

# Tuning Garbage Collection in an Embedded Java Environment

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## Abstract

*Java is being widely adopted as one of the software platforms for the seamless integration of diverse computing devices. Over the last year, there has been great momentum in adopting Java technology in devices such as cell-phones, PDAs, and pagers where optimizing energy consumption is critical. Since, traditionally, the Java virtual machine (JVM), the cornerstone of Java technology, is tuned for performance, taking into account energy consumption requires re-evaluation, and possibly re-design of the virtual machine. This motivates us to tune specific components of the virtual machine for a battery-operated architecture. As embedded JVMs are designed to run for long periods of time on limited-memory embedded systems, creating and managing Java objects is of critical importance. The garbage collector (GC) is an important part of the JVM responsible for the automatic reclamation of unused memory. This paper shows that the GC is not only important for limited-memory systems but also for energy-constrained architectures. In particular, we present a GC-controlled leakage energy optimization technique that shuts off memory banks that do not hold live data. A variety of parameters, such as bank size, the garbage collection frequency, object allocation style, compaction style, and compaction frequency, are tuned for energy saving.*

## 1 Introduction

Java is becoming increasingly popular in embedded/portable environments. It is estimated that Java-enabled devices such as cell-phones, PDAs and pagers will grow from 176 million in 2001 to 721 million in 2005 [20]. One of the reasons for this is that Java enables service providers to create new features very easily as it is based on the abstract Java Virtual Machine (JVM). Thus, it is currently portable to 80 to 95 percent of platforms and lets developers design and implement portable applications without the special tools and

libraries that coding in C or C++ normally requires [17]. In addition, Java allows application writers to embed animation, sound, and other features within their applications easily, an important plus in web-based portable computing.

Running Java in an embedded/portable environment, however, is not without its problems. First, most portable devices have very small memory capacities. Consequently, the memory requirements of the virtual machine should be reduced and, accordingly, the application code should execute with a small footprint. Second, along with performance and form factor, energy consumption is an important optimization parameter in battery-operated systems. Since, traditionally, the virtual machine is tuned for performance, taking into account energy consumption requires re-evaluation, and possibly re-design of the virtual machine from a new perspective. Third, the JVM in a portable environment is not as powerful as the JVM in a general-purpose system as many native classes are not supported. All these factors motivate us to tune specific components of the JVM (e.g., garbage collector, class loader) for a portable environment.

As embedded JVMs are designed to run for long periods of time on limited-memory embedded systems, creating and managing Java objects is of critical importance. The JVM supports automatic object reclamation, removing objects that are no longer referenced. Existing embedded JVMs such as Sun's KVM [2] and HP's ChaiVM [3] are already finely tuned to conform with three important requirements of embedded systems: soft real-time, limited memory, and long-duration sessions. However, currently, there is little support for analyzing and optimizing energy behavior of such systems. This is of critical importance for more widespread adoption of this technology in battery-constrained environments. In particular, the energy consumption in the memory system is a significant portion of overall energy expended in execution of a Java application [22]. Thus, it is important to consider techniques to optimize memory energy consumption. There are two important components of memory energy: dynamic energy and leakage energy. Dynamic energy is consumed whenever a memory array is referenced or

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precharged. Recent research has focused on the use of memory banking and partial shutdown of the idle banks in order to reduce dynamic energy consumption [8]. However, leakage energy consumption is becoming an equally important portion as supply voltages and thus threshold voltages and gate oxide thicknesses continue to become smaller [4]. Researchers have started to investigate architectural support for reducing leakage in cache architectures [23, 16]. In this paper, we show that it is possible to also reduce leakage energy in memory by shutting down idle banks using an integrated hardware-software strategy.

The garbage collector (GC) [13] is an important part of the JVM and is responsible for automatic reclamation of heap-allocated storage after its last use by a Java application. Various aspects of the GC and heap subsystems can be configured at JVM runtime. This allows control over the amount of memory in the embedded device that is available to the JVM, the object allocation strategy, how often a GC cycle is triggered, and the type of GC invoked. We exploit the interaction of these tunable parameters along with a banked-memory organization to effectively reduce the memory energy (leakage and dynamic) consumption in an embedded Java environment. Since garbage collection is a heap-intensive (i.e., memory-intensive) operation and directly affects application performance, its impact on performance has been a popular research topic (e.g., see [13] and the references therein). In an embedded/portable environment, however, its impact on energy should also be taken into account. This is important not because the garbage collector itself consumes a sizeable portion of overall energy during execution, but because it influences the energy consumed in memory during application execution. The GC can take the banked nature of main memory into account and (i) turn off unused memory banks and (ii) move objects (in memory) in a bank-sensitive manner so as to maximize energy reduction.

This paper studies the energy impact of various aspects of a mark-and-sweep (M&S) garbage collector (commonly employed in current embedded JVM environments) in a multi-bank memory architecture. The experiments are carried out using two different (compacting and non-compacting) collectors in Sun's embedded JVM called KVM [2]. Further, the virtual machine is augmented to include features that are customized for a banked-memory architecture. We also measure the sensitivity of energy behavior to different heap sizes, cache configurations, and number of banks. In order to investigate the energy behavior, we gathered a set of thirteen applications frequently used in hand-held and wireless devices. These applications include utilities such as calculator and scheduler, embedded web browser, and game programs.<sup>1</sup> We observe that the energy consumption of an embedded Java application can be significantly more if the GC param-

eters are not tuned appropriately. Further, we notice that the object allocation pattern and the number of memory banks available in the underlying architecture are limiting factors on how effectively GC parameters can be used to optimize the memory energy consumption.

The remainder of this paper is organized as follows. The next section summarizes the K Virtual Machine and its GCs. Section 3 explains the experimental setup used for our simulations. Section 4 gives the energy profile of the current KVM implementation and discusses the impact of dividing memory into multiple banks. This section also investigates the energy impact of different features of our garbage collectors from both the hardware and software perspectives. Section 5 discusses related work. Finally, Section 6 concludes the paper by summarizing our major contributions.

## 2 KVM and Mark-and-Sweep Garbage Collector

K Virtual Machine (KVM) [2] is Sun's virtual machine designed with the constraints of inexpensive embedded/mobile devices in mind. It is suitable for devices with 16/32-bit RISC/CISC microprocessors/controllers, and with as little as 160 KB of total memory available, 128 KB of which is for the storage of the actual virtual machine and libraries themselves. Target devices for KVM technology include smart wireless phones, pagers, mainstream personal digital assistants, and small retail payment terminals. The KVM technology does not support Java Native Interface (JNI). The current implementation is interpreter-based and does not support JIT (Just-in-Time) compilation.

An M&S collector makes two passes over the heap. In the first pass (called mark pass), a bit is marked for each object indicating whether the object is reachable (live). After this step, a sweep pass returns unreachable objects (garbage) to the pool of free objects. As compared to other garbage collectors such as reference counting and generational collectors [13], the M&S collector has both advantages and disadvantages. For example, unlike reference counting GC, M&S collector handles reference cycles naturally without any extra mechanism. Also, no pointer arithmetic is necessary during object assignments. As compared to generational collector, it has less information to maintain during garbage collection, is easier to implement, and has a simpler user interface.

The KVM implements two M&S collectors, one without compaction and one with compaction. In the non-compacting collector, in the mark phase, all the objects pointed at by the root objects, or pointed at by objects that are pointed at by root objects are marked *live*. This is done by setting a bit in the object's header called MARK BIT. In the sweep phase, the object headers of all objects in the heap are checked to see if the MARK BIT was set during the mark phase. All unmarked objects (MARK BIT=0) are added to the free list

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<sup>1</sup>Our applications and GC executables are publicly available from [www.cse.psu.edu/~gchen/kvmgc/](http://www.cse.psu.edu/~gchen/kvmgc/)

and for the marked objects (MARK BIT = 1), the MARK BIT is reset. While allocating a new object, the free list is checked to see if there is a chunk of free memory with enough space to allocate the object. If there is not, then garbage collector is called. After garbage collection (mark and sweep phases), object allocation is tried again. If there is still not any space in the heap, an out-of-memory exception is thrown. Note that since this collector does not move objects in memory, the heap can easily get fragmented and the virtual machine may run out of memory quickly.

In an embedded environment, this heap fragmentation problem brings up two additional issues. First, since the memory capacity is very limited, we might incur frequent out-of-memory exceptions during execution. Second, a fragmented heap space means more active banks (at a given time frame) and, consequently, more energy consumption in memory. Both of these motivate for compacting live objects in the heap. Compacting heap space, however, consumes both execution cycles and extra energy which also need to be accounted for.

In the compacting mark-and-sweep collector, permanent objects are distinguished from dynamic objects. A certain amount of space from the end of the heap is allocated for permanent objects and is called *permanent space*. This is useful because the permanent space is not marked, swept, or compacted (since it contains permanent objects which will be referenced until the end of execution of program). The mark and sweep part of this collector is same as the non-compacting collector. Compaction takes place on two occasions:

- after the mark and sweep phase if the size of the object to be allocated is still bigger than the largest free chunk of memory obtained after sweeping;
- when the first permanent object is allocated, and, as needed, when future permanent objects are allocated. Space for a permanent object is always allocated in steps of 2KB. If the object needs more space, then another 2KB-chunk is allocated, and so on until its space requirement is satisfied.

During compaction, all live objects are moved to one end of the heap. While allocating a new dynamic object, the free list is checked to see whether there is a chunk of free memory with enough space to allocate the object. If there is not, then the garbage collector is called. During garbage collection (after sweep phase), it is checked whether the largest free chunk of memory (obtained after sweep phase) satisfies the size to be allocated. If not, then the collector enters compaction phase. After compaction, object allocation is attempted again. If there still is not any space, an out-of-memory exception is signaled.

The default compaction algorithm in KVM is a Break Table-based algorithm[24]. Advantages of this algorithm are

that no extra space is needed to maintain the relocation information, objects of all sizes can be handled, and the order of object allocation is maintained. The disadvantage is that both sorting the break table and updating the pointers are costly operations both in terms of execution time and energy.

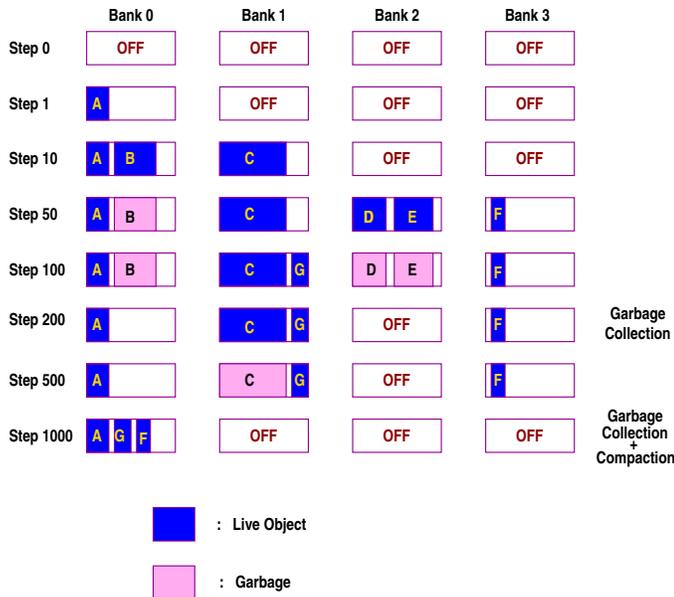
In the rest of the paper, we will refer to these compacting and non-compacting collectors as M&S and M&C, respectively. It should be noted that both the collectors are not optimal in the sense that they do not reclaim an object immediately after the object becomes garbage (as an object is not officially garbage until it is detected to be so).

Figure 1 shows the operation of garbage collection and compaction in our banked memory architecture that contains four banks for the heap. Each step corresponds a state of the heap after an object allocation and/or garbage collection/compaction. Step 0 corresponds to initial state where all banks are empty (turned off). In Step 1, object A is allocated and in Step 10, two more objects (B and C) are allocated. In Step 50, object B becomes garbage and three new objects (D, E, and F) are allocated. In Step 100, both D and E become garbage and G is allocated. Note that at this point all the banks are active despite the fact that Bank 2 holds only garbage. In Step 200, the garbage collector is run and objects B, D, and E are collected (and their space is returned to free space pool). Subsequently, since Bank 2 does not hold any live data, it can be turned off. In Step 500, object C in Bank 1 becomes garbage. Finally, Step 1000 illustrates what happens when both garbage collection and compaction are run. Object C is collected, live objects A, G, and F are clustered in Bank 0, and Banks 1 and 3 can be turned off. Two points should be emphasized. Energy is wasted in Bank 2 between steps 100 and 200 maintaining dead objects. Thus, the gap between the invocation of the garbage collection and the time at which the objects actually become garbage is critical in reducing wasted energy. Similarly, between steps 500 and 1000, energy is wasted in Banks 1 and 3 because the live objects that would fit in one bank are scattered in different banks. This case illustrates that compaction can bring additional energy benefits as compared to just invoking the garbage collector.

## 3 Experimental Setup

### 3.1 Banked Memory Architecture

The target architecture we assume is a system-on-a-chip (SoC) as shown in Figure 2. The processor core of the system is based on the microSPARC-IIep embedded processor. This core is a 100MHz, 32-bit five-stage pipelined RISC architecture that implements the SPARC architecture v8 specification. It is primarily targeted for low-cost uniprocessor applications. The target architecture also contains on-chip data and instruction caches that can be selectively enabled.

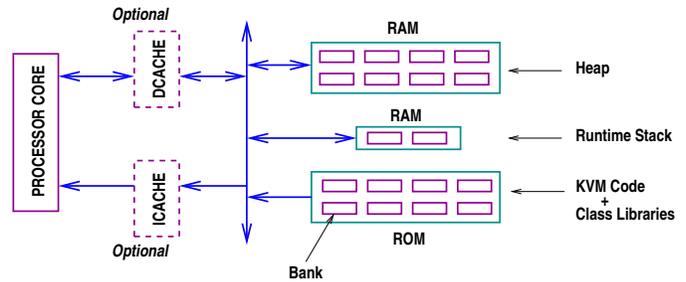


**Figure 1. Operation of garbage collector and compactor.**

Further, it contains an on-chip ROM and an on-chip SRAM. Figure 2 also shows both logical and physical views of the portion of the memory system of interest. This portion is divided into three logical parts: the KVM code and class libraries, the heap that contains objects and method areas, and the non-heap data that contains the runtime stack and KVM variables. Typically, the KVM code and the class libraries reside in a ROM. The ROM size we use is 128 KB for the storage of the actual virtual machine and libraries themselves [2]. The heap (a default size of 128KB) holds both application bytecodes and application data, and is the target of our energy management strategies. An additional 32KB of SRAM is used for storing the non-heap data. We assume that the memory space is partitioned into banks and depending on whether a heap bank holds a live object or not, it can be shutdown. Our objective here is to shutdown as many memory banks as possible in order to reduce leakage and dynamic energy consumption. Note that the operating system is assumed to reside in a different set of ROM banks for which no optimizations are considered here. Further, we assume a system without virtual memory support that is common in many embedded environments [12].

### 3.2 Energy Models

For obtaining detailed energy profiles, we have customized an energy simulator and analyzer using the Shade [6] (SPARC instruction set simulator) tool-set and simulated the entire KVM executing a Java code. Shade is an



**Figure 2. Major components of our SoC. Note that cache memories are optional.**

instruction-set simulator and custom trace generator. Application programs are executed and traced under the control of a user-supplied trace analyzer. Current implementations run on SPARC systems and, to varying degrees, simulate the SPARC (Versions 8 and 9) and MIPS I instruction sets.

Our simulator tracks energy consumption in the processor core (datapath), on-chip caches, and the on-chip SRAM and ROM memories. The datapath energy is further broken into energy spent during execution and energy spent during GC. The GC energy, itself, is composed of the energy spent in mark phase, sweep phase, and compaction phase (if used). Similarly, the memory energy is divided into three portions: energy spent in accessing KVM code and libraries, energy spent in accessing heap data, and energy spent in accessing the runtime stack and KVM variables. The simulator also allows the user to adjust the various parameters for these components. Energies spent in on-chip interconnects are included in the corresponding memory components.

The energy consumed in the processor core is estimated by counting (dynamically) the number of instructions of each type and multiplying the count by the base energy consumption of the corresponding instruction. The energy consumption of the different instruction types is obtained using a customized version of our in-house cycle accurate energy simulator [21]. The simulator is configured to model a five-stage pipeline similar to that of the microSPARC-IIep architecture. The energies consumed by caches are evaluated using an analytical model that has been validated to be highly accurate (within 2.4% error) for conventional cache systems [15]. All energy values reported in this paper are based on parameters for 0.10 micron, 1V technology. The dynamic energy consumption in the cache depends on the number of cache bit lines, word lines, and the number of accesses. In this paper, we model the SRAM-based memory using energy models similar to those used for caches. The number of banks and size of the banks in the SRAM-based memory are parameterizable.

In our model, a memory bank is assumed to be in *one of three modes (states)* at any given time. In the *read/write*

*mode*, a read or write operation is being performed by the memory bank. In this mode, dynamic energy is consumed due to precharging the bitlines and also in sensing the data for a read operation. For a write operation, dynamic energy is consumed due to the voltage swing on the bitlines and in writing the cells. In the *active mode*, the bank is active (i.e., holds live data) but is *not* being read or written. In this mode, we consume dynamic precharge energy as there is no read or write into the bank. In addition, leakage energy is consumed in both these modes. Finally, in the *inactive mode*, the bank does not contain any live data. Thus, the bank is not precharged. Further, in this mode, we assume the use of a leakage control mechanism to reduce the leakage current. Thus, a bank in this mode consumes only a small amount of leakage energy and no dynamic energy.

In optimizing leakage current, we modify the voltage down converter circuit [14] already present in current memory chip designs to provide a gated supply voltage to the memory bank. Whenever the *Sleep* signal is high, the supply to the memory bank is cut off, thereby essentially eliminating leakage in the memory bank. Otherwise, the *Gated  $V_{DD}$*  signal follows the input supply voltage ( $V_{DD}$ ). The objective of our optimization strategy is to put as many banks (from the heap portion of memory) as possible into the inactive mode (so that their energy consumption can be optimized). This can be achieved by compacting the heap, co-locating objects with temporal affinity, invoking the garbage collector more frequently, adopting bank-aware object allocation strategies, or a combination of these as will be studied in detail in Section 4. When a bank in the inactive mode is accessed to allocate a new object, it incurs a penalty of 350 cycles to service the request. The turn-on times from the inactive mode are dependent on the sizing of the driving transistors. Note that the application of this leakage control mechanism results in the data being lost. This does not pose a problem in our case as the leakage control is applied only to unused (inactive) banks.

The dynamic energy consumption for each of the modes is obtained by using scaled parameters for 0.10 micron technology from 0.18 micron technology files applying scaling factors from [1]. An analytical energy model similar to that proposed in [15] is used, and a supply voltage of 1V and a threshold voltage of 0.2V are assumed. We assume that the leakage energy per cycle of the entire memory is equal to the dynamic energy consumed per access. This assumption tries to capture the anticipated importance of leakage energy in future. Leakage becomes the dominant part of energy consumption for 0.10 micron (and below) technologies for the typical internal junction temperatures in a chip [4]. When our gated supply voltage scheme is applied, leakage energy is reduced to 3% of the original amount. This number is obtained through circuit simulation for 0.18 micron technology for a 64-bit RAM when using the scheme explained above with driver sizing to maintain the same read time.

### 3.3 Benchmark Codes and Heap Footprints

In this study, we used thirteen applications ranging from utility programs used in hand-held devices to wireless web browser to game programs. These applications are briefly described in Figure 3. The fourth column gives the maximum live footprint of the application; i.e., the minimum heap size required to execute the application without an out-of-memory error if garbage is identified and collected immediately. The actual heap size required for executing these applications are much larger using the default garbage collection mechanism without compaction. For example, `Kwml` requires a minimum heap size of 128KB to complete execution without compaction. The fifth column in the figure gives the effective live heap size; that is, the average heap size occupied by live objects over the entire duration of the application's execution. From detailed characterization, we observed that the size of the live heap varies across applications. Further, the live heap size varies with time even within a single application. For example, the `Manyballs` application exhibits an oscillating heap size requirement that increases and decreases periodically. The average live heap size of this application is only 62% of the maximum heap size. This indicates the potential for partially shutting down portions of the heap memory as the demand on the heap memory changes. The ability to exploit this potential depends on various factors. These factors include the bank size, the garbage collection frequency, object allocation style, compaction style, and compaction frequency as will be discussed in the next section.

## 4 Energy Characterization and Optimization

### 4.1 Base Configuration

Unless otherwise stated, our default bank configuration has eight banks for the heap, eight banks for the ROM, and two banks for the runtime stack (as depicted in Figure 2). All banks are 16KB. In this base configuration, by default, all banks are either in the active or read/write states, and *no* leakage control technique is applied. The overall energy consumption of this cacheless configuration running with M&S (GC without compaction) is given in the last column of Figure 3. The energy distribution of our applications is given in Figure 4. The contribution of the garbage collector to the overall datapath energy is 4% on average across the different benchmarks (not shown in the figure). We observe that the overall datapath energy is small compared to the memory energy consumption. We also observe that the heap energy constitutes 39.5% of the overall energy and 44.7% of the overall memory (RAM plus ROM) energy on the average.

Note that the memory energy consumption includes both the normal execution and garbage collection phases and is divided into leakage and dynamic energy components. On av-

Application	Brief Description	Source	Maximum Footprint	Effective Footprint	Base Energy (mJ)
Calculator	Arithmetic calculator	www.cse.psu.edu/~gchen/kvmgc/	18,024	14,279	0.68
Crypto	Light weight cryptography API in Java	www.bouncycastle.org	89,748	60,613	8.40
Dragon	Game program	comes with Sun's KVM	11,983	6,149	5.92
Elite	3D rendering engine for small devices	home.rochester.rr.com/ohommes/Elite/	20,284	11,908	3.67
Kshape	Electronic map on KVM	www.jshape.com	39,684	37,466	13.52
Kvideo	KPG (MPEG for KVM) decoder	www.jshape.com	31,996	14,012	1.52
Kwml	WML browser	www.jshape.com	57,185	49,141	34.97
Manyballs	Game program	comes with Sun's KVM	20,682	13,276	6.19
MathFP	Fixed-point integer math library routine	home.rochester.rr.com/ohommes/MathFP/	11,060	8,219	6.91
Mini	A configurable multi-threaded mini-benchmark	www.cse.psu.edu/~gchen/kvmgc/	31,748	16,341	1.46
Missiles	Game program	comes with Sun's KVM	26,855	17,999	4.28
Scheduler	Weekly/daily scheduler	www.cse.psu.edu/~gchen/kvmgc/	19,736	17,685	9.63
Starcruiser	Game program	comes with Sun's KVM	13,475	11,360	4.58

Figure 3. Brief description of benchmarks used in our experiments. The fourth and fifth columns are in bytes.

erage, 75.6% of the heap energy is due to leakage. The leakage energy is dependent on the duration of the application execution while the dynamic energy is primarily determined by the number of references. Considering this energy distribution, reducing the the heap energy through leakage control along with efficient garbage collection and object allocation can be expected to be very effective.

We also note from Figure 4 that overall ROM energy is less than the overall heap energy. This is mainly due to the following reasons. First, the dynamic energy for accessing a ROM is less than the corresponding value for a same size RAM. This difference results from the smaller capacitive load on the wordlines and bitlines. In the ROM, only the memory cells that store a value of zero contribute a gate capacitance to the wordline. Further, only these cells contribute a drain capacitance to the bitline [7]. In addition, the number of bitlines is reduced by half with respect to the RAM configuration and a single-ended sense amplifier is used for the ROM array as opposed to a differential sense amplifier in the RAM array. Our circuit simulations show that the per access energy of a RAM array can thus be as large as 10 times that of a ROM array. However, the difference is dependent on the actual bit pattern stored in the array. In our experiments, we conservatively used a dynamic energy cost for accessing the ROM to be half that of a corresponding RAM array access. Since the effective transistor width in the ROM array is also smaller than that in a correspondingly sized RAM array, the leakage energy of the ROM is also smaller. Another reason that the ROM energy is less than the heap energy is because of using a ROM configuration that implements a simple but effective energy optimization. In particular, we use a banked ROM configuration and activate the supply voltage selectively to only those banks that contain libraries that are accessed by the application. Note that this incurs a penalty at runtime when the bank is accessed the first time. However, we found this overhead to be negligible.

Another interesting observation is the relative leakage and dynamic energy consumption breakdowns in the heap memory and the ROM. We found that the dynamic energy of the

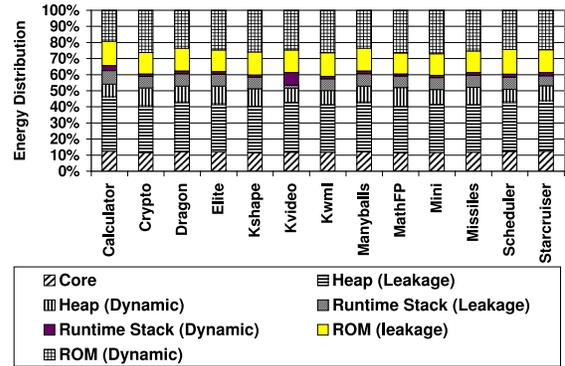


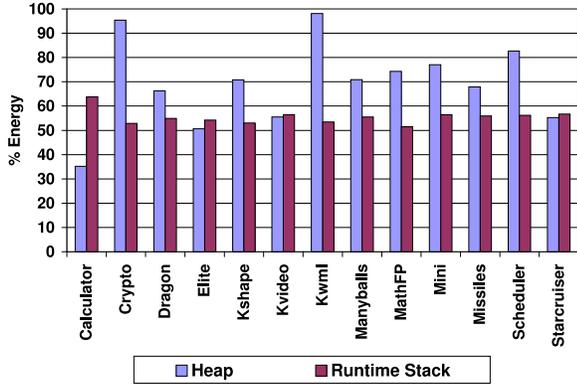
Figure 4. Energy distribution.

ROM is 63.7% of overall ROM energy which is much higher than the corresponding value in the heap. This difference is due to high access frequency of the ROM banks that contain the KVM code as well as class libraries.

## 4.2 Impact of Mode Control

Turning off a heap bank when it does not contain any live object can save energy in two ways. First, leakage energy is reduced as a result of the leakage reduction strategy explained earlier. Second, the precharge portion of dynamic energy is also eliminated when the bank is powered off. Figure 5 gives the heap energy consumption due to M&S when mode control (leakage control) is employed, normalized with respect to the heap energy due to M&S when no mode control is used (i.e., all partitions are active all the time). We observe from this figure that turning off unused banks reduces the heap energy consumption by 31% on the average (with savings ranging from 2% to 65%). On average, 90% of these savings come from leakage energy reduction.

Figure 5 also shows that the normalized runtime stack energy. This energy gain in runtime stack is achieved by not activating one of the banks of the runtime stack when it does not contain any useful data. Since we have two banks allo-



**Figure 5. Normalized energy consumption in heap and runtime stack due to mode control (M&S).**

cated to runtime stack (and the KVM variables) and many applications in our suite can operate most of the time with one bank only, on the average, we achieve around 50% energy saving on these banks.

These energy savings, however, do not come for free. As discussed earlier, accessing a powered off bank requires an extra 350 cycles for the supply voltage to be restored. During this time, a small amount of energy is also expended. However, we observed that the percentages of extra execution cycles and extra energy are no more than 3% and 5.2% respectively. Therefore, we can conclude that applying leakage control mechanism to the inactive heap banks can reduce energy consumption significantly without too much impact on execution time.

### 4.3 Impact of Garbage Collection Frequency

The M&S collector is called by default when, during allocation, the available free heap space is not sufficient to accommodate the object to be allocated. It should be noted that between the time that an object becomes garbage and the time it is detected to be so, the object will consume heap energy as a dead object. Obviously, the larger the difference between these two times, the higher the wasted energy consumption if collecting would lead to powering off the bank. It is thus vital from the energy perspective to detect and collect garbage as soon as possible. However, the potential savings should be balanced with the additional overhead required to collect the dead objects earlier (i.e., the energy cost of garbage collection).

In this subsection, we investigate the impact of calling the garbage collector (without compaction) with different frequencies. Specifically, we study the influence of a  $k$ -allocation collector that calls the GC once after every  $k$  object allocations. We experimented with five different values of  $k$ : 10, 40, 75, 100, and 250. The left graph in Figure 6

illustrates the heap energy (normalized with respect to M&S heap energy without mode control) of the  $k$ -allocation collector. The impact of pure mode control is reproduced here for comparison.

We clearly observe that different applications work best with different garbage collection frequencies. For example, the objects created by `Dragon` spread over the entire heap space very quickly. However, the cumulative size of live objects of this benchmark most of the time is much less than the available heap space. Consequently, calling the GC very frequently (after every 10 object allocations) transitions several banks into the inactive state and reduces heap energy by more than 40%. Reducing the frequency of the GC calls leads to more wasted energy consumption for this application. In `Kvideo`, we observe a different behavior. First, the energy consumption is reduced by reducing the frequency of collector calls. This is because each garbage collection has an energy cost due to fact that mark and sweep operations access memory. In this application, the overhead of calling GC in every 10 allocations brings an energy overhead that cannot be compensated for by the energy saving during execution. Therefore, calling the GC less frequently generates a better result. Beyond a point ( $k=75$ ), however, the energy starts to increase as the garbage collections become so less frequent that significant energy is consumed due to dead but not collected objects. Applications like `Mini`, on the other hand, suffer greatly from the GC overhead and would perform best with much less frequent garbage collector calls. Overall, it is important to tune the garbage collection frequency based on the rate at which objects become garbage to optimize energy consumption.

The GC overhead also leads to increased energy consumption in the ROM, runtime stack, and processor core. The energy increase in the ROM is illustrated on the right graph of Figure 6. Each bar in this graph represents the energy consumption in the ROM normalized with respect to the energy consumption of the ROM with M&S with mode control. It can be observed that the case with  $k = 10$  increases the energy consumption in ROM significantly for many of the benchmarks. On the other hand, working with values of  $k$  such as 75, 100, and 250 seems to result in only marginal increases, and should be the choice, in particular, if they lead to large reductions in heap energy. We also found that the energy overheads in the core and runtime stack were negligible and have less than 1% impact on overall energy excluding cases of  $k = 10$ . To summarize, determining globally optimal frequency demands a tradeoff analysis between energy saving in the heap and energy loss in the ROM. Except for cases when  $k = 10$ , the energy savings in the heap clearly dominate any overheads in the rest of the system.

A major conclusion from the discussion above is the following. Normally, a virtual machine uses garbage collector only when it is necessary, as the purpose of garbage collec-

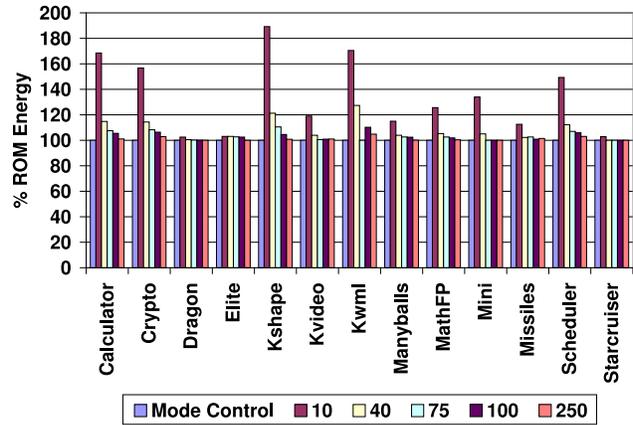
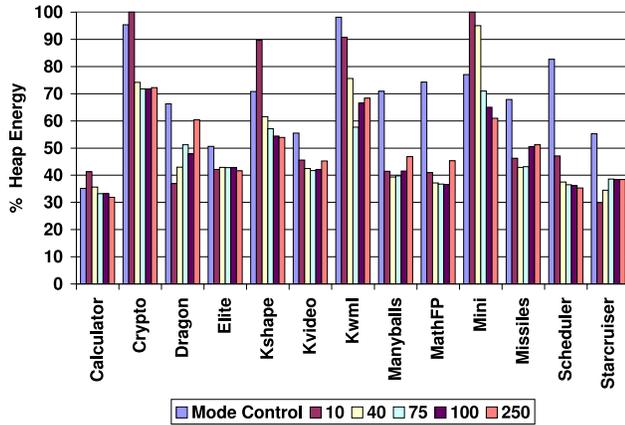


Figure 6. Normalized energy consumption in heap and ROM memory when M&S with mode control is used with different garbage collection frequencies.

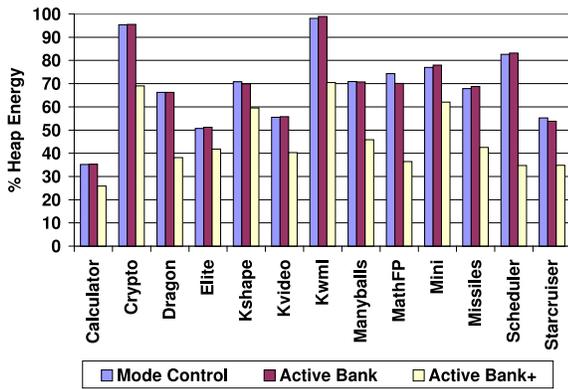


Figure 7. Normalized energy consumption in heap (active bank allocation versus default allocation).

tion is to create more free space in the heap. In an energy-sensitive, banked-memory architecture, on the other hand, it might be a good idea to invoke the collector even if the memory space is not a concern. This is because calling GC more frequently allows us to detect garbage *earlier*, and free associated space (and turn off the bank). This early detection and space deallocation might result in large number of banks being transitioned to the inactive state.

#### 4.4 Impact of Object Allocation Style

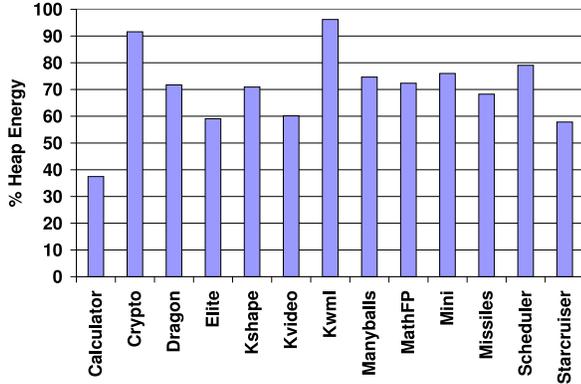
M&S in KVM uses a global free list to keep track of the free space in the heap. When an object allocation is requested, this free list is checked, the first free chunk that can accommodate the object is allocated, and the free list is updated. While in a non-banked architecture, this is a very rea-

sonable object allocation policy, in a banked-memory based system it might be possible to have better strategies. This is because the default strategy does not care whether the free chunk chosen for allocation is from an already used (active) bank or inactive bank. It is easy to see that everything else being equal, it is better to allocate new objects from already active banks.

To experiment with such a strategy, we implemented a new bank allocation method where each bank has its own private free list. In an object allocation request, first, the free lists of active banks are checked and, only if it is not possible to allocate the space for the object from one of these lists, the lists of inactive banks are tried. This strategy is called the *active-bank-first allocation*.

Figure 7 gives the energy consumption for three different versions. M&S with leakage control (denoted Mode Control), active-bank-first allocation (denoted Active Bank), and a version that combines active-bank-first allocation with a strategy that activates the GC only when the new object cannot be allocated from an already active bank (denoted Active Bank+). All values in this figure are normalized with respect to the heap energy consumption of M&S without mode control. We see from these results that Active Bank does not bring much benefit over Mode Control in most cases (except that we observe a 6% heap energy improvement in *MathFP*).

This can be explained as follows. Objects with long life time are typically allocated early (before the first GC is invoked) and occupy the first few banks. The younger objects that occupy banks with higher addresses seldom survive the next garbage collection. From the the traces of bank occupation, we observe that after each GC, the banks with lower address are always occupied and the higher addresses are typically free. Consequently, the default allocation acts like active-bank-first allocation. *MathFP* is an exception to this



**Figure 8. Energy consumption in heap due to mode control (M&C) normalized with respect to M&C without mode control.**

allocation behavior. In `MathFP`, after each GC, the occupied banks are not always contiguous. In this case, active-bank-first allocation can save energy by postponing the turning on a new bank. In contrast, in benchmarks such as `Kwm1` and `Scheduler`, the energy overhead of maintaining multiple free lists shows up as there is almost no gain due to the allocation strategy itself.

Thus, it is important to modify the default garbage collection triggering mechanism in addition to changing allocation policy to obtain any benefits. Active Bank+ combines the active-bank-first allocation mechanism along with a strategy that tries to prevent a new bank from being turned on due to allocation. As it combines an energy aware allocation and collection policy, Active Bank+ can lead to significant energy savings as shown in Figure 7. The causes for these savings are three-fold. First, Active Bank+ invokes the GC more frequently, and thus banks without live objects are identified and turned off early. Second, during allocation, it reduces the chances of turning on a new bank. Third, permanent objects are allocated more densely, thereby increasing the opportunities for turning off banks.

#### 4.5 Impact of Compaction

As explained earlier in the paper, the compaction algorithm in KVM performs compaction only when, after a GC, there is still no space for allocating the object. In a resource-constrained, energy-sensitive environment, compaction can be beneficial in two ways. First, it might lead to further energy savings over a non-compacting GC if it can enable turning off a memory bank that could not be turned off by the non-compacting GC. This may happen as compaction tends to cluster live objects in a smaller number of banks. Second, in some cases, compaction can allow an application to run to completion (without out-of-memory error) while the non-

compacting algorithm gives an out-of-memory error. In this subsection, we study both these issues using our applications.

Let us first evaluate the energy benefits of mode control when M&C (the default compacting collector in KVM) is used. The results given in Figure 8 indicate that mode control is very beneficial from the heap energy viewpoint when M&C is employed. Specifically, the heap energy of the M&C collector is reduced by 29.6% over the M&C without mode control. The left graph in Figure 9 compares heap energy of M&S and M&C with mode control. Each bar in this graph represents heap energy consumption normalized with respect to M&S without mode control. It can be observed that M&C does not bring significant savings over M&S (denoted Mode Control in the graph). First, moving objects during compaction and updating reference fields in each object consumes energy. In addition, compacting may increase the applications running time, which also means more leakage energy consumption. Therefore, a tradeoff exists when compaction is used. In our implementation, to lessen the performance impact, compaction is performed only when the object to be allocated is larger than any of the available free chunks, or if it can turn off more banks. `Kwm1` is one of the benchmarks where compaction brings some energy benefits over M&S with mode control. The execution trace of this code indicates that there are many scenarios where Mode Control does not turn off banks because all banks contain some small-sized permanent objects. M&C, on the other hand, turns off some banks after garbage collection due to the fact that it both compacts fragmented live objects with short life times and clusters permanent objects in a smaller number of banks. In some benchmarks such as `Dragon`, on the other hand, M&C does not create sufficient number of free banks to offset the extra energy overhead due to additional data structures maintained.

The original allocation policy in the compacting version distinguishes between permanent and dynamic objects as mentioned earlier. The default allocation policy always allocates dynamic objects from the first available bank while permanent objects from the last available bank. Thus this strategy requires activating at least two banks (The first one and the last one) when both permanent and dynamic objects are present. The active-bank-first strategy, on the other hand, always tries to allocate dynamic objects from the first active bank with enough space for the new object. Thus, until the total size of the allocated objects exceeds the bank size, only one bank is activated. Consequently, as opposed to the case without compaction, the Active Bank version (that is, allocating object from an already active bank if it is possible to do so) combined with M&C generates better results than M&C with default allocation, and consumes 10% less heap energy on the average. Finally, as before, the Active Bank+ outperforms other versions for most of the cases.

The right graph in Figure 9 compares heap energy con-

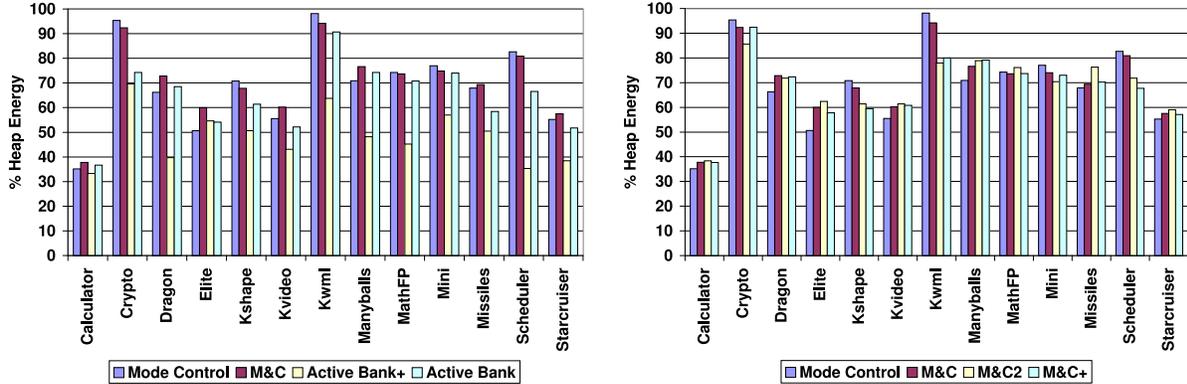


Figure 9. Left: Comparison of M&C and M&S. Right: Comparison of different compacting collectors.

assumption of three different compaction algorithms. M&C is the default compactor in KVM. The M&C+ version differs from M&C in that it performs compaction after each garbage collection (whether or not it is actually needed from the viewpoint of free space). Our results show that in some benchmarks such as *Kshape* and *Scheduler*, it generates better results than both M&S (denoted Mode Control in the figure) and M&C. This is due to the fact that, with M&C collector, objects are allocated linearly, which eliminates the cost for scanning and maintaining free list. M&C2, on the other hand, is a collector that uses the Lisp2 Algorithm, as opposed to the default Break Table-based algorithm in KVM. In the Lisp2 algorithm, during compaction, first, the new addresses for all objects that are live are computed. The new address of a particular object is computed as the sum of the sizes of all the live objects encountered until this one, and is then stored in an additional ‘forward’ field in the object’s header. Next, all pointers within live objects which refer to other live objects are updated by referring to the ‘forward’ field of the object they point to. Finally, the objects are moved to the addresses specified in the “forward” field, and then the ‘forward’ field is cleared so that it can be used for the next garbage collection. The advantages of this algorithm are that it can handle objects of varying sizes, it maintains the order in which objects were allocated, and it is a fast algorithm with an asymptotic complexity of  $O(M)$ , where  $M$  is the heap size. Its disadvantage is that it requires an additional four-byte pointer field in each object’s header that increases the heap footprint of the application.

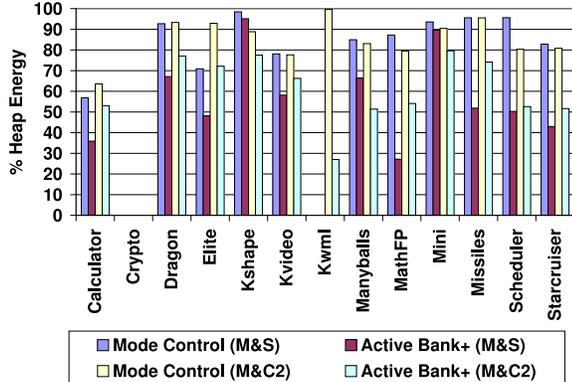
There are two potential energy benefits due to this compaction style. First, objects can be relocated accounting for temporal affinities and object lifetimes, instead of sliding-only compaction as in M&C. For example, clustering objects with similar lifetime patterns increases the potential for deactivating an entire bank (when the objects it holds die together). Secondly, reference fields can be updated more efficiently as compared to M&C and M&C+, where updating each reference field needs to look up the Break Table. Finally,

the extra forward field can be used as a stack in the marking phase to reduce the overhead during the scanning phase.

In case that the heap is severely fragmented, M&C2 will out perform M&C+ because it treats each object individually, and does not need to copy the Break Table (in this case, the Break Table will be large) when moving objects. On the other hand, when most live objects are placed contiguously, M&C+ will perform better because it can move objects in fewer chunks. Further, the smaller Break Table reduces the look up cost (whose time complexity increases logarithmically with respect to the Break Table size) when updating each reference field during compaction. Obviously, if the total number of reference fields is large, M&C+’s performance will suffer a lot during the updating phase.

*Crypto* is an example application with rather big heap footprint that benefits from M&C2’s cheaper marking and updating. In contrast, *Elite* is an application with very small footprint. Due to the 4-byte’s overhead in each objects, M&C2 turns on a new bank much earlier than M&C+. Specifically, M&C2 turns on the third bank about 5.6 seconds after program initialization while the corresponding value for M&C+ is 6.2 seconds. Initializing the forwarding fields of each objects also consumes some extra energy.

As we mentioned earlier, a compacting GC can run an application in a smaller heap memory than a corresponding non-compacting version. For example, *Missiles* can run using a 32KB heap when M&C is employed while requiring a minimum of 64KB heap when executing using M&S. Comparing the energy consumption for systems with these configurations, we found that the M&S that uses a 64KB heap with four 16KB-banks consumes a heap energy of 1.02mJ, which is much larger than 0.71mJ, the heap energy consumed by M&C2 when using a 32KB heap using two 16KB-banks. Similarly, *Kwml* can run using a 64KB heap when M&C is employed, while requiring a minimum of 128KB heap when executing using M&S. For this application, the M&S that uses a 128KB heap with eight 16KB-banks consumes a heap energy of 13.15mJ, which is much larger than 7.66mJ, the



**Figure 10. Impact of cache memory. All numbers are normalized with respect to the heap energy consumed using the same configuration with no mode control. Note that `Crypto` does not run with 64KB heap. Also, `Kwm1` cannot complete using the M&S GC.**

heap energy consumed by M&C2 when using a 64KB heap using four 16KB-banks.

#### 4.6 Impact of Cache Memory

The presence of a cache influences the energy behavior in two ways. First, the number of references to the memory, both the ROM and RAM, are reduced. This reduces the dynamic energy consumed in the memory. In particular, we find that the heap energy reduces to 23% of the overall energy in the presence of the 4KB data and 4KB instruction caches. Note that embedded cores typically have small caches. Second, the cache can account for a significant portion of the overall system energy. In particular, the instruction cache is a major contributor as it is accessed every cycle. In the context of this work, it is important to evaluate how the cache influences the effectiveness of mode control strategy and the additional gains that energy-aware allocation and collection provide over pure mode control. Figure 10 shows the normalized heap energy in the presence of a 4K 2-way instruction cache and a 4KB 2-way data cache when a 64KB heap is used. Pure mode control with M&S reduces 15% of heap energy on the average across all benchmarks. An additional 28% heap energy saving is obtained through the energy-aware active bank allocation and garbage collection before new bank activation. The corresponding figures when M&C2 is used are 14% and 25%, respectively. These results show that the proposed strategies are effective even in the presence of a cache.

## 5 Related Work

Automatic garbage collection has been an active research area for the last two decades. The current approaches to garbage collection focus on locality-aware garbage collection (e.g., [5]), concurrent and hardware-assisted garbage collection (e.g., [11]), and garbage collection for Java among others. A comprehensive discussion of different garbage collection mechanisms can be found in [13]. All these techniques are geared towards improving performance rather than energy consumption. We showed in this paper that for an energy-aware collection, different GC parameters should be tuned. Diwan et al. [9] analyzed four different memory management policies from the performance as well as energy perspectives. Our work differs from theirs in that we focus on a banked-memory architecture, and try to characterize and optimize energy impact of different garbage collection strategies when a leakage control mechanism is employed.

Most of the Java-specific optimizations proposed so far focus on improving performance whereas we target improving energy consumption without unduly increasing execution time. Our work differs from these in that we specifically target embedded Java environments and focus mainly on exploiting leakage control mechanisms for reducing energy. We also illustrate how garbage collector can be tuned to maximize the effectiveness of leakage control. Flinn et al. [10] quantifies the energy consumption of a pocket computer when running Java virtual machine. In [22], the energy behavior of a high-performance Java virtual machine is characterized. In contrast to these, our work targets a banked-memory architecture and tunes garbage collector for energy optimization. Finally, numerous papers attempt to optimize energy consumption at the circuit and architectural levels. In particular, the leakage optimization circuit employed here tries to reduce leakage current and is similar to that used in [23, 16]. We employ a design that is a simple enhancement of existing voltage down converters present in current memory designs. Further, the circuit with the differential feedback stage helps to respond to load variations faster during normal operation.

## 6 Conclusions

As battery-operated Java-enabled devices continue to grow, it is becoming important to design resource-constrained Java virtual machines. Simply porting a desktop JVM to run on an embedded device can produce a large fixed memory overhead and result in a large energy consumption; both are unacceptable in most embedded products. Therefore, it is important to design virtual machines components afresh for embedded environments. In embedded environments, memory leaks combined with the limited memory capacity can be potentially crippling. Thus, garbage collection

that automatically reclaims dead objects is a critical component. In this work, we characterized the energy impact of GC parameters built on top of Sun's embedded Java virtual machine, KVM. Further, we showed how the GC can be tuned to exploit the banked nature of memory architecture for saving energy.

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