Power-Aware Storage Cache Management

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Abstract—Reducing energy consumption is an important issue for data centers. Among the various components of a data center, storage is one of the biggest energy consumers. Previous studies have shown that the average idle period for a server disk in a data center is very small compared to the time taken to spin down and spin up. This significantly limits the effectiveness of disk power management schemes. This article proposes several power-aware storage cache management algorithms that provide more opportunities for the underlying disk power management schemes to save energy. More specifically, we present an offline energy-optimal cache replacement algorithm using dynamic programming, which minimizes the disk energy consumption. We also present an offline power-aware greedy algorithm that is more energy-efficient than Belady's offline algorithm (which minimizes cache misses only). We also propose two online power-aware algorithms, PA-LRU and PB-LRU. Simulation results with both a real system and synthetic workloads show that, compared to LRU, our online algorithms can save up to 22 percent more disk energy and provide up to 64 percent better average response time. We have also investigated the effects of four storage cache write policies on disk energy consumption.

Index Terms—Power management, disk storage, storage cache replacement, write policies.

1 Introduction

Trends in Internet infrastructure are driving a shift toward service-based computing. Data centers are playing a key role in this new architecture since they are commonly used to provide a wide variety of services, including Web hosting, application services, outsourced storage, and other network services. Storage is one of the biggest components in data centers. Storage demand is also growing by 60 percent annually [36]. By 2008, data centers will manage 10 times as much data as they do today.

The steady growth of data centers introduces a significant problem: *energy consumption*. Data centers typically have very high power requirements. According to EUN (Energy User News) [35], today's data centers have power requirements that range from 75 W/ft^2 for small to medium-sized enterprises to 150-200 W/ft^2 for typical service providers. In the future, this is predicted to increase to 200-300 W/ft^2 [35]. These increasing power requirements are driving energy costs up as much as 25 percent annually and making it a growing consideration in the TCO (total cost of ownership) for a data center [36]. High energy consumption also prevents easy expansion and has negative environmental implications.

Among various components of a data center, storage is one of the biggest consumers of energy. A recent industry report [2] shows that storage devices account for almost 27 percent of the total energy consumed by a data center. This problem is exacerbated by the availability of faster disks with higher power needs as well as the increasing shift from tape backups to disk backups for better performance.

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Although disk power management for mobile devices has been well studied in the past, only a few recent studies [8], [17], [16], [6], [40], [50], [51] have looked at power management for the multiple-disk storage systems of data centers. The large volume of activity on these servers keeps the average idle period between requests too small to justify the costs of spinning the disks up and down. Thus, the potential for saving energy is very limited. To address this problem, multiple-speed disks have been proposed by Gurumurthi et al. [16] and Carrera et. al [6]. By introducing intermediate power modes, the spin-up and spin-down costs are reduced and more energy can be saved in spite of the small idle periods [16].

Not all accesses to a storage system go to disks. A typical architecture for a modern storage system is shown in Fig. 1. Many modern storage systems use a large storage cache to reduce the number of disk accesses and improve performance. For example, the EMC Symmetrix storage system with a capacity of 10-50 TBytes can be configured with up to 128 GB of nonvolatile memory as the storage cache [10]. The IBM ESS system can also have up to 64 GB of storage cache [1]. Different from those small (usually 1-4 MB) buffers on a SCSI disk, which are mainly used for read-ahead purposes, these large caches are used to cache blocks for future accesses. Therefore, the cache replacement algorithm plays a very important role in a storage system [49], [44], [34], [7].

The storage cache management policy influences the sequence of requests that access disks. Different cache management policies may generate different disk request sequences, which directly affects disk energy consumption. In other words, by changing the cache management scheme, it is possible to change the average idle time between disk requests, thus providing more opportunities for the disk power management scheme to save energy. For example, if the cache replacement algorithm can selectively keep some blocks from a particular disk in the cache (without significantly increasing the number of misses to other disks), that disk can stay in a low power mode longer. Since storage caches are critical to storage system performance, our study assumes that storage caches are active all the time.

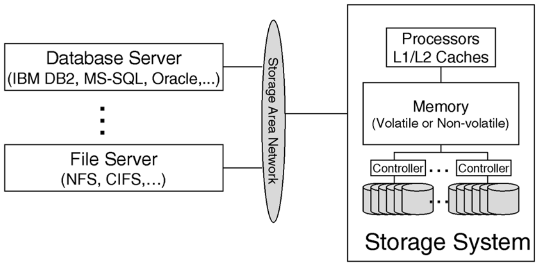


Fig. 1. Modern storage architecture.

Besides disk energy consumption, I/O response time is another concern. If underlying disks use power management schemes, some requests can be significantly delayed because it takes a long time (a few seconds) for a disk to spin up from a low power mode to the active mode. Consequently, if a cache replacement algorithm is only designed to minimize the number of cache misses and ignores the underlying disk power management schemes, it can result in very high I/O response time. Therefore, it is important to design cache management schemes that are power-aware (aware of the underlying disk energy consumption and power management schemes).

This paper studies the effects of storage cache management schemes on disk energy consumption and proposes *power-aware* cache management schemes. We look into both cache management for read accesses and for write accesses. Specifically:

- For read accesses, we first present an energy-optimal offline cache replacement algorithm using dynamic programming which minimizes the underlying disk energy consumption.
- Since the energy-optimal algorithm is too complicated to evaluate, we present a simple offline power-aware greedy algorithm. Simulations show that the greedy algorithm is more energy-efficient than Belady's offline algorithm while still providing acceptable average response time.
- Based on the insights from our analysis of offline algorithms, we propose two new online power-aware replacement algorithms, PA-LRU and PB-LRU, that are based on the same observation, but use very different approaches. Our simulation results with both real system and synthetic workloads show that these two power aware algorithms can reduce disk energy consumption by up to 22 percent compared to LRU and also provide up to 64 percent better average response time.
- For write accesses, we study the effects of storage cache write policies on disk energy consumption. Our results show that write-back can save up to 20 percent more energy compared to write-through. Write-back with eager updates further reduces disk energy consumption of write-back up to 45 percent. We also propose a policy called write-through with deferred updates that reduce energy consumption up to 55 percent while still providing persistency semantics comparable to write-through.

This paper is organized as follows: The next section briefly describes the background. Section 3 discusses the offline energy-optimal algorithm and the offline greedy power-aware algorithm. Section 4 presents two online power-aware algorithms. Section 5 describes our evaluation methodology, followed by simulation results for power-aware replacement algorithms in Section 6. Section 7 discusses the effects of four storage cache write policies on energy consumption. Several related issues are discussed in Section 8. Section 9 summarizes related work. Finally, Section 10 concludes this paper.

2 Background

2.1 Disk Power Model

To reduce energy consumption, modern disks use multiple power modes that include active, idle, standby, and other intermediate modes. In active mode, the platters are spinning and the head is seeking or the head is actively reading or writing a sector. In idle mode, a disk is spinning at its full speed, but no disk activity is taking place. Therefore, staying in the idle mode when there is no disk request provides the best possible access time since the disk can immediately service requests, but it consumes the most energy. To simplify discussion, we do not differentiate active mode and idle mode since, in both modes, the disk is operating at full power. In the standby mode, the disk consumes much less energy, but, in order to service a request, the disk has to incur significant energy and time to spin up to active mode.

Recently, Gurumuthi et al. have proposed multispeed disks to increase the amount of energy saved with data center workloads [16]. Lower rotational speed modes consume less energy compared to higher speed modes and the energy and time costs to shift between different rotational speeds are relatively small compared to the costs for shifting from standby to active. Such multispeed disks are still only a design on paper and there are no real products yet. We, however, simulate and use multispeed disks in our experiments because of their potential to save more energy. A multispeed disk can be designed to either serve requests at all rotational speeds or serve requests only after a transition to the highest speed. We choose the second option since it is a simple extension to the traditional 2-mode power model.

2.2 Disk Power Management

The goal of disk power management is to try and save energy by switching disks to lower power modes whenever possible without adversely affecting performance [8], [6], [17], [16]. If the entire disk request sequence is known in advance, the power management scheme can make perfect decisions. This "Oracle"-based disk power management scheme (Oracle DPM) [31] gives us an upper bound on the energy that can be saved for a given request sequence, assuming requests will not be prefetched or delayed. The *break-even time* of a disk is defined as the minimum length of idle period which would justify the energy cost of spinning the disk down and up [6]. At the end of every request, the Oracle DPM looks at the time till the next request, t. If t is greater than the break-even time, then the disk is spun down and later spun up just in time for the next request. If t is less than the break-even time, the Oracle DPM decides that it is better to keep the disk in idle mode.

This scheme can easily be extended to disk models with multiple power modes. Let us assume that P_i $(0 \leq i \leq m)$ is

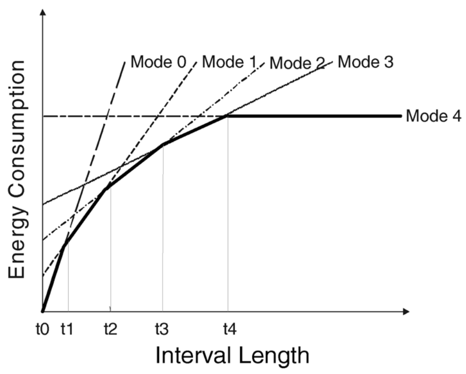


Fig. 2. Energy consumption for each mode in a 5-mode disk power model and the lower envelope $LE(t)$ function.

the power consumed in mode i and that P_i is greater than P_j for all $i < j$. Once an idle interval starts, Oracle DPM has to switch the disk to one of the m modes that minimizes energy consumption. The disk must also be back in mode 0 when the next request arrives.

To get the minimum energy consumption, we plot lines $E_i(t) = P_i * (t - T_i) + C_i$ as in Fig. 2 for each power mode i, where P_i is the power dissipation in mode i and T_i and C_i are the time and energy required to spin-down and spin-up from mode i to 0 (T_0 and C_0 is 0). $E_i(t)$ is the energy consumed if the disk spends the entire interval of length t in mode i. Let us call the lower envelope of all of these lines $LE(t) = min_i\{P_i * (t - T_i) + C_i\}$. This gives us the minimum energy consumption possible for an interval of length T. If the next request is time T away from the current request, Oracle DPM can use $LE(t)$ to determine which power mode to switch the disk to: If the disk is switched to the power mode j where $LE(T) = E_j(T)$, the energy consumption during this interval is minimized.

Practical disk power management (Practical DPM) schemes use thresholds to determine when to spin down disks. In such schemes, after the disk remains idle at a power mode for a certain threshold time, it is switched into the next lower power mode. Irani et al. have shown if the threshold values are determined by the intersection points of the lines in Fig. 2, the power management scheme is 2-competitive to the Oracle scheme in terms of energy consumption [23]. This scheme transitions the disk from mode i to mode $i+1$ after time t_{i+1}, where t_{i+1} is the time corresponding to the intersection point of lines $E_i(t)$ and $E_{i+1}(t)$, as shown in Fig. 2. We use thresholds obtained by this method in our study.

3 Power-Aware Offline Caching Algorithms

Offline caching algorithms have knowledge about the future. Such algorithms are usually studied because they provide upper and lower bounds for all online algorithms. For example, Belady's offline algorithm [4], [33], which replaces the block with the longest future reference distance, is used to derive a lower bound on the cache miss rate. Since the study of offline algorithms is important to gain insights into the problem, we first investigate offline algorithms for power aware cache management. We will describe two new online algorithms in Section 4 and discuss the effects of write policies in Section 7.

3.1 Energy-Optimal Problem

The goal of a power-aware cache replacement algorithm is to take a given request sequence as input and generate a miss sequence for which the disks consume the least energy. If we use S to denote an I/O request sequence, a replacement algorithm A is a function that maps S and a cache with k blocks into a miss request sequence S', i.e., $A : (S, k) \rightarrow S'$ or $A(S, k) = S'$. Given a disk power management scheme P and a disk request sequence X, let $P(X)$ be the total energy consumed by the disks. Therefore, we have the following definition of an energy-optimal replacement algorithm:

Remark. Given an I/O request sequence S, a cache replacement algorithm A, a cache with k blocks, and a disk power management scheme P, the total disk energy consumption is $P(A(S, k))$.

Definition. *A storage cache replacement algorithm A is energy-optimal iff, for any other algorithm B,* $P(A(S, k)) \leq P(B(S, k))$ *for any I/O request sequence S and any storage cache size k.*

The number of misses resulting from a storage cache replacement algorithm obviously affects disk energy consumption. One would expect that, if there are few cache misses, the disks would consume little energy. However, the energy consumption is also affected by the arrival patterns of the cache misses. If misses are clustered together leaving long idle periods, it would allow disks to stay in the low power mode for longer periods of time. On the other hand, if the misses arrive uniformly spaced, most idle periods may be too small for a disk to save energy by going to the low power mode or the disk may spin up and down frequently, wasting a lot of energy in transitions. Furthermore, when there are multiple disks, it is better if misses are directed to a cluster of disks rather than uniformly distributed over all the disks. This allows the other disks to be in standby mode more often and thus save energy.

There are two reasons why Belady's algorithm is not optimal for disk energy consumption. First, it only minimizes the number of misses and pays no attention to arrival patterns of cache misses or how they are clustered. In other words, it ignores all information about time. Below, we give an example of this case. Second, it does not consider the number and characteristics of disks in a multiple disk scenario.

Fig. 3 gives an example to show why Belady's cache replacement algorithm is not energy-optimal. In this example, the storage cache has only four entries and the power model is the simple 2-mode model. For simplicity, we assume that the disk can spin up and spin down instantaneously. We also assume that the disk spins down after 10 units of idle time. This disk power management scheme is a threshold-based scheme (described in Section 2.2). The area of the shaded region in the figure represents the energy consumed. In this example, using Belady's algorithm results in more disk energy consumption than the alternative algorithm, even though the alternative algorithm has two more misses than Belady's algorithm.

Time	Req	Belady		Alternative	
		cache	Hit?	cache	Hit?
0	A	[A,-,-,-]	Miss	[A,-,-,-]	Miss
1	B	[A,B,-,-]	Miss	[A,B,-,-]	Miss
2	C	[A,B,C,-]	Miss	[A,B,C,-]	Miss
3	D	[A,B,C,D]	Miss	[A,B,C,D]	Miss
4	E	[E,B,C,D]	Miss	[A,E,C,D]	Miss
5	B	[E,B,C,D]	Hit	[A,B,C,D]	Miss
6	E	[E,B,C,D]	Hit	[A,E,C,D]	Miss
7	C	[E,B,C,D]	Hit	[A,E,C,D]	Hit
8	D	[E,B,C,D]	Hit	[A,E,C,D]	Hit
...					
16	A	[A,B,C,D]	Miss	[A,E,C,D]	Hit

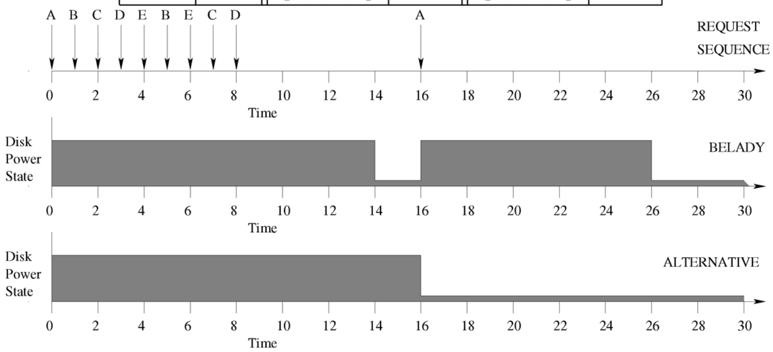


Fig. 3. An example showing that Belady's algorithm is not energy-optimal.

3.2 Energy-Optimal Algorithm

In this section, we present an energy-optimal cache replacement algorithm using dynamic programming. For simplicity, we will consider only two power modes and a single disk with b blocks. Let the sequence S of disk references be $a_0, a_1, \dots a_{n-1}$, where n is the input size. Let k be the number of blocks in the cache. When a block is read from the disk, it is to be stored in the cache. If the cache is full, a cache block is replaced. The disk spends one unit of energy per reference when it is switched on and does not consume energy in standby mode. For simplicity, we also assume that the disk is back to standby after m units of time and I/O requests arrive uniformly at the rate of one per time unit. For other arrival distributions, the optimal algorithm can be modified slightly by inserting some fake requests that will always hit in the cache (e.g., repeat the last I/O request) at each idle time unit. Due to space constraints, we do not go into the details of this extension. The goal of an energy-optimal cache replacement algorithm is to determine the sequence of cache replacement decisions that minimizes disk energy consumption.

We can construct a DAG (directed acyclic graph) to demonstrate a cache replacement algorithm. The state of the cache can be represented by the tuple (C, t, i), which means that the cache contains the blocks in set C after the first $i+1$ references $a_0, a_1, \dots a_i$ and the last t consecutive references were cache hits. If the next reference a_{i+1} is found in the cache ($a_{i+1} \in C$), the next state is $(C, t+1, i+1)$. If $a_{i+1} \notin C$, the next state could be one of several possible states $(C', 0, i+1)$, where C' is one of k possible sets that result from replacing one block in C by a_{i+1}. Since the disk is accessed due to a cache miss, t goes to 0.

$$A(C,t,i) = \begin{cases} max_{t',C'}(A(C',t',i-1) | \\ \quad C \in repl(C',a_i) \wedge a_i \notin C' & \text{if } a_i \in C \wedge t = 0 \\ A(C,t-1,i-1)+1 & \text{if } a_i \in C \wedge t \neq 0 \wedge t > m \\ A(C,t-1,i-1) & \text{if } a_i \in C \wedge t \neq 0 \wedge t \leq m \\ \infty & \text{if } a_i \notin C. \end{cases} \quad (1)$$

In this model, minimal energy consumption corresponds to the maximum time that the disk can spend in the standby mode. We define $A(C,t,i)$ as the maximum time that the disk spends in standby mode until some appropriate sequence of cache replacements result in state (C,t,i) being reached. $A(C,t,i)$ can be obtained in a recursive manner as in (1). $repl(C, a_i)$ is the set of possible resulting caches after replacing some block in C with a_i. The equation can be explained as follows: If $t \neq 0$, then, from the transition diagram, it is clear that state (C,t,i) can be reached only from $(C, t-1, i-1)$, where $a_i \in C$, hence the second and third cases. The second case adds 1 since, if the disk is not accessed for $t > m$ references, the disk goes to standby mode. The fourth case states that (C,t,i) can never occur if $a_i \notin C$ since every page reference has to be cached. However, $(C,0,i)$ can be reached from any of the states $(C', t', i-1)$ such that $a_i \notin C'$ and C can be obtained by replacing one block in C' with a_i. The first case maximizes over those possibilities. By computing $A(C,t,i)$ in the lexical ordering of the pair (i,t) such that $t \leq i$, we can ultimately arrive at $max_{C,t}(A(C,t,n-1))$, which is the maximum time for which the disk can stay in standby mode over the entire input sequence. The algorithm is shown below.

for $i = 0$ to $n-1$ **do**
  for $t = 0$ to i **do**

for all C such that C is a set of b distinct disk blocks **do**
  if $a_i \in C \wedge t = 0$ **then**
    $A(C,t,i) \leftarrow max_{t',C'}(A(C',t',i-1)|C \in repl(C',a_i) \wedge a_i \notin C')$
  else if $a_i \in C \wedge t \neq 0 \wedge t > m$ **then**
    $A(C,t,i) \leftarrow A(C,t-1,i-1)+1$
  else if $a_i \wedge t \neq 0 \wedge t \leq m$ **then**
    $A(C,t,i) \leftarrow A(C,t-1,i-1)$
  else
    $A(C,t,i) \leftarrow \infty$
  end if
end for
end for
Maximum Standby Time $\leftarrow max_{C,t}(A(C,t,n-1))$
end for

Now, we analyze the algorithm's worst-case time complexity. Let us assume that $A(C',t',i')$ values are known for all C', t', and $i' < i$. If $t \neq 0$, then, by the second and third cases in (1), we need $O(1)$ time to find $A(C,t,i)$. If $t = 0$, then we will have to maximize, over all possible cache configurations, C' such that $C \in repl(C',a_i)$ and $t' \leq i-1$. The number of different C' values is b, the number of possible different blocks in the cache that a_i can replace. The number of different t' values is i. Thus, the total number of choices to be considered when computing $A(C,0,i)$ is $i \times b$. t can vary from 0 to i. Thus, time taken to compute $A(C,t,i)$ for all possible $t \leq i$ is $i \times b + i$. This has to be done for b^k possible cache configurations. When summed over all $i < n$, we get the time complexity as $\Sigma_i b^k i \times (b+1)$, which is $O(b^{k+1}n^2)$.

The above algorithm can be extended to work with multiple disks with multiple power modes as well. After representing the state as $(C, t_1, t_2, \ldots, t_r, i)$, a recursive formula can be written for $A()$, which would be the maximum time that is spent in standby mode by putting all the disks together. We do not go into the details due to space constraints.

3.3 Offline Power-Aware Greedy Algorithm

Since the energy-optimal algorithm is too complex to implement and evaluate, we propose a heuristic offline power-aware greedy (OPG) algorithm that consumes less energy than Belady's algorithm for representative workloads. The main goal of the OPG algorithm is to minimize energy consumption by taking advantage of information about future bound-to-happen misses based on cache content at some point in time. We will call the bound-to-happen misses *deterministic misses* because they will happen no matter what the replacement algorithm does later on.

If we know that there is a deterministic miss at a future time t, the disk from which this missed block will be accessed has to be active at t to service this request. For convenience of description, for any access a, we call the closest deterministic miss to the same disk but occurring before a a's *leader*. Similarly, we call the closest deterministic miss to the same disk as a but occurring after a a's *follower*.

If the disk power management uses the Oracle scheme, the energy consumption for an idle period of length t is $LE(t) = min\{E_i(t)\}$, as described in Section 2.2 (see Fig. 2). If the disks use the Practical DPM, the disk energy consumption $OL(t)$ during an idle period of length t can be calculated as follows: $\sum_{i=0}^{l-1}(P_i * (t_{i+1} - t_i)) + P_l * \delta + C_l$, where the disk goes to power mode i at time t_i, $t_l (< t)$ is the cross point closest to t, and δ is the distance between t and t_l, i.e., $t = t_l + \delta, 0 \leq \delta < t_{l+1} - t_l$ (see Fig. 2).

The cache replacement algorithm uses energy penalties to choose from all the resident blocks $B_1, \cdots, B_i, \cdots, B_k$ when it needs to evict a block, where k is the number of cache blocks. For any i, let b_i represent the next access to B_i. Suppose b_i is, respectively, L_i and F_i time apart from its leader and its follower. If the algorithm evicts B_i, it will cause a miss for b_i, whose energy penalty is as follows:

$$\begin{cases} LE(L_i) + LE(F_i) - LE(L_i + F_i) & \text{if Oracle DPM} \\ OL(L_i) + OL(F_i) - OL(L_i + F_i) & \text{if Practical DPM.} \end{cases}$$

Intuitively, with the Oracle DPM, the energy cost for the idle period between the *leader* and *follower* is $LE(L_i + F_i)$ if b_i is not a miss (therefore, there are no misses to this disk between *leader* and *follower* based on the definitions of *leader* and *follower*). If b_i is a miss, the original idle period is cut into two chunks whose aggregate energy cost is $LE(L_i) + LE(F_i)$. Thus, the energy penalty for evicting block B_i is the difference between the two energy costs $LE(L_i) + LE(F_i) - LE(L_i + F_i)$. The energy penalty with the Practical DPM can be calculated in a similar way, replacing $LE()$ by $OL()$ in the formula.

Once the algorithm calculates the energy penalty for evicting every resident block, it evicts the block with the minimum energy penalty. If multiple blocks have the same energy penalty, it evicts the one with the largest forward distance, i.e., whose next access is the furthest in the future.

Initially, the set of deterministic misses, S, only includes all the cold misses. After each replacement, the algorithm updates the set S. Suppose the currently accessed (missed) block is B_1 and the evicted block is B_2. The algorithm deletes B_1 from the set S and adds the first future reference to B_2 into S. Then, the algorithm moves on to the next request until all requests are processed. The time complexity for a list of n requests is at most $O(n^2)$ since the newly inserted deterministic miss can become the leader or follower of many block accesses and the energy penalties of those blocks should thus be updated.

This algorithm is heuristic because it looks at only the current set of deterministic misses when calculating the energy penalty for evicting a block. Thus, it may not make the best decision at a replacement. As we discussed in Section 3.1, each cache miss leads to a disk access, which costs additional energy. Hence, higher miss ratios would increase the energy consumption. We use a simple mechanism to consider both miss ratio and energy penalty for a miss: not to differentiate among blocks whose energy penalties are smaller than a threshold η. Any energy penalty smaller than η is rounded up to η. Obviously, when η is large enough, it is Belady's algorithm; when $\eta = 0$, it is the pure OPG algorithm. This mechanism thus subsumes Belady's algorithm at one extreme and the pure OPG algorithm at the other.

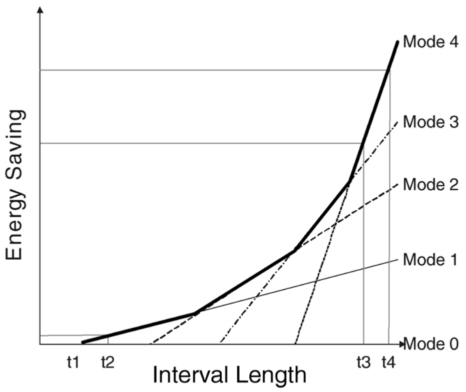


Fig. 4. Energy savings (not energy consumption) over mode 0 for each mode in a 5-mode disk as a function of interval length.

4 Power-Aware Online Caching Algorithms

In practice, we do not have knowledge about future accesses and thus cannot use the offline power-aware greedy algorithm. However, it gives us some insights on how to design a power-aware online algorithm that saves energy. Such an algorithm should avoid evicting blocks with larger energy penalties.

In this section, we present two new power-aware online caching algorithms. Both are based on the above observation but use very different approaches. The first one, PA-LRU, evicts blocks that have the largest estimated energy penalties at replacement. The second one, PB-LRU, divides the storage cache into different partitions (with one for each disk) in a way to minimize energy consumption.

4.1 The First Algorithm: PA-LRU

PA-LRU is based on the observation that different disks have different workload characteristics such as requests interarrival time distribution, the number of cold misses. These characteristics of a disk directly affect the energy cost of an access to this disk.

We first investigate how the length of idle intervals affects energy saving. Fig. 4 shows energy savings that can be obtained by switching to lower power modes given an idle interval. Similarly to Fig. 2, we plot lines $ES_i(t) = E_0(t) - E_i(t)$ for each power mode i, where ES_i is the energy saved by going into mode i ($ES_0 = 0$) and E_i is defined in Section 2. The upper envelope of all of these lines, $UE(t) = max_i\{ES_i\}$, gives us the maximum energy saved for an idle interval of length t.

The superlinear property of the upper envelope function, $UE(t)$, indicates that even small increases in the idle interval length of inactive disks can result in significant energy savings. By keeping more blocks from inactive disks in the cache, we can make the average interval length for these disks larger. Then, these disks could stay in the low power modes longer. Although the average interval lengths for other active disks may be decreased due to an increased number of misses, the energy penalty we pay for these other disks is much smaller than the energy savings we gain from the inactive disks. As shown in Fig. 4, even though the average idle period of disk 0 is reduced from t_2 to t_1, it results in the stretching of disk 1's average interval from t_3 to t_4. Based on the superlinear property of $UE(t)$, the amount of energy saving at disk 1 is more than the energy cost at disk 0. Thus, overall energy saving is achieved.

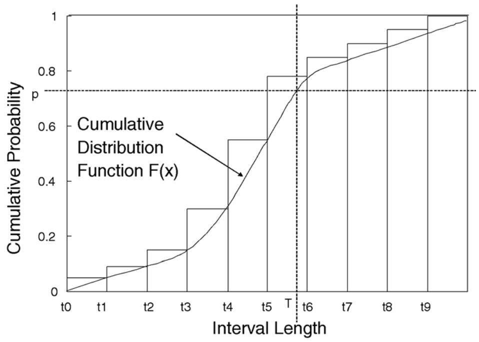


Fig. 5. The histogram approximates the cumulative distribution function of interval lengths.

However, average interval length is not the only factor that affects the amount of energy that can be saved: 1) **The percentage of capacity misses** (misses caused by previous evictions) should be reasonably large since a cache replacement algorithm cannot avoid any cold misses (misses due to first-time accesses). If most of the accesses to a disk are cold misses, we cannot do much to avoid expensive disk spin-ups or make interval lengths longer. 2) **The distribution of accesses** also affects the opportunities to save energy. For example, for the same average interval length t_2 in Fig. 4, disks with larger deviation have more opportunities to save energy than disks with uniform arrivals.

To keep track of the number of cold misses, we use a *Bloom Filter* [5], [11] to identify cold misses. The idea is to allocate a vector v of m bits, all set to 0 initially, and then choose k independent hash functions, $h_1, h_2, \ldots, h_k$, each with range $\{1, \ldots, m\}$. Given an access for block a, we check the bits at positions $h_1(a), h_2(a), \ldots, h_k(a)$. If any of them is 0, a is definitely a cold miss. In this case, the bits at positions $h_1(a), h_2(a), \ldots, h_k(a)$ in v are set to 1. Otherwise, we conjecture that a is already in the set, which means it is not a cold miss, though there is a certain probability that we are wrong due to hash collisions. But, fortunately, the probability of collisions is low if the bloom vector is reasonably large. For example, if the system has $1.6M$ blocks and the bloomfilter vector has 2M entries with seven hash functions , the collision probability is only 0.0082.

To estimate the distribution of accesses for each disk, instead of using mean and standard deviation, we employ a simple but effective epoch-based *histogram* technique [46]. In each epoch, we keep track of the interval length between two consecutive accesses for each disk. We obtain a histogram as shown in Fig. 5. Let n_i be the number of intervals of length between $[t_i, t_i + 1)$ and let n be the total number of intervals. The height of each bin in Fig. 5 is $\sum_{j=0}^{i} \frac{n_j}{n}$, which approximates the cumulative probability of the interval length being less than t_{i+1}. All the bins together form a histogram, which approximates the cumulative distribution function of interval length for a disk, i.e., $F(x) = P[X \leq x]$, where X is a random variable that represents the interval length for a disk.

PA-LRU is based on these observations. Its main idea is to dynamically keep track of workload characteristics for each disk, including the percentage of cold misses and the cumulative distribution of interval lengths. Based on these characteristics, PA classifies all disks into two categories, *regular* and *priority*. Disks that exhibit 1) a small percentage of cold misses and 2) large interval lengths with high probability belong to the "priority" class and others belong to the "regular" class. To adapt to workload changes, the classification is *epoch-based*, adjusted periodically based on the latest workload.

This idea can be combined with most existing storage cache replacement algorithms to make them "power aware." This includes several recently proposed algorithms, such as ARC [34], LIRS [24], DEMOTE [44], and MQ [49]. In this paper, we use the common LRU algorithm as an example and refer it as the Power-Aware LRU algorithm (PA-LRU).

PA-LRU maintains two LRU stacks, LRU0, which keeps blocks that belong to disks in the "regular" class, and LRU1, which keeps blocks that belong to disks in the "priority" class. When choosing a block to evict, PA-LRU always evicts the bottom block of LRU0 if it is not empty. If LRU0 is empty, PA-LRU evicts the bottom block from LRU1.

PA-LRU uses the request sequence's characteristics during the previous epoch for each disk. If the percentage of cold misses is larger than a threshold α, blocks from this disk go to LRU0 during the current epoch. As shown in Fig. 5, given a cumulative probability p, we can easily calculate the corresponding T based on the cumulative distribution function, that is, $P(X \leq T) = p$. If T is less than a threshold β, the blocks from this disk go to LRU0 as well. Otherwise, blocks go to LRU1. α, β, p, and the length of the epoch are tunable parameters.

4.2 The Second Algorithm: PB-LRU

Although the PA-LRU algorithm is more energy-efficient than LRU, as shown in Section 6, it requires some parameter tuning to set the values of α, β, p, and the length of the epoch. In this section, we present the second online power-aware algorithm, called PB-LRU, that requires little parameter tuning.

4.2.1 Main Idea

Similarly to PA-LRU, PB-LRU (Partition-Based LRU) also differentiates disks with different characteristics. But, it does it in a very different way. PB-LRU differentiates disks by dynamically controlling the number of cache blocks allocated to each disk. It divides the entire cache into separate partitions, one for each disk. The partitions are divided in a way to minimize the total storage subsystem energy consumption. The partition sizes are adjusted periodically at every epoch to adapt to workload changes. Within an epoch, each partition is managed independently using the original replacement algorithm (e.g., LRU). The epoch length is the only parameter. But, our results show relative insensitiveness of PB-LRU's results to this parameter (see Section 6.2.2).

In order to find an energy-optimal partitioning, we first estimate, for each disk, the energy that *would be* consumed with different partition sizes. Symbolically, if we have n disks $\{1 \ldots n\}$, we estimate the energy, $E(i, s)$, that would be consumed by disk i if it had a partition of size s. These estimates are then used to find a partitioning that will minimize the total energy consumption of all disks. Of course, the sum of each partition size cannot exceed the total cache size S.

Let us first formalize the problem. Suppose there are m possible partition sizes: $0 < p_1 < p_2 < \ldots < p_m \leq S$. Let x_{ij} indicate whether disk i has a partition of size j (1 means "yes" and 0 means "no"). Obviously, each disk can only have one partition size, so we have $\sum_{j=1}^{m} x_{ij} = 1$. For disk i, its partition size S_i would be $\sum_{j=1}^{m} p_j x_{ij}$. Therefore, we have the following:

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^{n} E(i, S_i) \\ \text{subject to} \quad & \sum_{i=1}^{n} S_i \leq S, S_i = \sum_{j=1}^{m} p_j x_{ij} \\ & \sum_{j=1}^{m} x_{ij} = 1, x_{ij} = 0 \text{ or } 1. \end{aligned}$$

This problem is a form of the Multiple Choice Knapsack Problem (MCKP) [32], a variant of the famous 0-1 knapsack problem. To solve this, PB-LRU needs to address two issues: 1) accurate estimation of the energy, $E(i, s)$, that would be consumed by disk i if it had a partition size s and 2) solving the MCKP which has been proven to be NP-hard [32].

4.2.2 Runtime Energy Estimation for Different Partition Sizes

In this subsection, we describe a technique to dynamically determine the energy that each disk would consume with various possible partition sizes. A disk's energy consumption depends on the sequence of cache misses and the time of each miss. Since we must estimate energy for various possible partition sizes at runtime, it is infeasible to conduct a real measurement on the energy consumption with each different partition size using real organizations.

Instead, PB-LRU uses a much more elegant technique to do the estimation. Essentially, we expect to obtain a curve showing energy consumption as a function of partition size, for each disk, at runtime. This is similar to the miss ratio versus cache size curve, which has been dynamically obtained in several previous studies [26], [39] using the Mattson's Stack algorithm. To our knowledge, our study is the first to dynamically estimate how energy consumption varies with cache (partition) size.

Mattson's Stack algorithm was initially proposed by Mattson et al. in 1970 [33] to reduce trace-driven processor cache simulation time. It can determine the hit ratio of all processor cache sizes with a single pass through the trace file. It was later extended by Hill and Smith [21], [20] and Wang and Baer [42] to provide efficient trace simulations for set-associative caches. The main idea of this algorithm is to take advantage of the *inclusion property* in many cache/memory replacement algorithms [33] including the commonly used Least Recently Used (LRU) algorithm, the Least Frequently Used (LFU) algorithm, and the offline Belady's algorithm. The inclusion property states that, at any given time, the contents of a cache of k blocks is a subset of the contents of a cache of $k+1$ blocks for the same sequence of accesses. Therefore, if we maintain a "stack" (e.g., an LRU stack), an access to a block at depth i in the stack would lead to a miss in caches with size smaller than i and a hit in others. Since the stack records only addresses of blocks and not their data, the space overhead of the stack is small.

Unfortunately, the Mattson's stack algorithm only gives us the correlation between cache size and cache miss ratio.

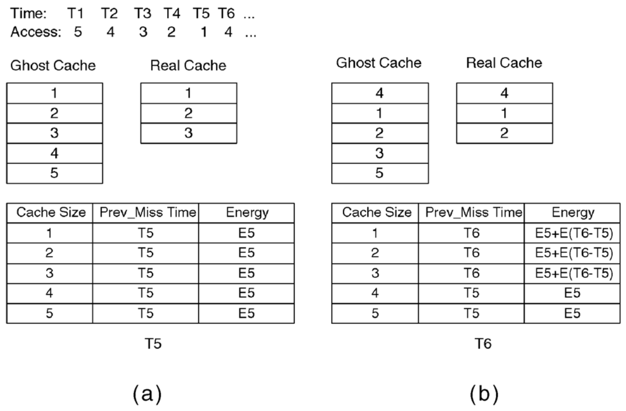


Fig. 6. An example of energy estimate in PB-LRU for a disk.

Our goal is to minimize total disk energy consumption, not the cache miss ratio. Even though the miss ratio for two partition sizes may be significantly different, the resulting disk energy consumption can still be similar because extra misses may not cause any disk spin-ups.

We extend Mattson's Stack algorithm to dynamically track the variation of energy-consumption with possible partition sizes for each disk. PB-LRU first uses the Mattson's Stack algorithm to determine whether a request would result in a cache hit or miss for different partition sizes. If a request is a miss in a partition of size p (and all smaller sizes), the request will access the corresponding disk. If we know the last access time to this disk (with partition size p), we can estimate the energy consumption from the last access to the current one based on the underlying power management scheme. For example, if Practical DPM is used, we can decide what the current disk power mode is and thus calculate how much *idle energy* is consumed during this idle period (including the spin-up energy). The idle period is obtained from the current and previous disk access times. To get the *active energy*, we first measured the average disk access time on an IBM Ultrastar36Z15 disk and used this value (10ms) in our simulation. As shown in Section 6, our energy estimation is very accurate with an error of at most 1.8 percent.

Therefore, for each disk and each possible partition size, PB-LRU maintains the last access time to the disk (i.e., previous cache miss time) and its energy consumption. In our experiments, we set the basic allocation unit to be 1MB. Thus, if the total cache size is 128MB, for each disk, we maintain 128 energy estimates and last access times corresponding to partition sizes of $1, 2, 3, \ldots, 128\text{MB}$. At each access, besides changing the real cache to service this access based on the replacement algorithm, we also

1. Search the requested block number in the stack of the appropriate disk. If it is found to be the ith element from the top of the stack, its depth is i. If it is not found, its depth is ∞.
2. For all partition sizes less than the depth, increment the energy estimates. Update the previous miss time to the current access time.
3. Update the stack using the same replacement policy as the real cache, e.g., PB-LRU brings the requested block number to the top of the stack.

Fig. 6 illustrates the process of energy estimation for a disk with PB-LRU. Since the first five accesses are cold misses, at time $T5$, the prev_miss_time is $T5$ and the energy consumed is $E5$, for all partition sizes. At time $T6$, block 4 is accessed, which has a depth of 4 in the stack. For the partition sizes less than 4, a miss would occur. So, the prev_miss_time for those sizes is set to $T6$ and the total energy consumption is incremented by the sum of idle energy consumed during the last idle period and the active energy, which is $E(T6 - T5) + 10ms * ActivePower$ (calculated based on the underlying DPM). However, if the partition for this disk has size of 4 or 5 blocks, there would have been a hit and no change is needed. Finally, both the stack and the real cache are updated based on LRU.

Although, in our study, we use LRU as the basic replacement algorithm, the methodology of partitioning described above is applicable to all policies that exhibit the property of inclusion, such as LFU, 2Q [25], and MQ [49].

4.2.3 Solving the MCKP Problem

The Multiple-Choice Knapsack Problem has been proven to be NP-hard [32]. However, it can be solved in pseudopolynomial time by dynamic programming, as described below. The time complexity of the solution is $O(nm^2)$, where n is the number of disks and m is the number of potential partition sizes. Let $K(i, s)$ ($s \in \{p_1, p_2, \ldots, p_m\}$, $0 < p_1 < \ldots < p_m \le S$) be the energy consumed by i disks when a total cache size of s is partitioned among those disks. K^* gives the minimum total energy consumption when a storage cache of size S is partitioned among all n disks.

$$K(0, s) = \begin{cases} 0 & \text{if } s = 0 \\ \infty & \text{otherwise} \end{cases}$$

$$K(i, s) = \begin{cases} \min_{\{j|0<p_j \le s\}}\{K(i-1, s-p_j) + E(i, p_j)\} \\ \qquad\qquad \text{if } s > 0 \\ \infty \qquad\qquad \text{otherwise} \end{cases}$$

$$K^* = min_{\{s|0 \le s \le S\}}\{K(n, s)\}.$$

As results will demonstrate, this technique has a tendency to increase the size assigned to relatively inactive disks and give only small sizes to active disks. This is because the energy penalty incurred by reducing the partition size of an active disk is small, whereas the energy saved by increasing the partition size of a relatively inactive disk is large.

5 Evaluation Methodology

5.1 Test Bed

We simulate a complete storage system to evaluate our power-aware cache management schemes. We have enhanced the widely used DiskSim simulator [12] and augmented it with a disk power model. The power model we use is similar to that used by Gurumurthi et al. [16] for multispeed disks. We have also developed a storage cache simulator, CacheSim, and we use it together with DiskSim to simulate a complete storage system. CacheSim implements several cache management policies. Accesses to the simulated disks first go through the simulated storage cache. The simulator reports the energy consumed by each disk in every power mode and the energy consumed in

TABLE 1
Simulation Parameters

IBM Ultrastar 36Z15	
Individual Disk Capacity	18.4 GB
Maximum Disk Rotation Speed	15000 RPM
Minimum Disk Rotation Speed	3000 RPM
RPM Step-Size	3000 RPM
Active Power(Read/Write)	13.5 W
Seek Power	13.5 W
Idle Power@15000RPM	10.2 W
Standby Power	2.5 W
Spinup Time(Standby to Active)	10.9 secs
Spinup Energy(Standby to Active)	135 J
Spindown Time(Active to Standby)	1.5 secs
Spindown Energy(Active to Standby)	13 J

servicing requests (energy to perform seek, rotation, and transfer). Therefore, if a power-aware replacement algorithm introduces extra misses, the disk energy consumed in servicing those extra misses is also reported.

The specifications for the disk used in our study are similar to that of the IBM Ultrastar 36Z15. The parameters are taken from the disk's data sheet [22], [6]. Some of these parameters are shown in Table 1.

Other than active and standby, we use four low-speed power modes: 12k RPM, 9k RPM, 6k RPM, and 3k RPM. For convenience of description, we call them NAP modes: NAP1, NAP2, NAP3, and NAP4. To calculate the parameters for each NAP mode, we use the linear power and time models proposed in [16]. We use the 2-competitive thresholds described in Section 2 for Practical DPM. For PA-LRU, we use an epoch length of 15 minutes. Other parameters are $\alpha = 50\%$, $p = 80\%$, and $\beta = 5 seconds$. α, β, p are described in Section 4. β is set to be the same as the break-even time for NAP1 mode. All PB-LRU results are achieved with the epoch length as $16,000$ requests. Section 6.2.2 will show that PB-LRU results are insensitive to the epoch length as long as it is long enough for the cache to "warm-up" after the repartitioning.

5.2 Traces

Our experiments use two real system traces (OLTP and Cello96) and two synthetic traces (Exponential and Pareto) to evaluate the power-aware cache replacement algorithms.

The OLTP trace is an I/O trace collected on our previously built VI-attached database storage system connected to a Microsoft SQL Server via a storage area network. The Microsoft SQL Server client connects to the Microsoft SQL Server via Ethernet and runs the TPC-C benchmark [28] for 2 hours. The OLTP trace includes all I/O accesses from the Microsoft SQL server to the storage system. Writes to log disks are not included in the trace. A more detailed description of this trace can be found in our previous work [49], [7]. OLTP trace has 21 disks (two volumes, each organized as a 10-disk RAID0 and an additional single disk). The other trace, Cello96, is obtained from HP and was collected from the Cello File Server. This is a more recent trace similar to the Cello92 trace [41]. The Cello file system is used by a small group of researchers at Hewlett-Packard Laboratories to do simulation, compilation, editing, and mail. The Cello96 trace has 20 disks which include news partitions, swap partitions, and other file system partitions. In our experiments, we use the same disk layout as specified in these traces. We use 128 MBytes as the storage cache size for the OLTP trace and 32 MBytes for the Cello96 trace because its working set size is smaller than that of the OLTP trace.

TABLE 2
Default Synthetic Trace Parameters

Request Number	1 million
Disk Number	24
Exponential Distribution	$\frac{1}{\lambda} = 100ms$
Pareto Distribution	$1 < \alpha \leq 2, \beta = 50ms$
Write Ratio	0.2
Disk Size	18 GB
Sequential Access Probability	0.1
Local Access Probability	0.2
Random Access Probability	0.7
Maximum Local Distance	100 blocks

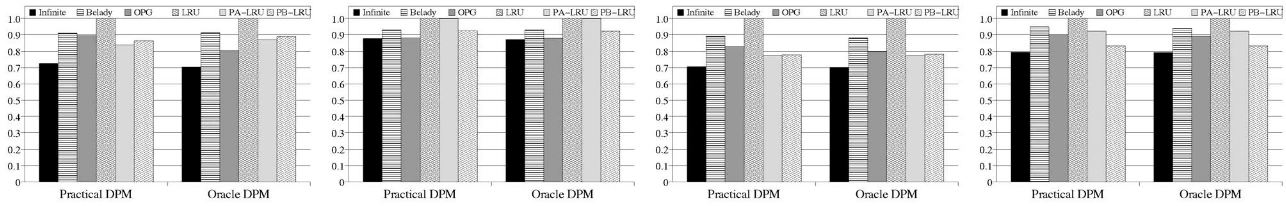
The two synthetic traces are generated based on storage system workloads observed in previous studies [49], [7]. For example, most workloads have an uneven distribution among disks and also among blocks. To simulate these characteristics, we use zipf distribution to distribute requests among 24 different disks and also among blocks in each disk. Moreover, as observed by previous studies [49], requests to storage systems have poorer temporal locality than those to first-level buffer caches and the reuse distances are distributed in a "hill" shape or, theoretically speaking, are log-normally distributed. Based on these characteristics, we use a log normal distribution with mean 32,000 references to reflect temporal locality. Spatial locality is controlled by the probabilities of sequential accesses, local accesses, and random accesses. A sequential access starts at the address immediately following the last address accessed by the previously generated request. A spatially local request begins some short distance (smaller than Maximum Local Distance) away from the previous request's starting address.

Similarly to [16], we consider two types of distributions for interarrival time: Exponential and Pareto. Exponential distribution models a Poisson process, which is almost regular traffic without burstiness, while the Pareto distribution introduces burstiness in arrivals. The Pareto distribution is controlled by two parameters, Shape α and Scale β. We use a Pareto distribution with a finite mean and infinite variance. We call these two synthetic traces Exponential and Pareto in the rest of this paper. The default parameters for the trace generator are listed in Table 2.

6 Evaluation of Power-Aware Cache Replacement Algorithms

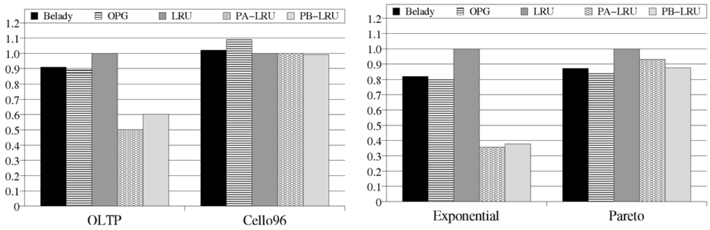
6.1 Overall Results

We evaluate five cache replacement algorithms: OPG, Belady, PA-LRU, PB-LRU, and LRU using the two real-



(a) (b) (c) (d)

Fig. 7. Energy Consumption (normalized to LRU). (a) OLTP. (b) Cello96. (c) Exponential. (d) Pareto.



(a) (b)

Fig. 8. Average Response Time (normalized to LRU). (a) OLTP and Cello96. (b) Synthetic traces.

system traces and two synthetic traces. We have also measured the disk energy consumption with an infinitely large cache size, in which case, only cold misses go to disks. This serves as a lower bound for the energy consumed as a result of any cache replacement algorithm because no cache replacement algorithm with a limited cache size can save more energy if the underlying disks use the Oracle DPM.

With the Practical DPM, infinite storage cache size may cause more energy consumption than limited cache sizes, so it cannot serve as a theoretical lower bound. To give an example, suppose the interarrival time between two consecutive cold misses to the same disk is just slightly larger than the idle threshold value. After the first cold miss, the disk will transition into a low-power mode after remaining idle for a threshold period of time. Then, it has to immediately transit back to active in order to service the second cold miss. So, it spends extra energy in disk spin-down/spin-up. However, if a replacement algorithm can introduce another miss in between these two cold misses, it is possible to avoid the disk spin-down/spin-up.

Fig. 7 compares the disk energy consumption for all five storage cache replacement algorithms and an infinite cache with both Oracle DPM and Practical DPM. Fig. 8 shows the average response time for the five storage cache replacement algorithms with the Practical DPM. Since the Oracle DPM can always spin up disks in time for the next request, the average response time difference among the five schemes is very small, which we do not present here.

Comparing two offline algorithms, though Belady's algorithm gives the optimal cache miss ratios, OPG can consume up to 9.8 percent less energy than Belady's algorithm. With the Cello96 trace, OPG consumes 5.7 percent less energy than Belady's algorithm. For the OLTP trace, OPG consumes 9.8 percent less energy than Belady's algorithm if disks use the Oracle scheme. With the Practical DPM, OPG's energy savings is smaller, only 1.4 percent. In terms of average response time, OPG is 4.2 percent better for OLTP, but 6.3 percent worse for Cello96. For two synthetic traces, OPG can consume 5.3-9.3 percent less energy than the Belady's algorithm while providing 2.5-3.5 percent better average response time.

For two online power-aware algorithms, Fig. 7 shows they can save up to 22 percent more energy compared to LRU. For the OLTP trace, PA-LRU consumes 14-16 percent less and PB-LRU consumes 11-13 percent less energy than LRU. For the Exponential trace, both PA-LRU and PB-LRU can save 22 percent energy over LRU. PB-LRU performs better than PA-LRU in other two traces: for the Pareto trace, PB-LRU saves 16.6 percent more and PA-LRU saves 7.7 percent more energy than LRU; for the Cello96 trace, PA-LRU saves less than 1 percent energy over LRU, while PB-LRU is 7.6-7.7 percent more energy-efficient than LRU.

The reason why PA-LRU can only save less than 1 percent energy for Cello96 is because, in Cello96, 64 percent of accesses are cold misses. In other words, 64 percent of accesses will go to disk no matter what cache replacement policy is used. In addition, the requests' interarrival gap is very small, even for the cold miss sequence, which does not allow PA-LRU to save much energy. Even with the infinite-size cache, the largest possible energy savings are only 12.4-12.6 percent. In this sense, PB-LRU does a decent job.

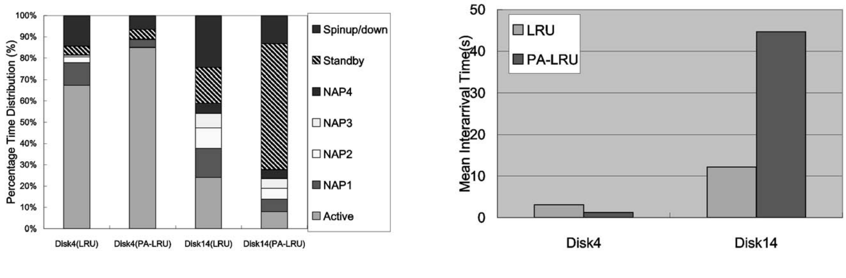
In terms of average response time with Practical DPM, Fig. 8 shows that PA-LRU and PB-LRU improve the average response time by 62-64 percent for the Exponential trace, 40-50 percent for the OLTP trace, and 7-13 percent for the Pareto trace while, for Cello96, the improvements by both are less than 1 percent. Again, the dominant cold misses in Cello96 account for this.

6.2 Performance Analysis

In the next two subsections, we use the OLTP with Practical DPM to understand why PA-LRU and PB-LRU can save more energy and provide better response time.

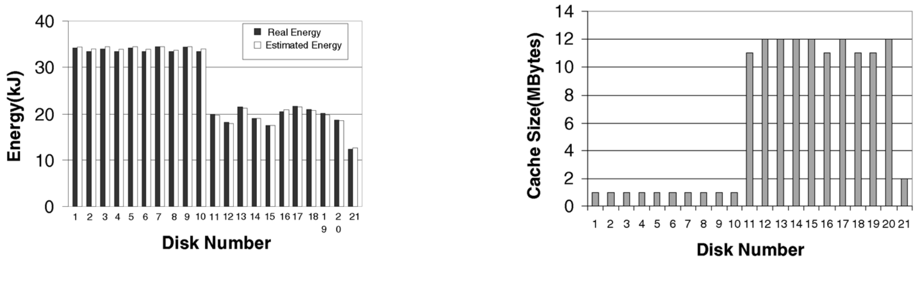
6.2.1 Analyzing PA-LRU

Fig. 9a shows the percentage time breakdowns for two representative disks. Each breakdown gives the percentage



(a) (b)

Fig. 9. (a) Percentage time breakdown and (b) mean request interarrival time for two representative disks in OLTP.



(a) (b)

Fig. 10. Validation of PB-LRU in a random epoch for OLTP. (a) Real energy versus estimation. (b) Cache sizes assigned.

of time consumed in each power mode and also during spin-up/spin-downs. Disk 14 spends 59 percent of time in standby mode with PA-LRU, whereas it spends only 16 percent of time in standby mode with LRU. Moreover, PA-LRU significantly reduces time in performing spin-up/downs from 25 percent to 13 percent. Even though PA-LRU increases the percentage of time in active mode for other disks, such as disk 4 from 78 percent to 84 percent, the amount of increase is very small. PA-LRU also reduces the time that disk 4 spends in spin-up/downs from 16 percent to 6 percent. Also, because of the significantly fewer disk spin-up/downs, PA-LRU has 50 percent lower average I/O response time.

Fig. 9b shows the mean request interarrival time for the same two representative disks (disk 4 and disk 14). The mean request interarrival time shown is much larger than the interarrival time in the original application I/O sequence because requests are first filtered through a 128 MByte storage cache.

Since PA-LRU keeps blocks from disk 14 in the priority LRU list, there are fewer accesses to disk 14. As a result, the mean request interarrival time on disk 14 from a PA-LRU-managed cache is three times as large as that from an LRU-managed cache. With 40 second interarrival gaps, disk 14 has a lot of long idle periods to stay in low power modes and, thus, saves significant amounts of energy.

To favor disk 14's blocks, disk 4's blocks are more likely to be evicted with PA-LRU than with LRU. Thus, the mean request interarrival time on disk 4 with PA-LRU is a factor of 2.4 shorter than that with LRU, which explains why PA-LRU causes disk 4 to stay in the active mode longer. Since the original mean interarrival time with LRU is already smaller than the threshold, disk 4 does not have much opportunity to go to the low power modes. Thus, shortening the mean interarrival time on disk 4 does not cause disk 4 to spend significantly less time in low power modes.

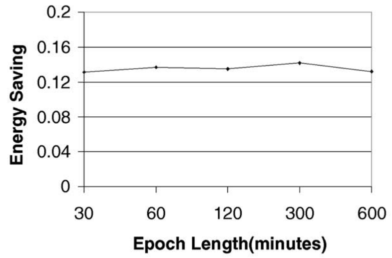
6.2.2 Analyzing PB-LRU

Accuracy of Energy Estimation. Fig. 10a shows the difference between energy actually consumed by real cache and that estimated by PB-LRU for the same size, for each of the 21 disks in a random epoch. We can see the largest deviation of estimated energy from real energy is 1.8 percent, suggesting that the energy estimation is accurate.

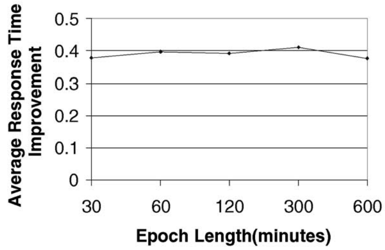
Assignment of Cache Sizes. Fig. 10b shows, in a random epoch, the partition sizes which were assigned by the MCKP solver. For the first 10 disks, the MCKP solver only assigns 1MB to their caches while 11-12MB is given to the next 10 disks. The OLTP workloads are such that the first 10 disks are active while the next 10 are relatively inactive. The MCKP solver has a tendency to increase the size assigned to relatively inactive disks and give only small sizes to disks which remain active. This is because the energy penalty incurred by reducing the cache size of a disk that remains active is small, while large gains are made by increasing the cache size of a relatively inactive disk, as doing so allows it to remain in lower-power modes longer. In this way, overall energy savings can be made.

Cache partition size also affects the response time. Since the first 10 disks are in active modes, accesses to those disks do not need to wait several seconds for the disk to spin-up before requests are serviced. Because of the greater partition space given to the next 10 disks, the number of misses and, consequently, the number of expensive spin-ups from low-power to active mode, is reduced and, thus, response time improves.

Effects of Epoch Length. One drawback of many previous studies [8], [16], [17], [6], including our PA-LRU, is that they depend on multiple parameters. Tuning those parameters to adapt to different characteristics of workloads is time-consuming and hard. An important benefit of PB-LRU is that it does not need much parameter tuning for different workloads. The only parameter is the epoch length.



(a)



(b)

Fig. 11. The energy saving and average response time improvement (PB-LRU over LRU) for OLTP trace change with the increasing of epoch length. (a) Energy consumption. (b) Average response time.

The epoch length cannot be too small or infinitely large. Fortunately, our results indicate that, once it is large enough to accommodate the "warm-up" period after repartitioning, the results of PB-LRU are relatively insensitive to the epoch length within a very large range, as shown in Fig. 11. The results for the other traces are similar. In real systems, it is not difficult to pick a large enough epoch length, especially since most data center workloads are continuously running for days or even months.

6.3 Effects of Spin-Up Cost

In our simulations, we use the spin-up cost of the IBM Ultrastar 36Z15 (135J) from standby to active mode. In this section, we discuss how spin-up cost affects the energy-savings of PA-LRU and PB-LRU over LRU using the OLTP trace. We vary spin-up costs as energy needed for transitioning from standby to active mode. The spin-up costs from other modes to active mode are still calculated based on the linear power model described earlier.

Fig. 12 shows the percentage energy-savings for PA-LRU and PB-LRU over LRU for the OLTP trace. Both algorithms demonstrate the same effects. Between 67.5J and 270J, the energy savings of PA-LRU and PB-LRU over LRU are fairly stable. The spin-up costs of most current SCSI disks lie in this range. At one extreme, with the increase of spin-up cost, the break-even times increase. Therefore, the thresholds calculated based on the break-even times also increase. In this case, due to the lack of long enough intervals, disks have fewer opportunities to stay in low power modes even using power-aware algorithms such as PA-LRU and PB-LRU. At the other extreme, if the spin-up cost decreases a lot and spin-up becomes very cheap, the energy savings of PA-LRU and PB-LRU decrease because, in this case, even with LRU, disks are already in low-power modes most of the time.

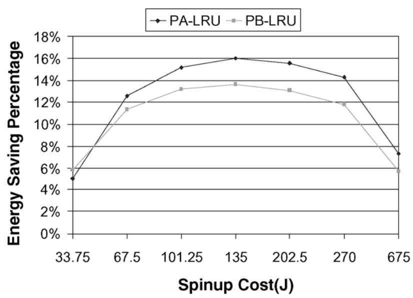


Fig. 12. Percentage energy-savings for PA-LRU and PB-LRU over LRU versus spin-up cost (energy needed for transitioning from standby mode to active mode) for the OLTP trace.

Since both the energy and time cost of spin-down account for only 1/10 of spin-up in the IBM Ultrastar 36Z15, the effect of considering both spin-up and spin-down cost is similar to that of Fig. 12.

7 Effects of Write Policies on Disk Energy Consumption

In this section, we investigate the effects of four storage cache write policies on energy consumption. The first two policies, write-back and write-through, are commonly used in caches. The write-back caching policy only writes a dirty block to disks when the block is evicted from the cache. This policy reduces the number of disk writes and enables fast response to clients, but could compromise data persistency if the cache is on volatile storage. The write-through caching policy always writes dirty blocks to disk immediately and does not tell clients that the writes are successful until the data is committed to disks. The two other policies are variations of the write-back and write-through policies. "Write-back with eager update" (WBEU) does not wait for a dirty block to be evicted from the cache before writing it to the disk. The policy writes back dirty blocks of a disk whenever that disk becomes active. "Write-through with deferred update" (WTDU) temporarily writes dirty blocks to a log instead of writing them to their true destinations if the destination disks are in low power modes.

To evaluate the effects of write policies, we use the two synthetic traces with varying write/read ratios. We use LRU as the cache replacement algorithm in our simulation.

Write-Back (WB) versus Write-Through (WT). Intuitively, write-back is more energy-efficient than write-through due to a reduced number of writes and potentially longer idle periods. However, few studies have measured the difference in energy consumption quantitatively. Is the difference large enough to justify trading persistency for energy?

Fig. 13a and Fig. 13d show the percentage energy savings of write-back over write-through. Fig. 13a shows the results for a mean interarrival time of 250ms and varying write ratios from 0 percent to 100 percent. Fig. 13d shows the results when the write ratio is 50 percent and the mean interarrival time varies from 10ms to 10,000ms. The results with Oracle DPM are similar to those with Practical DPM, so we only present results with Practical DPM. For the extremely small or large interarrival time, the differences between write polices are small since disks are active or

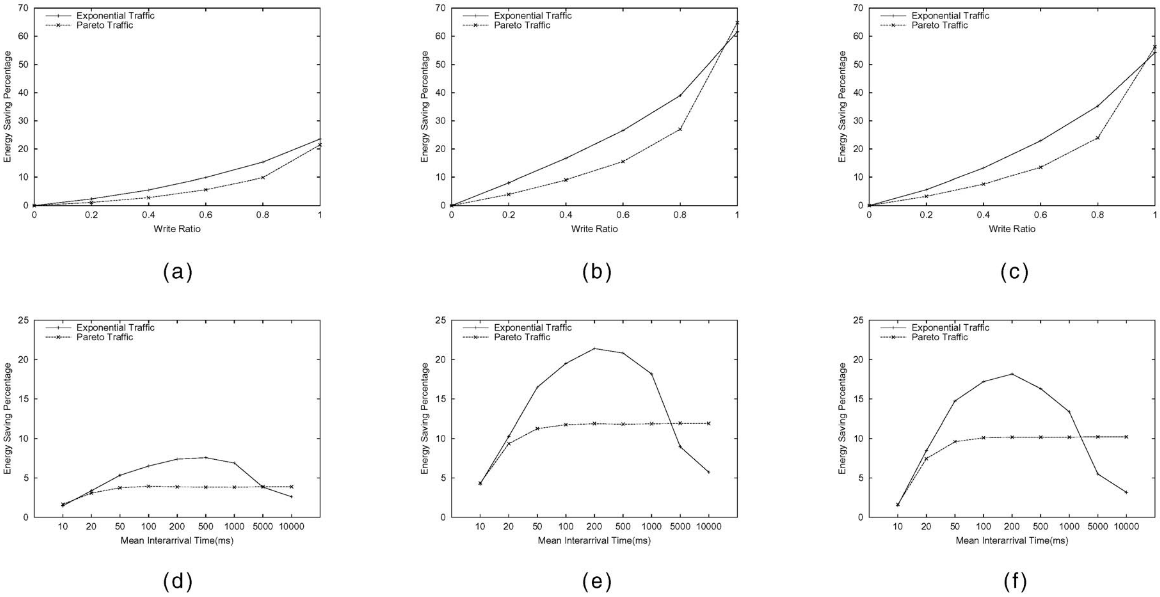


Fig. 13. Effects of write policies on disk energy consumption. (All the numbers are percentage energy savings relative to the write-through policy. The underlying disk uses the Practical DRM. Results with the Oracle DPM are similar.) Note that the X-asis is not uniform in (d)-(f). (a)-(c) Percentage energy savings for different write ratios (interarrival time: 250 ms). (d)-(f) Percentage energy savings for different mean interarrival time (write ratio: 50 percent). (a) and (d) WB versus WT. (b) and (e) WBEU versus WT. (c) and (f) WTDU versus WT.

sleeping most of the time already. In a medium range, the results exhibit the similar effects to those of 250ms. For write ratio close to zero, write policies do not matter and, thus, make no difference. However, the energy benefit over write-through policy increases with write ratio. With 100 percent writes, write-back can save around 20 percent energy compared to write-through. When fewer than 40 percent of the requests are writes, the percentage energy savings of write-back over write-through is less than 5 percent. As shown in Fig. 13d, with a write ratio of 0.5, the benefits of write-back peaks during 100ms to 1,000ms mean interarrival time, but the benefits are always smaller than 10 percent. The benefits of write-back over write-through are slightly better in the traces with exponential distributions than in the traces with Pareto distributions because the latter has bursty requests, which can reduce the number of disk spin-ups.

Write-Back with Eager Updates (WBEU). The energy consumption with write-back can be further reduced by eagerly flushing dirty blocks to disks when the corresponding disks become active due to a read miss. In the extreme case, if a disk D always stays in a low-power mode, the storage cache will end up with a lot of D's dirty blocks. To avoid this scenario, if the number of such dirty blocks reaches a certain threshold, D is forced to transition into active mode and the storage cache flushes D's dirty blocks. This policy is similar to the ones used in [45], [37], [8]. The advantage of this write policy is that writes avoid causing energy-expensive disk spin-ups.

Fig. 13b and Fig. 13e show the percentage energy savings of WBEU over write-through. WBEU can significantly reduce energy consumption. If 100 percent of the requests are writes, WBEU can save 60-65 percent more energy than write-through. Therefore, when the percentage of writes is significant in a workload, it is much more energy-efficient to use WBEU if persistency is not a big concern.

For the traces with exponential distributions, WBEU is more sensitive to the mean interarrival time. With a write ratio of 0.5, if the mean interarrival time is large (10,000ms), the benefits of WBEU are very small. This is because disks are "sleeping" most of the time and requests only cause a little energy consumption. If the mean interarrival time is small (10ms), WBEU does not provide huge benefits either. This is because disks are active most of the time due to fast arriving read requests. Mean interarrival time has less effect on WBEU's benefits with Pareto traffic because disks have longer idle periods and tend to stay in low power modes.

Write-Through with Deferred Update (WTDU). Since write-through causes a lot of energy consumption, WTDU defers updates using a persistent log to avoid spinning up a disk in low power mode. This log can reside in any persistent device such as NVRAM or a log disk that is likely to be always active. In databases, log disks are usually always active because databases rely on their performance for fast transaction commits. With such a log, we can defer energy-expensive updates in write-through.

To ensure persistency, we divide the log space into log regions with one for each disk. The first block of a log region keeps the timestamp for the corresponding disk. This timestamp is also stored together with each block in the log region. The storage cache also keeps a pointer for each disk to remember the next free block in the corresponding log region. When a write request arrives for an inactive disk D, the blocks are first written to the corresponding log region and each block is timestamped with D's timestamp. The cache copies of these blocks are marked as "logged." When D becomes active due to a read miss, all "logged" blocks are flushed from the storage cache into D before servicing any write requests. Then, the timestamp stored in the first block of D's log region is incremented by one. Finally, the corresponding free block pointer is reset.

The timestamp is used to ensure consistent recovery when the system crashes. After the system reboots, it first checks each log region to get the timestamps from its first block. Suppose the timestamp for a region A is n. If the timestamps of some blocks in the same region are also n, it means some blocks may not have been written back to the data disk. Thus, the recovery process will write all blocks with the same timestamp back to the data disk. Otherwise, all blocks are already written back and the recovery process does not need to do anything for this log region and can move on to the next log region.

Fig. 13c and Fig. 13f show the percentage energy savings for WTDU over write-through. When we evaluate WTDU, the extra energy consumption for writing to log regions is included in WTDU's results. If all accesses are writes, WTDU can reduce the disk energy consumption by 55 percent compared to write-through, which indicates WTDU is quite effective. Since this scheme can also provide persistency, it is good for workloads which have a high percentage of writes and require persistency semantics.

8 Discussions

In this section, we discuss several issues, such as the effects of disk layout, how to apply our scheme to the other multispeed power modesl which service requests in low-power modes, how to solve disk contention due to a small subset of active disks, and interaction with CPU energy.

8.1 Effects of Disk Layout

In our simulation, we use the same disk layouts as indicated in the trace documents. However, it is true that if all disks belong to the same striping group, all disks would have similar characteristics and both PA-LRU and PB-LRU would behave similarly to LRU.

Fortunately, in reality, most data center workloads run on configurations with multiple striping groups for two reasons: 1) Scalability limitation: Due to the throughput limitation of RAID controllers, most commercial storage systems usually configure only 20-40 disks to each RAID controller, but, internally, a storage system is connected to many such RAID controllers. 2) Reliability concern: Since the multiple-disk failure rate grows quickly with the number of disks in a striping group, it is much more reliable to use multiple smaller striping groups than one large group. Therefore, most users of high-end storage systems (e.g., EMC Symmetrix) are recommended to configure the system with multiple striping groups, all of which share the storage cache and the storage processors inside the storage box.

Therefore, both PA-LRU and PB-LRU would be useful to partition the storage cache in a way according to the different characteristics of each striping group. As a matter of fact, our OLTP trace was collected on a real system that the DBMS (Microsoft SQL Server) creates the TPC-C database on two striping groups (this is specified by the TPC-C benchmark kit, which was provided by Microsoft).

Recently, Pinheiro and Bianchini have proposed PDC (Popular Data Concentration) [40] to employ energy-aware disk layout. PDC keeps track of file popularity and periodically migrates most popular files to the first disk, the second most popular files to the second disk, and so on. By concentrating loads to a small set of disks, other disks can stay in a low power mode longer. Our power-aware cache algorithms can be combined with their disk layout to further reduce disk energy consumption.

8.2 Effects of the Multispeed Power Model

The multispeed disk architecture proposed by Gurumurthi et al. [16] can be designed to either serve requests at all rotational speeds or serve requests only after a transition to the full-speed mode. We choose the second option because it is a simple extension to the traditional 2-mode power model. Recently, Pinheiro and Bianchini [40] have used the first power model in designing energy-efficient disk layout. Therefore, it is interesting to consider using our power-aware cache algorithm with multispeed disks that serves requests at low speeds.

The ideas of both PA-LRU and PB-LRU can be directly applied to this type of multispeed disk. For example, by selectively keeping blocks from certain disks or assigning large cache partition size to them, those disks can serve requests at a lower speed due to lighter load and thus save energy. However, to make things work, significant changes are needed because of its different underlying disk power management scheme. For example, currently, both PA-LRU and PB-LRU use the length of idle periods as an important energy implication. Moreover, these two algorithms count spinup/spindown cost as a major part of energy penalty. Therefore, the modified PA-LRU and PB-LRU need to keep track of the load (IO/s) instead and use a different method to calculate energy penalty since spinup/spindown is not a big issue any more. We plan to investigate more in this direction in our future work.

8.3 Disk Contention

Both PA-LRU and PB-LRU might incur disk contention because lots of requests are concentrated to a small set of active disks. As a result, those requests might have larger response times due to queuing delay. We have developed a new technique that guarantees that performance will not be degraded beyond a user-specified limit [30]. It dynamically monitors the performance degradation at runtime and forces it to shut down the power management scheme when the degradation exceeds the specified limit. When this method is combined with power-aware cache management, it may turn off the energy-optimizing features of our algorithm, for example, by switching from PA-LRU to traditional LRU or preventing PB-LRU from assigning small cache partition size to a certain disk.

8.4 Impacts on CPU Energy

A smarter cache management policy such as PA-LRU and PB-LRU might incur more processor cycles and, thus, more CPU energy. However, disk drives in data centers consume more energy than processors because of their high volume. For example, in Dell PowerEdge6650 reporting TPC-C performance [3], which is equipped with four Intel Xeon 2.0GH processors (58W each) and 292 15K RPM hard disks (15W each), hard disks consume 19 times as much energy as processors. Moreover, our cache management can be handled by those relatively slow but low-power processors inside the storage system.

9 Related Work

Modeling Disk Power Consumption. Modeling disk energy consumption is important to designing effective power management schemes. Greenawalt, for example, uses a purely analytical model which assumes requests arrive according to a Poisson distribution [15]. Helmbold et al. model disk power consumption in terms of seconds of activity instead of using joules [19]. A recent study conducted by Zedlewski et al. [47] presented a disk simulator called Dempsey which can accurately model energy consumption of a single disk for mobile devices.

Power Management for Mobile Devices. Most of the previous research has focused on power management for single disks in mobile devices such as laptops. These studies can be roughly divided into two categories. The first one does not change the timing for a given request sequence, but tries to dynamically adapt thresholds used to switch to low power modes based on these workloads. Many adaptive schemes have been proposed to vary thresholds [14], [9], [27], [19]. Li et al. [29] and Irani et al. [23] calculate the threshold analytically. A recent study [13] uses program counter-based techniques to predict the length of upcoming idle periods.

The second category investigates ways to reorganize idle periods in I/O request sequences by delaying or prefetching requests. Weissel et al. proposed a scheme called Cooperative I/O to allow applications to specify deferrable or abortable I/O operations which provide more flexibility for underlying disk power management [43]. Heath et al. considered application transformation to increase idle periods and inform the operating system about the length of each upcoming idle period [18]. Papathanasiou and Scott suggested delaying asynchronous requests when the disk is at low-power mode and prefetching some requests when the disk is at full power mode [37], [38].

Our study also tries to reorganize idle periods in I/O request sequences, however, it differs from other studies in two aspects. First, our work uses the storage cache to reorganize idle periods and does not require any modifications to applications. Second, our work focuses on multiple disks with data center workloads instead of a single disk with interactive I/O workloads.

Power Management for Data Centers. Some recent studies [8], [16], [17], [6], [40] have looked into energy management for high-end storage systems. A number of them [6], [16], [17] have shown that the average idle period between requests in server workloads is small compared to the spin-up and spin-down cost of server disks, which limits the possible energy saving. Gurumurthi et al. have proposed multispeed disks to address this problem [16]. Carrera et al. have studied a combination of laptop disks and server disks and also suggested the use of multispeed disks to save energy [6]. These works motivate our study on power-aware cache management. However, these studies do not look at the effect of storage cache on disk energy consumption.

Colarelli and Grunwald [8] proposed a disk backup organization called MAID that uses a small number of disks as "cache drives" to save energy by reducing the spin-ups of data drives. However, they rely on the traditional LRU algorithm to manage the cache disks. Our algorithm can be directly used for cache disks to further reduce energy consumption.

10 Conclusions

In this paper, we show that power-aware storage cache management policies can help the underlying disk energy management scheme save more energy and provide better I/O response time. More specifically, we present an offline energy-optimal cache replacement algorithm using dynamic programming which minimizes the underlying disk energy consumption. Moreover, we present an offline power-aware greedy algorithm that is more energy-efficient than Belady's offline algorithm. We also propose two online power-aware cache replacement algorithms. Our simulation results in both real system and synthetic workloads show that, compared to LRU, our online algorithms can save up to 22 percent more disk energy and provide up to 64 percent better average response time. Even though PA-LRU and PB-LRU are based on LRU, these techniques can also be applied to other replacement algorithms such as ARC [34] or MQ [49]. We also evaluate the effects of different cache write policies on disk energy consumption.

Our study has some limitations that remain as our future work. First, since our study focuses on high-end storage systems, our power-aware online algorithms are designed for multiple disks only. We are still in the process of designing power-aware online algorithms that work for a single disk. Second, we are in the process of adding a disk power model to our previously built V3 storage system [48] to emulate disk spin up/spin down. This will allow us to measure energy consumption in a real storage system. Third, we plan to combine the performance-guaranteed techniques with our power-aware cache management and evaluate its effectiveness. Fourth, it is also interesting to investigate how to modify our algorithm to work with a multispeed disk which services requests at low speeds.

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