blocks and replicas evenly across nodes, rather than concentrating data on small subsets of nodes.

Popularity-aware Replication and Reclamation. Replication in DFSs is common to tolerate node failures and improve read throughput. Likewise, migrating popular replicas to active nodes is common in energy-efficient DFSs [13, 18, 22, 23]. BlinkFS also uses replication to mitigate its latency penalty as power varies. Additionally, BlinkFS employs popularity-aware replication and reclamation to further reduce access latency for popular blocks. Note that our replication strategy is independent of the power level, since replicating at low power levels may be infeasible. In this case, a modest amount of battery-based storage may be necessary to spawn the appropriate replicas to satisfy performance demands [10]. By default, BlinkFS maintains three replicas per block, and uses any remaining capacity to potentially store additional latency-improving replicas.

As clients create new files or blocks become less popular, BlinkFS lazily reclaims replicas as needed. Using staggered blinking and a power-balanced data layout, the number of replicas r required to ensure a block is available 100% of each blink interval, based on the total nodes N, blink interval t, available power p, and active node power consumption p_{node}, is $r = \lceil \frac{N}{\lfloor \frac{(N-1)p}{N * p_{\text{node}} - p} \rfloor} \rceil$. At low enough power levels, i.e., where $1 > \frac{p}{p_{\text{node}}}$, there are

FUSE Functions
`getattr(path, struct stat *)`
`mkdir(path, mode)`
`rmdir(path)`
`rename(path, newpath)`
`chmod(path, mode)`
`chown(path, uid, gid)`
`truncate(path, offset)`
`open(path, struct fuse_file_info *)`
`read(path,buff,size,offset,fusefileinfo*)`
`write(path,buff,size,offset,fusefileinfo*)`
`release(path,fuse_file_info*)`
`create(path,mode,fuse_file_info*)`
`fgetattr(path, stat*,fuse_file_info*)`
BlinkFS-specific Functions
`getBlinkState(int nodeid)`
`getBlockInfo(int blockid)`
`getFileInfo(path)`
`getServerLoadStats(int nodeId)`

Table 1: API for BlinkFS, including POSIX file system calls and BlinkFS-specific calls.

periods within each blink interval where no nodes are active. In this case, the minimum possible fraction of each blink interval the block is unavailable is $1 - \frac{p}{p_{\text{node}}}$, assuming it is replicated across all nodes.

The master uses the relationships above to compute a block's access latency, given its replication factor and the current power level, assuming requests are uniformly distributed over each blink interval. There are many policies for spawning new replicas to satisfy application-specific latency requirements. In our prototype, the master tracks block popularity as an exponentially weighted moving average of a block's I/O (read) accesses, and replicates blocks every period in proportion to their relative popularity, such that all replicas consumes a pre-set fraction of the unused capacity. For frequently updated blocks, BlinkFS caps the replication factor at three, since excessive replicas increase write overhead.

5 Implementation

We implement a BlinkFS prototype in C, including a master (∼3000LOC), proxy (∼1000LOC), client (∼1200LOC), power manager (∼100LOC), power client (∼50LOC), and block server (∼900LOC). The client uses the FUSE (Filesystem in Userspace) library in Linux to transfer file system-related system calls from kernel space to user space. Thus, BlinkFS clients expose the POSIX file system API to applications. BlinkFS also extends the API with a few blink-specific calls, as shown in Table 1. These system calls enable applications to inspect information about node blinking patterns to improve their data access patterns, job scheduling algorithms, etc., if necessary. All other BlinkFS components run in user space. While the master, proxy, and power manager are functionally separate and communicate via event-based APIs (using libevent), our prototype executes them on the same node. To experiment with a wide range of unmodified applications, we chose to implement our prototype in FUSE, rather than extend an existing file system implementation, such as HDFS.

Our prototype includes a full implementation of BlinkFS, including the staggered blinking policy, power-balanced data layout, and popularity-aware replication. Our current implementation redirects all writes through the proxy to maintain consistency for concurrent writes, but permits clients to issue reads directly to block servers if both are concurrently active. Since our prototype has a modular implementation, we are able to insert other blinking policies and data layouts. We implement the migration-based approach and Rabbit from §2, which both use an activation policy, to compare with BlinkFS. We also implement a *load-proportional blinking policy*, which we used with memcached in prior work [19], that blinks nodes in proportion to the popularity of the blocks they store. The policy is useful for access patterns with skewed popularity distributions, e.g., Zipf, but does not require migrations (as in PDC [18]).

Hardware Prototype. We construct a small-scale hardware prototype that uses intermittent power to experiment with BlinkFS in a realistic setting. We extend our prototype from prior work with more powerful desktop-class nodes [19]. We use a small cluster of ten Mac minis running Linux kernel 2.6.38 with 2.4Ghz Intel Core 2 Duo processors and 2GB of RAM connected together using an energy-efficient switch (Netgear GS116) that consumes 15W. Each Mac mini uses a flash-based SSD with a 40GB capacity. We also use a separate server to experiment with external always-on clients, not co-located with block servers. To minimize S3 transition times, we boot each Mac mini in text mode, and unload all unnecessary drivers. With the optimizations, the time to transition to and from ACPI's S3 state on the Mac mini is one second. Note that much faster sleep transition times, as low as a few milliseconds, are possible [19]. Unfortunately, manufacturers do not optimize sleep transition time in today's desktop and server-class nodes. Faster transition times would improve performance, especially worst-case latency, by reducing the blink interval's length.

We select a blink interval of one minute, resulting in a transition overhead of $\frac{1}{60}$=1.67% every blink interval. We measure the power of the Mac mini in S3 to be 1W and the power in S0 to be 25W. Thus, in S3, nodes operate at 4% peak power. Since BlinkFS requires at least one node (to host the master, proxy, and power manager) and the switch to be active, its minimum power consumption is 40W, or 15% of its maximum power consumption. The remaining nine nodes each run a power client, block server, and BlinkFS client. We power the cluster from a battery that connects to four ExTech 382280 programmable power supplies, each capable of producing 80W, that replay the variable power traces below. Our experiments use the battery as only a short-term buffer of

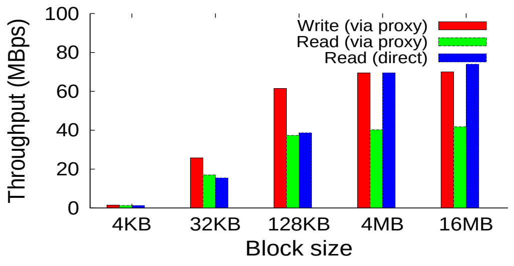


Figure 6: Maximum sequential read/write throughput for different block sizes with and without the proxy.

Latency (ms)		*Power (%)*				
⇓		***20***	***40***	***60***	***80***	***100***
Replication factor = 1						
Std Dev	W	1619	1069	1014	9	7
	R	15524	12701	1692	725	9
90th per	W	60	60	61	62	65
	R	46058	33636	64	64	63
Replication factor = 3						
Std Dev	W	6017	4475	2089	22	22
	R	5476	322	309	9	7
90th per	W	79	103	131	145	147
	R	13065	64	63	63	63
Replication factor = 6						
Std Dev	W	8883	5743	2467	703	372
	R	523	7	7	7	7
90th per	W	127	183	257	258	263
	R	63	63	63	63	63

Table 2: Standard deviation and 90th percentile latency at different power levels and block replication factors.

5 minutes; optimizations that utilize substantial battery-based storage are outside the scope of this paper.

Power Signals. We program our power supplies to replay DC current traces from a distributed generation deployment, including both solar panels and wind turbines, and a signal based on wholesale electricity prices. In our benchmarks, we also experiment with both different steady power and power oscillation levels as a percentage, where 0% oscillation holds power steady throughout the experiment and N% oscillation varies power between $(45 + 0.45N)$% and $(45 - 0.45N)$% every 5 minutes.

For our renewable trace, we combine traces from our solar/wind deployment, and set a minimum power level equal to the power necessary to operate BlinkFS's switch and master node (40W). We compress our renewable power signal to execute three days in three hours, and scale the average power to 50% of the cluster's maximum power. Note that the 24X compressed power signal is not unfair to the migration-based approach, since our data sets are relatively small (less than 20GB). We would expect large clusters to store more than 24X this much data, increasing the relative transfer time for migration. BlinkFS's performance is by design not dependent on the data set size. For our price trace, we use the New England ISO 5-minute spot price of energy for the 3-hour period from 7am to 10am on September 22, 2011, assuming a fixed monetary budget of 1¢/kWh; ISO's regulate wholesale electricity markets in the U.S. The average price in the trace is 4.5¢/kWh, the peak price is 5.2¢/kWh, and the minimum price is 3.5¢/kWh.

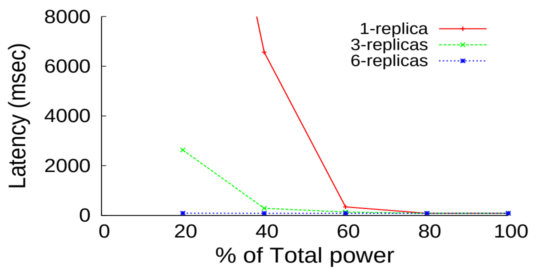
6 Evaluation

We evaluate BlinkFS using the hardware prototype and power signals described in §5 with three different applications: a MapReduce-style application [6] (a throughput-sensitive batch system), unmodified MemcacheDB [2] (a latency-sensitive key-value store), and file system traces from a search engine. Since our implementation uses FUSE, applications run as normal processes with access to the BlinkFS mount point. Before describing each case study, we benchmark BlinkFS's overheads as a baseline for understanding its performance at different steady and oscillating power levels.

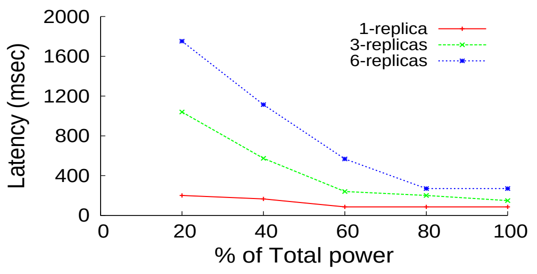
6.1 Benchmarks

To benchmark BlinkFS, we wrote a single-threaded application that issues blocking read/write requests to the client's interface, rather than through FUSE, to examine performance independent of FUSE overheads. One limitation of FUSE is that the maximum size of write and read requests are 4KB and 128KB, respectively, irrespective of BlinkFS's block size. BlinkFS has a configurable block size, since we intend it for multiple types of applications. Our benchmarks examine performance using multiple block sizes. The breakdown of the latency overhead at each component for a sample 128KB read is 2.5ms at the proxy, 0.57ms at the block server, 2.7ms at the client, and 0.33ms within FUSE for a total of 6.1ms. The results demonstrate that BlinkFS's overheads are modest. We also benchmark BlinkFS's maximum sequential read and write throughput at full power for a range of block sizes. Figure 6 shows that, as expected, read and write throughput increase with increasing block size. However, once block size exceeds 4MB throughput improvements diminish, indicating that I/O transfer overheads begin to dominate processing overheads.

Read and write throughput via the proxy differ because clients off-load writes to proxies, which return before applying the writes to block servers. We also benchmark the throughput for reads sent directly to the proxy, which shows how much the proxy decreases maximum throughput (∼40% for large block sizes). The overhead motivates our client optimization that issues reads directly to the block server, assuming both are concurrently active. The throughput of writes sent directly to block servers is similar to that of reads. We ran a similar experiment using 4MB blocks that scales the number of block servers, such that each block server continuously receives a stream of random I/O requests from multiple clients (using a block size of 4MB). In this case, write throughput reaches its maximum (75MBps) when using



(a) Reads



(b) Writes

Figure 7: Read and write latency in our BlinkFS prototype at different power levels and block replication factors.

three block servers, due to CPU overheads. The result shows that in the worst case a proxy-to-block server ratio larger than 1:3 does not improve write throughput. As our case studies demonstrate, for realistic workloads, each proxy is capable of supporting at least ten nodes.

We also benchmark the read and write latency for different block replication factors for a range of power levels. Figure 7(a) shows that average read latency increases rapidly when using one replica if available power drops below 50%, increasing to more than 8 seconds. Additional replicas significantly reduce the latency using staggered blinking: in our prototype, all blocks are always available, i.e., stored on an active node, when using six replicas at 20% power. Write latency exhibits worse performance as we increase the number of replicas. In this benchmark, where clients issue writes as fast as possible, the proxy must apply writes to all replicas, since its log of pending writes becomes full (Figure 7(b)). Since the increase in the write latency is much less than the increase in read latency, the trade-off is acceptable for workloads that read data. Table 2 shows the standard deviation and 90th percentile latency for read and write requests as the replication factor and power levels change.

Finally, we benchmark the overhead to migrate data as power oscillates, to show that any approach that involves significant data migration is not appropriate for significant and frequent power variations. To demonstrate the point, we implement a migration-based approach that equally distributes data across the active nodes. As power varies, the number of active nodes also varies, forcing migrations to the new set of active nodes. We oscillate available power every 5 minutes, as described in §5. We wrote a simple application that issues random (and blocking) read requests; note that the migration-based approach does not respond to requests while it is migrating data. Figure 8 shows that read throughput remains nearly constant for BlinkFS at different oscillation levels, whereas throughput decreases for the migration-based approach as oscillations increase. Further, the size of the data set significantly impacts the migration-based approach. At high oscillation levels, migrations for a 20GB data set result in zero effective throughput. For smaller data sets, e.g., 10GB, the migration-based approach performs slightly better than BlinkFS at low oscillation levels, since the overhead to migrate the data is less than the overheads associated with BlinkFS.

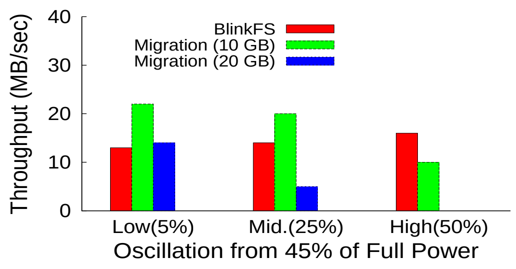
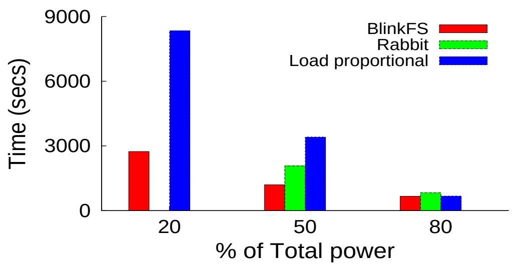


Figure 8: BlinkFS outperforms a migration-based approach as power oscillation levels increase.

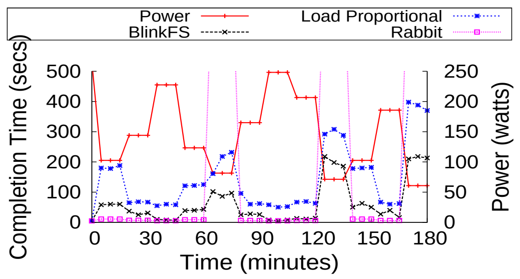
In large clusters, even small power variations trigger substantial migrations. For instance, consider a 1000 node cluster, where each node stores 500GB. If available power varies even 2% (near the average change in hourly spot prices), the cluster must deactivate 20 nodes, necessitating a 10 terabyte migration in the worst case. Migrating this data over a ten gigabit link would take more than two hours, and prevent the cluster from performing useful work. We compare the migration-based approach with BlinkFS for these small power variations.

6.2 Case Studies

We experiment with a MapReduce-style application, MemcacheDB, and file system traces from a search engine using the real-world renewable and price traces discussed in §5 for three different approaches: BlinkFS, Rabbit, and Load-proportional. Since MapReduce is a type of batch processing system, it is well-suited for intermittent power if its jobs are tolerant to delays. We also experiment with more interactive applications (MemcacheDB and file system traces) to demonstrate BlinkFS's flexibility to handle challenging applications in difficult circumstances, e.g., extended low power periods from blackouts. To fairly compare with Rabbit, we use an equal-work layout where the first two nodes store primary replicas, the next five nodes store secondary replicas, and the last two nodes store tertiary replicas.

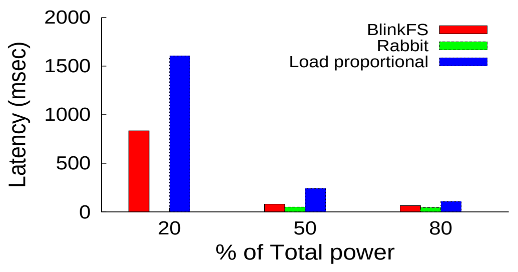


(a) Steady Power

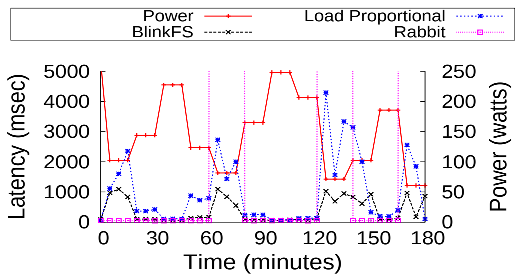


(b) Solar/Wind Power Signal

Figure 9: MapReduce completion time at steady power levels and using our combined wind/solar power trace.



(a) Steady Power



(b) Solar/Wind Power Signal

Figure 10: MemcacheDB average latency at steady power levels and using our combined wind/solar power signal.

Note that, while Rabbit performs better than BlinkFS in some instances, it relies on severe capacity limitations, as described in §2, to eliminate migrations. For BlinkFS's power-balanced data layout, we use 2/9ths of the capacity to store one replica of each block, and the rest to store additional replicas. We set the default number of replicas to be three, with a maximum replication factor of six for our popularity-aware replication policy. For the load-proportional policy, we arrange blocks on nodes *a priori* based on popularity (from an initial run of the application) to eliminate data migrations, which provides an upper bound on load-proportional performance. Since MapReduce co-locates computation and data, the nodes execute both a client and a block server. For the other applications, we use an external, e.g., always-on, client. Finally, we use a block size of 4 MB.

MapReduce. For MapReduce, we create a data set based on the top 100 e-books over the last 30 days from Project Gutenberg (http://www.gutenberg.org/). We randomly merge these books to create 27 files between 100 and 200MB, and store them in our file system. We then write a small MapReduce scheduler in Python, based on BashReduce, that partitions the files into groups for each job, and sends each group to a MapReduce worker node, co-located on each block server. We execute the simple WordCount MapReduce application, which reads files on each node, counts the words in those files, and sends the results back to the scheduler. The scheduler then executes a final reduce step to output a file containing all distinct words and their frequency in the data set.

We experiment with MapReduce using both constant and intermittent power. At constant power levels, Figure 9(a) shows that the completion time is nearly equal for all three policies at high power, but BlinkFS outperforms the others at both medium and low power levels. For instance, at 50% power BlinkFS improves completion time by 42% compared with Rabbit and 65% compared with load-proportional. Note that at low power (20%), MapReduce stalls indefinitely using Rabbit, since it requires at least two active nodes to ensure all data is accessible. Both Rabbit and Load-proportional also impact MapReduce computations by deactivating or reducing, respectively, the active time of cluster nodes as power decreases. BlinkFS does not affect the scheduling or placement policy as power varies.

For variable power, we execute a stream of smaller jobs, which process data sets that only consist of 27 e-books, to track the number of jobs we complete every five minutes. For this experiment, Figure 9(b) shows that BlinkFS outperforms Load-proportional at all power levels, since it does not skew the active periods of each node. While Rabbit performs better at high power levels, it stalls indefinitely whenever power is unable to keep all data accessible, i.e., two active nodes.

MemcacheDB Key-Value Store. MemcacheDB is a persistent version of memcached, a widely-used distributed key-value store. MemcacheDB uses BerkeleyDB as its backend. We installed MemcacheDB on our external node, and configured it to use BlinkFS to store its BerkeleyDB. To avoid any BerkeleyDB caching effects, we configure MemcacheDB to use only 128 MB of RAM and set all caching-related configuration options to their minimum possible value. We then populated the DB with 10,000 100KB objects, and wrote a MemcacheDB workload generator to issue key requests at a steady rate according to a Zipf distribution.

Our results show that both BlinkFS and Rabbit perform equally well at high and medium constant power levels (Figure 10(a)), while the load-proportional approach performs slightly worse. Load-proportional does not benefit from replication, since replicas of popular blocks are inevitably stored on unpopular nodes. As a result, BlinkFS significantly outperforms Load-proportional at low power levels. As with MapReduce, Rabbit has infinite latency at low power, since its data is inaccessible. Next, we run the same experiment using our wind/solar power signal and observe the average request latency over each 5-minutes interval. As shown in Figure 10(b), BlinkFS performs better than the load-proportional policy at nearly all power levels. The latency for BlinkFS scales up and down gracefully with the power signal. As in the MapReduce example, Rabbit performs better, except when the available power is not sufficient to keep the primary servers active.

Search Engine. We emulate a search engine by replaying file system traces, and measuring the number of queries serviced each minute. The trace is available at http://www.storageperformance.org/specs/. To emulate the trace, we created a large 30GB file divided into $491,520$ blocks of size 64KB. To replay the trace, we implement a simulator in Python to issue its I/O requests. We run the experiment with the variable price power signal described in the previous section. As Figure 11 shows, BlinkFS outperforms the load-proportional policy at all power levels. As expected, the migration-based approach performs slightly better than BlinkFS at steady power levels, but much worse for even slight ($\sim$10%) fluctuations in the available power. Since the available power is always more than the power required to run two nodes, Rabbit (not shown), outperforms (57 queries/minute) the others, since it stores primary replicas on these two nodes. Even for such a small dataset and power fluctuations, BlinkFS satisfies 12% and 55% more requests within a 3-hour period than the migration-based and Load-proportional approaches, respectively.

7 Conclusion

We optimize BlinkFS for intermittent power, resulting from cost optimizations in market-based pricing, intermittent renewables, or blackout/brownout scenarios. We envision rising energy prices incentivizing data centers to design systems optimized for intermittent power.

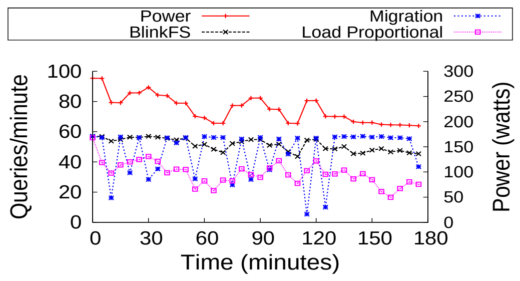


Figure 11: Search engine query rate with price signal from 5-minute spot price in New England market.

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