Alpaca: Intermittent Execution without Checkpoints

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The emergence of energy harvesting devices creates the potential for batteryless sensing and computing devices. Such devices operate only intermittently, as energy is available, presenting a number of challenges for software developers. Programmers face a complex design space requiring reasoning about energy, memory consistency, and forward progress. This paper introduces Alpaca, a low-overhead programming model for intermittent computing on energy-harvesting devices. Alpaca programs are composed of a sequence of user-defined tasks. The Alpaca runtime preserves execution progress at the granularity of a task. The key insight in Alpaca is the privatization of data shared between tasks. Updates of shared values in a task are privatized and only committed to main memory on successful execution of the task, ensuring that data remain consistent despite power failures. Alpaca provides a familiar programming interface and a highly efficient runtime model. We also present an alternate version of Alpaca, Alpaca-undo, that uses undo-logging and rollback instead of privatization and commit. We implemented a prototype of both versions of Alpaca as an extension to C with an LLVM compiler pass. We evaluated Alpaca, and directly compared to three systems from prior work. Alpaca consistently improves performance compared to the previous systems, by up to 23.8x, while also improving memory footprint in many cases, by up to 17.6x.

1 INTRODUCTION

The emergence of extremely energy-efficient processor architectures creates the potential for computing and sensing systems that operate entirely using energy extracted from their environment. Such energy-harvesting systems can use energy from radio waves [Sample et al. 2008; Zhang et al. 2011a], solar energy [Lee et al. 2012; Zac Manchester 2015], and other environmental sources. An energy-harvesting system operates only intermittently when energy is available in the environment and experiences a power failure otherwise. To operate, a device slowly buffers energy into a storage element (e.g., a capacitor). Once sufficient energy accumulates, the device begins operating and quickly consumes the stored energy. Energy depletes more quickly during operation (e.g., milliseconds) than it accumulates during charging (e.g., seconds). When energy is depleted and the device powers off, volatile state, e.g., registers and stack memory, is lost, while non-volatile state, e.g., ferroelectric memory (FRAM), persists. The charge/discharge cycle of an energy-harvesting device forces software to execute according to the intermittent execution model [Colin and Lucia 2016; Lucia and Ransford 2015; Van Der Woude and Hicks 2016]. An intermittent execution includes periods of activity perforated by power failures. The key distinction between intermittent execution and continuously-powered execution is that in the intermittent model a computation may execute only partially before power fails and must be resumed after the power is restored. Correct and efficient intermittent execution requires a system to meet a set of correctness requirements (C1-3) and performance goals (G1-3).

**C1:** A program must preserve progress despite losing volatile state on power failures.

**C2:** A program must have a consistent view of its state across volatile and non-volatile memory.

**C3:** A program must respect atomicity constraints (e.g., sampling related sensors together).

**G1:** Applications should place as few restrictions on the hardware as possible.
G2: Applications should be tunable at design time to use the energy storage capacity efficiently. 
G3: Applications should minimize runtime overhead and memory footprint.

Recent work made progress toward several of these goals, but necessarily compromised on others. This paper develops Alpaca 1, a programming and execution model that allows software to execute intermittently. Like state-of-the-art systems, Alpaca preserves progress despite power failures (C1) and ensures memory consistency (C2). Alpaca uses a static task model that can adhere to programmer-provided atomicity constraints and energy availability (G2, C3). Memory updates made by an Alpaca task only commits atomically when the task completes. By discarding memory updates on power failure, Alpaca can restart a task with negligible cost, without checkpointing the volatile state as in prior work [Lucia and Ransford 2015; Ransford et al. 2011a; Van Der Woude and Hicks 2016] (G3). Unlike prior work that requires the entire memory to be non-volatile [Van Der Woude and Hicks 2016], Alpaca can leverage both volatile and non-volatile memory (G1). We present two different versions of Alpaca with different design choices. Alpaca’s design differences, relative to state-of-the-art systems, translate into performance gains of 4-5.2x on average (up 23.8x in some cases). Also, Alpaca shows smaller memory footprints compared to most of the previous systems.

Section 2 provides background on intermittent computing. Sections 3 and 4 describe the Alpaca programming model and its implementation. Section 5 presents an alternate design choice of Alpaca. Section 6 discusses key design decisions. Sections 7 and 8 describe our benchmarks and evaluation. We conclude with a discussion of related (Section 9) and future (Section 10) work.

2 BACKGROUND AND MOTIVATION
Energy-harvesting systems operate intermittently, losing power frequently and unexpectedly. Intermittent operation compromises forward progress and leads to inconsistent device and memory states, with unintuitive consequences that demand abstraction by new programming models.

2.1 Energy-Harvesting Devices and Intermittent Operation
Energy-harvesting devices operate using energy extracted from their environment, such as solar power [Lee et al. 2012; Zac Manchester 2015], radio waves (RF) [Sample et al. 2008], or mechanical interaction [Karagozler et al. 2013; Paradiso and Feldmeier 2001]. As the processor on such a device executes software to interact with sensors and actuators or communicate via radio, it manipulates both volatile and non-volatile memory. An energy-harvesting device can operate only intermittently, when energy is available. Common energy-harvesting platforms [Sample et al. 2008] use a power system that charges a capacitor slowly to a threshold voltage. At the threshold, the device begins operating, draining the capacitor’s stored energy much more quickly than it can recharge. The system eventually depletes the capacitor, and the device turns off and waits to again recharge to its operating voltage. These power cycles can occur frequently: RF-powered devices may reboot hundreds of times per second [Sample et al. 2008].

2.2 Device Model and Hardware Assumptions
Our work makes few assumptions about device hardware. A device’s memory system can include an arbitrary mixture of volatile and non-volatile memory, unlike prior work that requires all memory to be non-volatile [Ma et al. 2015; Ransford et al. 2011b; Van Der Woude and Hicks 2016]. Alpaca works on devices with non-volatile memories that support atomic read and write operations, e.g. Ferroelectric RAM [TI Inc. 2017] and Flash. In commercially available FRAM implementations that rely on destructive reads (i.e., rewrite-on-read), access atomicity is satisfied by means of an

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1Alpaca: Adaptive Lightweight Programming Abstraction for Consistency and Atomicity
internal capacitor that buffers sufficient energy to complete an in-progress access. Our model allows arbitrary peripheral (I/O) devices as detailed in Section 6.

2.3 Intermittent Execution and Memory Consistency

Software on an energy-harvesting device operates intermittently: an intermittent execution does not end when power fails; instead the execution alternates between active periods and inactive periods. On each power failure, the register file and volatile memory (i.e., stack and globals) are erased. Variables in non-volatile memory persist. Prior work [Balsamo et al. 2016, 2015; Mirhoseini et al. 2013; Ransford et al. 2011a,b] checkpoints volatile state periodically and restores a checkpoint after a power failure. Other prior work [Colin and Lucia 2016; Lucia and Ransford 2015; Van Der Woude and Hicks 2016] found that if an application directly manipulates non-volatile memory, checkpointing only the volatile state is not enough to guarantee consistency. The problem exists because some memory operations may repeat after restarting from a checkpoint. Non-volatile state written before a power failure persists after a restart, and if re-executing code reads the non-volatile state without first overwriting it, the code may operate using inconsistent values. The resulting program behavior is impossible if the device were powered continuously. Precisely, a non-volatile value that may be read and later written (i.e., a “write-after-read”, or W-A-R) between two consecutive checkpoints can become inconsistent [De Kruijf and Sankaralingam 2013; Lucia and Ransford 2015; Van Der Woude and Hicks 2016].

Figure 1 illustrates how the combination of a W-A-R dependence and volatile-only checkpointing can leave data inconsistent. The code, excerpted from our implementation of RSA [Rivest et al. 1978], multiplies two numbers in1 and in2 digit by digit, accounting for carries. A task boundary or a checkpoint is denoted uniformly by TaskBoundaryOrCheckpoint(). The NV prefix denotes non-volatile data. The code preserves per-digit progress using non-volatile variables d, carry, and prod[], the output digit index, most recent carry value, and output product. In the execution, carry is updated, power fails, and after restarting, mult() uses the already-updated value of carry, producing the wrong result (Figure 1b). The code first reads, then writes carry (a W-A-R), putting it at risk of inconsistency. While the figure shows a problem with carry only, d is also read, then written, presenting another potential consistency problem.

2.4 Overhead of Existing Approaches

Intermittent programming systems that handle volatile and non-volatile memory consistency preserve progress across power failure by either taking checkpoints [Van Der Woude and Hicks 2016] or bounding tasks [Colin and Lucia 2016; Lucia and Ransford 2015]. Compiler-automated checkpointing approaches [Ransford et al. 2011a; Van Der Woude and Hicks 2016] are limited to
their static analysis, often resulting in much frequent checkpointing then necessary [Van Der Woude and Hicks 2016]. They also often copies the entire memory, wastefully copying even what has not been updated [Ransford et al. 2011a], or copies much more than necessary due to the limitation of pointer aliasing [Lucia and Ransford 2015]. Moreover, they cannot adhere to high-level atomicity constraints. System asking the programmer to place boundaries [Colin and Lucia 2016; Lucia and Ransford 2015] does not incur frequent checkpointing overhead. However, to make memory consistent across power failure, previous work relied on a custom data structure with high space overhead (i.e., a “channel”) [Colin and Lucia 2016], or a compiler analysis which is prone to high overhead due to conservatism of the static analysis [Lucia and Ransford 2015].

3 ALPACA PROGRAMMING MODEL

Alpaca is a programming interface that allows programmers to write software that behaves correctly under an intermittent execution model. Alpaca aims to overcome the limitations of prior work described in Section 2 and to meet design requirements C1–C3 and design optimization goals G1–G3 from Section 1. The Alpaca programming model consists of two core concepts, tasks and privatization. A task is a programming abstraction that is useful for preserving progress, implementing atomicity constraints, and controlling an application’s energy requirements. Privatization is a language feature that guarantees that any volatile or non-volatile memory accessed by a task remains consistent, regardless of power conditions.

3.1 Task-Based Programming

A task in Alpaca is a user-defined region of code that executes on a consistent snapshot of memory and produces a consistent set of outputs. An Alpaca task that eventually has sufficient energy to execute to completion is guaranteed to have behavior (i.e., control-flow and memory reads and writes) that is equivalent to some continuously-powered execution regardless of arbitrarily-timed power failures. As Section 4 describes, if power fails during a task’s execution, Alpaca effectively discards intermediate results and execution starts again from the beginning of the task. Consequently, a programmer can reason as though tasks are atomic, like transactions in a TM system. Computations that consume more energy than the hardware can provide between two consecutive power failures must be split into multiple tasks.

To program in Alpaca, the programmer decomposes application code into tasks, each marked with the task keyword. Each task explicitly transfers control to another task (or to itself). A program’s control flow is defined by the execution of tasks in the sequence specified by the transfer statements. To transfer control from a task to one of its successors, the programmer uses the transition_to keyword, which takes the name of a task as its argument and immediately jumps to the beginning of that task. transition_to statements are valid along any control-flow path within a task, and all paths through a task must end in a transition_to statement or program termination. The programmer specifies which task should run on when the system powers on for the first time using entry keyword. Figure 2 shows a sensing application written using Alpaca.

Alpaca guarantees to the programmer that a task executes atomically even if power fails during its execution. When the task completes and the next task begins, changes to memory made by the completed task are guaranteed to be visible and control never flows backward to the completed task again, unless an explicit transition_to statement executes. Conversely, if a task does not complete due to a power failure, control does not advance to any other task, which prevents the partially updated state from becoming visible. Alpaca allows only a single task sequence and does not support parallel task execution. This design choice is reasonable because parallel hardware is
extremely rare in intermittent devices due to its relatively high power consumption. Alpaca does not support concurrent (i.e., interleaved as threads) task sequencing. Concurrency is limited to I/O routines only, which are addressed in Section 6.3.

Task atomicity guarantees correctness by ensuring that if any of a task execution’s effects become visible, then all of them are visible, and by ensuring that a completed task’s execution takes effect only once. Moreover, task-based execution preserves progress, assuming that eventually the system buffers sufficient energy to complete any task. Alpaca’s atomicity property derives from its memory model and data privatization mechanism.

### 3.2 Alpaca Memory Model and Data Privatization

Alpaca’s memory model provides a familiar programming interface allowing tasks to share data via global variables. At the same time, the memory model design allows an efficient implementation of the task-atomicity guarantee. The Alpaca memory access model divides data into task-shared and task-local data. Multiple tasks or multiple different executions of the same task may share data using task-shared variables. Task-shared variables are named in the global scope and are allocated in non-volatile memory. Task-shared variables have a typical load/store interface: once a task wrote a value to a task-shared variable, that same task or another task may later read the value by referencing the variable name. Task-local variables are scoped only to a single task, must be initialized by that task, and are allocated in the efficient volatile memory.

As discussed in Section 2.3, directly manipulating non-volatile memory in an intermittent execution can leave data inconsistent due to W-A-R dependencies. To prevent these inconsistencies, Alpaca privatizes task-shared variables to a task during compilation. Privatization creates a task-local copy of a task-shared variable in a privatization buffer. As the task executes, it manipulates the copies in the privatization buffer. When the task completes it copies data to a commit list that the task uses to atomically commit all updates buffered in the privatization buffer. Section 4.2 describes how privatization works and why it is sufficient to keep data consistent. We emphasize, however, that from the programmer’s perspective, privatization is invisible. To support our privatization analysis, the programmer need only specify (1) tasks and (2) task-shared variables. With this information alone, Alpaca provides its consistency guarantee automatically and efficiently.

The new syntactic elements Alpaca introduce is summarized in Table 1.

### 4 ALPACA IMPLEMENTATION

Our prototype implements the programming model defined in Section 3 using a compiler analysis and a runtime library. The key requirements for an Alpaca implementation are (1) preserving
Table 1. Summary of Alpaca keywords.

| Keyword     | Description                                      |
|-------------|--------------------------------------------------|
| task        | Identifies a function as an Alpaca task.         |
| transition_to | Ends a task and start another task.              |
| TS          | Identifies a variable as task-shared.            |
| entry       | Task that executes when the device boots for the first time. |
| init        | Function that executes on every reboot, to reinitialize peripherals. |

progress at the granularity of tasks, (2) ensuring that task-shared and task-local data are consistent, and (3) doing so efficiently.

To meet these requirements, our Alpaca implementation uses two techniques. The first technique is data privatization, which ensures that data remain consistent by transparently copying selected values into temporary buffers and redirecting the task’s accesses to the buffer. The second technique is two-phase commit, which both preserves progress and guarantees that a completed task’s updates to its privatized values are all rendered consistently in memory. Alpaca’s use of task-based execution is the foundation of its efficient support for privatization and two-phase commit.

4.1 Task-Based Execution

Alpaca tasks are void functions with arbitrary code identified with the task keyword. Alpaca maintains a global cur_task pointer in non-volatile memory that records the address of the task that began executing at the last successful task transition. Alpaca also maintains a global non-volatile 16-bit counter, cur_version, which is initially 1, is incremented on each reboot or task transition, and is reset to 1 when it reaches its maximum value. The counter is used to privatize arrays efficiently (Section 4.4). To transition from one task to the next at a transition_to statement, Alpaca assigns cur_task to the address of the next task and jumps to the start of that task. When task execution resumes after a power failure, control transfers to the start of cur_task.

4.2 Privatization

Alpaca privatizes a subset of task-shared variables in a task to keep them consistent in case power fails as the task executes. We describe privatization of scalar (i.e., non-array) data first. Privatization of arrays is described later in Section 4.4. To privatize a variable, Alpaca statically allocates a privatization buffer and copies the variable that may become inconsistent to its local privatization buffer. Alpaca re-writes subsequent memory access instructions to refer to the privatization buffer instead of the original memory location of the variable. At the end of the task, right before the transition to the following task, Alpaca commits any changes made to the privatized copy to its original location, using the two-phase commit procedure (Section 4.3). Privatization ensures that tasks execute idempotently because updates to memory are committed only after a task has completed. Idempotent execution ensures that a task’s effects are atomic, which is one of Alpaca’s main language-level guarantees.

The correctness and efficiency of Alpaca’s privatization analysis rely on several key properties of Alpaca’s design. For efficiency, Alpaca does not privatize all task-shared variables. Instead, Alpaca detects W-A-R dependencies during compilation and privatizes only the variables involved in the dependencies (Section 2). To identify affected variables, Alpaca performs an inter-procedural, backward traversal of each task’s control-flow graph, tracking accesses to each task-shared variable along each path. If a write and then a read to the same task-shared variable are encountered along any path in the backward traversal, Alpaca privatizes that task-shared variable.

6
Alpaca’s compiler generates the instructions for privatizing a variable. The compiler first allocates a privatization buffer in non-volatile memory for each variable that needs to be privatized. At the beginning of the task, the compiler inserts code that copies the variable value from its original location to its privatization buffer. Then, the compiler replaces each reference to the original value inside the task with a reference to the privatization buffer. Before each transition_to statement, the compiler invokes the first phase of the two-phase commit operation, pre_commit (Section 4.3), passing as arguments the addresses of the original variable and its privatization buffer along with its size.

Figure 3 shows a sketch of Alpaca’s instrumentation for an example task code. Compiler-inserted privatization code is in green and code deleted by the compiler is struck-through. As in Line 1, the user defines task-shared variable by annotating it as TS. TS variables are saved in non-volatile memory. The code in this example requires only c to be privatized because it is the only W-A-R variable; code accessing all other data requires no instrumentation. Variable c is privatized on Line 3, and the access to it on Line 6 is re-written to refer to the private copy c_priv (Line 7). After privatization, only the commit operation can modify the location c. Selective instrumentation avoids runtime overhead and is the key to Alpaca’s high performance.

Our implementation of the compiler analysis privatizes variables in functions called from multiple tasks, assuming the variable requires privatization in some of its callers. During analysis of a task that calls a function that accesses such a variable, the compiler rewrites the function’s body to refer to the variable’s privatized copy. Consequently, the variable will remain privatized for any other caller of the same function, even if that caller does not involve the variable in a W-A-R dependency. This “contagious” privatization is safe, conservative, and could be eliminated by replicating the function body, creating a version for each combination of privatized and non-privatized variables that the function refers to. We allow contagious privatization in favor of the code bloat from replication. In practice, redundant privatization is rare in the benchmarks that we studied.

Algorithms 1–3 depict Alpaca’s privatization analysis. The analysis identifies variables potentially involved in W-A-R dependences, adds code to privatize those variables, and adds code to atomically commit privatized copies when a task completes. The code at the end of Algorithm 1 identifies the largest possible number of variables that may need to be committed by a single task and statically allocates a commit list that accommodates them all. Section 4.3 explains in detail how Alpaca uses its commit_list to commit privatized data.

Algorithm 1 Pseudo-code for Alpaca Compiler.

```
1: function ALPACACompiler(Module M)  
2:     for t ∈ M.tasks do  
3:         warSet ← ALPACAFindWAR(t)  ▷ Find W-A-R variables  
4:         ALPACATransform(t, warSet)  ▷ Modify code for W-A-R variables  
5:         maxCommitListSize ← MAX(maxCommitListSize, warSet.size)  
6:     SETCOMMITLISTSIZE(maxCommitListSize)  ▷ Determine commit_list size  
```

Fig. 3. Privatization and commit. transition_to calls commit.
Algorithm 2 Function Finding W-A-R Variables for Each Tasks.

1: function ALPACA_FINDWAR(Task t)
2:   warSet ← ∅
3:   for i ∈ t.instructions do
4:     for v ∈ i.possibleWriteAddress do  ▷ Find writes
5:       if v ∈ taskSharedVariables then
6:         i.writeSet ← i.writeSet ∪ v
7:     for v ∈ i.possibleReadAddress do  ▷ Find reads
8:       if v ∈ taskSharedVariables then
9:         i.readSet ← i.readSet ∪ v
10:    for i ∈ t.instructions do  ▷ Detect W-A-R
11:       for j ∈ i.possiblePreviousInst do
12:         for v ∈ i.writeSet ∩ j.readSet do
13:            warSet ← warSet ∪ v
14:       if i.isFunctionCall then  ▷ For function call (See Section 4.2)
15:         f ← i.getCalledFunction
16:         for v ∈ f.usedTaskSharedVariables do
17:            warSet ← warSet ∪ v
18:   return warSet

Algorithm 3 Function Inserting Privatization and Pre-commit Code When Needed.

1: function ALPACA_TRANSFORM(Task t, Set warSet)
2:   for v ∈ warSet do
3:     if v.isPrivatizationBufferAbsent then  ▷ Create privatization buffer
4:       CREATEBUFFER(v)
5:     INSERTPRIVATIZATIONCODE(t, v)  ▷ Insert privatization code
6:     for i ∈ t.instructions do
7:       if v ∈ i.usedOperands then  ▷ Redirect accesses
8:         REDIRECTUSAGETOBUFFER(i, v)
9:       if i.isTransitionTo then  ▷ Insert pre-commit code
10:         INSERTPRECOMMITBEFORE(i, v)

4.3 Committing Privatized Data

At the end of a task’s execution (i.e., upon reaching a transition_to statement) Alpaca performs a two-phase commit of updates made to privatized data by that task. The commit operation atomically applies all updates to variables’ original locations. The operation is divided into two phases: pre-commit and commit. The pre-commit operation is implemented by the pre_commit function in Alpaca runtime library. This function takes the variable information as an argument and records it in an entry in the commit_list table, depicted in Figure 4a. The commit_list is a table with exactly one entry for each privatized variable. A variable’s commit_list entry contains the variable’s original address, privatization buffer’s address, and size. Calls to pre_commit are inserted by the compiler at transition_to statements, as was described in Section 4.2.

The commit_list generated in the first phase records updates to privatized data that must be committed in the second phase. Alpaca stores an end-index that always points to the entry after the last valid entry in the commit_list. The commit_list must be stored in non-volatile memory since
its contents must persist if a failure happens during the second phase. As seen in Algorithm 1, our implementation statically allocates a region of memory large enough to fit the maximum number of entries that may be required by any task in the program (i.e., the maximum number of calls to pre_commit at any transition_to statement in any task). After the last pre_commit call before each transition_to, the compiler inserts an instruction to set a non-volatile commit_ready bit that marks the task ready for the second phase, as shown in Figure 4b. Alpaca runtime checks commit_ready on boot. If commit_ready is unset, the previously executing task was either in progress or had completed only a partial pre_commit, so that task is re-executed from its start, discarding the partial execution or the partial pre_commit. Otherwise, the second phase is invoked.

The second phase, commit, is implemented in the Alpaca runtime library by a void function, commit. The function iterates over entries in the commit_list from the first up to end-index. For each entry, the variable value is copied from its privatization buffer to its original memory location. The commit operation succeeds when it copies all entries in the commit_list and sets end-index to zero. After a successful commit, the runtime clears the commit_ready bit and proceeds to the following task (Figure 4c). If power fails during commit, commit_ready remains set. Since the runtime checks the bit on boot, it will retry the commit operation until it completes successfully. If power fails after commit but before transition_to completes the transition to the next task, then commit will re-execute on next boot and will trivially complete since end-index is zero. The transition_to that failed to complete will then run again.

4.4 Privatizing and Committing Arrays

Alpaca privatizes and commits array variables differently from scalar variables because naively privatizing an entire array (i.e., copying the entire array to a privatization buffer as a task starts) is...
unnecessary if the task accesses only part of the array. Alpaca statically pre-allocates a privatization buffer for each array that may be read then written (i.e., may be involved in a W-A-R dependence). The array’s privatization buffer contains the same number of entries as the original array. Privatization takes place at the granularity of an array element. In the example in Figure 5, to privatize array $C$, the compiler allocates $C_{\text{priv}}$ buffer (Line 2) and inserts the instrumentation code that is highlighted in green (and explained below).

Like a scalar variable, privatizing an array element involves initializing a copy in the privatization buffer (Line 11), redirecting accesses to the buffer (Lines 12-13), and adding the variable to the commit_list via a call to pre_commit (Line 16). Alpaca uses the compiler to redirect array element accesses to their privatization buffers the same as for scalars, but initializing privatization buffers and pre-commit for arrays are different. Alpaca initializes an array element’s privatization buffer the first time an execution accesses the element: either explicit instrumentation inserted by Alpaca initializes the buffer before the element’s first read or the element’s first write directly writes to the buffer. Alpaca does pre-commit for an array element only once after the first write to it.

One key design choice in Alpaca was to decide when instrumentation on a read operation should initialize an array element’s privatization buffer. Read instrumentation should not initialize the privatization buffer after a previous write in the task because the initialization would overwrite the written value. Instead, the read instrumentation can initialize the privatization buffer either once before the first read that happens before the first write or (possibly redundantly) at every read before the first write. We chose the latter option to avoid the overhead of dynamically tracking the first read, which incurs a high runtime overhead.

We avoid invoking pre-commit unconditionally after every write because multiple writes to the same element would append duplicate entries to the commit_list, which is inefficient and precludes a statically sized commit_list. Furthermore, pre-commits cannot be batched and executed before a task transition (like for scalar variables), because the set of elements dynamically accessed is unknown statically. batching would require dynamically tracking the set of modified elements in a data structure that supports efficient insertion and traversal which is complex. Executing pre-commit after the first write obviates the complexity of batching and only requires Alpaca to identify the first write to an array element.

Correctly handling array privatization and pre-commit requires some instrumentation to execute conditionally, only on an element’s first write. To identify an element’s first write, Alpaca must track the set $U$ of array elements that have been written since the beginning of the task in the current execution attempt. A write of an element is first if and only if the element is not in this set $U$ at the time of the access. The data structure that represents $U$ needs only to provide efficient insertion and lookup, which our version-backed bitmask data structure does. A version-backed bitmask is a bitmask that supports a constant-time clear operation using a versioning mechanism described later in this section. We represent $U$ by setting logical bits (i.e., “entries”) in a version-backed bitmask.

```
1 TS int A[30], B[30], C[30];
2 NV int C_priv[30];
3 NV int C_vbm[30];
4 task example_1() {
5   int r = 0;
6   for (int k=0; k<15; k++) {
7     A[r] = 3;
8     int d = B[r];
9     if (!vbm_test(C_vbm[r]))
10        C_priv[r] = C[r];
11     @r++;
12     C_priv[r]++;
13     if (!vbm_test(C_vbm[r]))
14        vbm_set(C_vbm[r]);
15     pre_commit(&C_priv[r], &C[r],
16                sizeof(C[r]));
17   }
18 }
19 transition_to(example_2)
20 }
```

Fig. 5. Privatization and commit for arrays.
that is statically allocated for each array being privatized. In Figure 5, the version-backed bitmask for \( C \) is \( C_{vbm} \) allocated on Line 3.

Each version-backed bitmask entry is a 16-bit integer version. To set an entry (vbm_set), Alpaca copies the global cur_version counter into the entry. To test an entry (vbm_test), Alpaca compares the version stored in that entry to the global cur_version counter; equality indicates the entry is set, inequality indicates unset. Consequently, when the global cur_version counter changes, all version-backed bitmasks are implicitly cleared. When the cur_version counter overflows and rolls over, the runtime explicitly resets all entries in all version-backed bitmasks to zero.

To track the set \( U \) of array elements updated in the current task execution attempt, the Alpaca compiler instruments reads and writes to array elements with code to set and test entries in the array’s version-backed bitmask. When reading from an array element that has not been modified yet, i.e. its entry in \( U \) is unset (Line 10), then the runtime initializes the element copy in the privatization array (Line 11). When writing to an array element for the first time, after checking that its entry in \( U \) is not set (Line 14), it inserts the element into \( U \) by setting its entry (Line 15), and appends the written array element to the commit_list by calling pre_commit (Line 16). The set \( U \) is cleared at the next task transition or reboot, since the cur_version counter increments on each task transition and reboot (Section 4.1), which implicitly clears the version-backed bitmask.

5 ALPACA WITH UNDO-LOGGING
The design of Alpaca described up to this point relies on privatization and commit, which is a redo-logging approach Maeng et al. [2017] to keeping memory consistent across intermittent failures. We also developed a more efficient Alpaca design variant that relies instead on undo-logging. Both design variants use the same programming interface, differing only in how they manage memory. Section 8 compares undo- and redo-logging, showing that Alpaca-undo is on average 1.53x faster than its redo-logging counterpart. This text refers to the Alpaca design using privatization and commit as Alpaca-redo, refers to the undo-logging variant as Alpaca-undo, and refers to both generally as Alpaca.

5.1 Undo-Logging Instead of Privatization
Redo-logging and undo-logging each present advantages and disadvantages. Alpaca-redo privatizes variables involved in W-A-R dependences and commits updates to those data, when a task completes. Redo-logging affords zero-cost recovery: requiring no action before continuing after a power failure. However, redo-logging pays a cost in its need to first privatize data and later commit them, which requires two copy operations per variable per completed task. In contrast, undo-logging backs up a variable and subsequently manipulates the variable in place, requiring no action when a task completes. However, an undo-logging system must restore values saved in the undo log before continuing execution after a power failure. While restoring from power failure is more costly than in a redo-logging system, undo-logging requires only one copy operation (to back a variable up) per variable per completed task. When successful completion of a task is more common than the interruption of a task by a power failure, undo-logging will be more efficient than redo-logging. In Alpaca, successful task completion is usually more common than interruption by a power failure because a typical task requires much less energy than the maximum energy that the device can buffer. In the worst case when all tasks require the maximum amount of energy that the device can buffer, the task will fail once for each completion. Under Alpaca’s assumptions, undo-logging is appealing because tasks cannot fail more often than they complete.
5.2 Undo-logging Compiler and Runtime System

Similarly to Alpaca-redo, Alpaca-undo relies on a compiler to transform code and insert calls to the Alpaca-undo runtime system into the program.

Figure 6 shows how Alpaca-undo transforms code to implement undo-logging. Instead of allocating a private copy, the compiler allocates a static undo log (Line 2). Alpaca-undo selectively backs up non-array W-A-R variables at the start of the task (Line 5). For an array, Alpaca-undo uses Alpaca’s version-backed bitmask scheme to detect the first write, as discussed in Section 4.4 (Line 10). Alpaca-undo backs up an array value before its first write (Line 12). Unlike Alpaca-redo, Alpaca-undo need not redirect memory accesses to a copy because operations manipulate data in place (Line 6, 9, 14). Additionally, Alpaca-undo does not need instrumentation before an array read (Line 9). Alpaca-undo detects variables involved in W-A-R dependences using Algorithms 1—3, identically to Alpaca-redo.

Figure 7 shows how Alpaca-undo backs up and restores data to keep memory consistent. At the beginning of a task, Alpaca-undo backs up the task’s W-A-R variables (Figure 7a). Alpaca-undo maintains a list of backed-up variables (backup_list). Alpaca-undo also sets the need_rollback flag, indicating that there are variables backed up. Then, Alpaca-undo manipulates variables in place (Figure 7b). Even after the update to a variable’s original value remains in the backed-up copy. When a task successfully completes, Alpaca-undo clears the need_rollback flag and backup_list (Figure 7c). The runtime system clears the list efficiently by resetting the list’s iterator, without zeroing its contents. After a power failure, Alpaca-undo rolls back changes by iterating through the backup_list if the need_rollback flag is set. For each entry, the runtime system writes the backed-up value into its corresponding memory location. After processing all entries, the runtime unsets the need_rollback flag and continues. Section 4.2 discusses sizing the backup list.

6 ALPACA DISCUSSION

Alpaca’s programming model guarantees that tasks will execute atomically. Our Alpaca implementation efficiently provides this atomicity guarantee by selectively privatizing data. Besides programmability, efficiency, and consistency, Alpaca supports I/O operations and allows modular re-use of code. This section discusses these aspects of Alpaca and characterizes its main limitations.

6.1 Low Overhead

A key contribution of this work is that our Alpaca implementation has low overhead compared to existing systems to which we can directly compare (we quantify the difference in Section 8). Alpaca’s overhead is low, because privatization is simple and because Alpaca privatizes variables selectively. Privatization has a low cost, primarily because it rarely occurs: most variables are not privatized because they are either local to a task or shared but not involved in W-A-R dependences. Furthermore, Alpaca’s task-based execution avoids all checkpointing cost. Alpaca needs to retain only the information about which task was last executing. Alpaca does not incur the cost of tens of
writes to non-volatile memory to save registers, like Ratchet [Van Der Woude and Hicks 2016], nor the even higher additional cost to save the stack, like DINO [Lucia and Ransford 2015]. By reducing copying and privatizing only when necessary, Alpaca saves time and energy.

6.2 Memory Consistency

Alpaca preserves memory consistency despite arbitrarily-timed power failures by making each attempt to execute a task idempotent. Task idempotence guarantees that if any attempt has sufficient energy to complete, the effects of a single, atomic execution of the task are made visible in memory. The memory state immediately after a task transition is equivalent to the corresponding state in execution on continuous power. Alpaca guarantees idempotence by privatizing non-volatile variables involved in W-A-R dependences and requiring volatile state to be task-local.

6.2.1 Non-volatile Memory Consistency. Taking a cue from prior work [De Kruifj and Sankaralingam 2013; de Kruifj et al. 2012; Lucia and Ransford 2015; Van Der Woude and Hicks 2016], Alpaca privatizes only non-volatile variables involved in W-A-R dependencies. We show that privatizing only this subset is sufficient by proving that only memory accesses related by W-A-R can cause a value written by the task before a power failure to be read by the same task after the power failure.

Consider one task and assume that control flows along the same path each time the task re-executes, which is true of all code that does not perform I/O operations (we discuss I/O later in this section). Consider one memory location and let $R^i_j$ and $W^i_j$ respectively denote the $i$th memory read and write to that location during the $j$th attempt to execute the task. If power fails in attempt $j$ after $k$ accesses and the task re-executes, then the sequence of memory accesses is: $X^1_j, \ldots, W^p_j, \ldots, X^k_j - [\text{power failure}] - X^p_{j+1}, \ldots, R^p_{j+1}, \ldots, X^k_{j+1}$, where $X$ stands for either read or write and our hypothesis postulates a write $W^i_p$ before the power failure and a read $R^i_q$ that returns the same value. The hypothesis implies that $q < p$, otherwise, $W^i_p$ would overwrite the value written by $W^i_p$ before $R^i_q$ reads it. The order $q < p$ implies that $R^i_q$ precedes $W^i_p$ in the task code, which is the definition of a W-A-R dependence.

Fig. 7. Making progress in Alpaca-undo. Each panel shows the execution at left and the system state at right. The current phase is shaded. Initially, $a=1$ and $b=0$. (a) Before executing Task 1, Alpaca-undo copies the value of $a$ to its backup copy. Backed up variables are marked in backup_list. (b) Task 1 gets executed, updating variables in-situ. (c) When Task 1 is finished, Alpaca-undo simply clears the backup_list and related flags.
6.2.2 Volatile Memory Consistency. In Alpaca, the only volatile data are task-local variables. Since all local variables must be initialized before use in a task, local reads after a power failure will never access uninitialized memory. Since volatile memory clears on reboot, local reads will never observe a value written before the power failure.

Like prior work [Van Der Woude and Hicks 2016], Alpaca conservatively assumes that compiler optimizations cannot introduce memory read or write instructions and Alpaca safely interacts with any compiler optimization that adheres to this assumption.

6.3 I/O

Code that interacts with sensors and actuators poses three difficulties: (1) some I/O-related actions must execute atomically, (2) external inputs introduce non-determinism, and (3) actuation or output cannot be undone. Alpaca allows the programmer to express (1) and (2) through careful coding patterns that we describe below. Alpaca targets applications that can tolerate repeated outputs, where (3) is acceptable.

Some applications include I/O-related code that should execute atomically, such as the code in Figure 8. The code reads temperature and pressure sensors and sets the heaterOn or coolerOn flag, based on the sensed data. The temperature and pressure values should be consistent. Alpaca lets the programmer ensure that the values will be consistent by putting the actions in the same task. In contrast, a system with dynamic [Balsamo et al. 2015; Ransford et al. 2011a] or compiler-inserted [Van Der Woude and Hicks 2016] task boundaries gives the programmer no way to ensure that the input operations execute atomically.

The code in the example asserts that heaterOn and coolerOn are never both true. The code misbehaves if a power failure occurs after assigning one of the flags (e.g., heaterOn). If the sensor’s result is different in the following execution attempt, the code could set the other flag (e.g., coolerOn), violating the assertion. The core issue is that non-volatile memory updates are conditionally dependent on sensed inputs. If control-flow depends on the input, then conditional non-volatile memory updates can violate task idempotence. We note that this problem also afflicts prior efforts [Colin and Lucia 2016; Lucia and Ransford 2015; Van Der Woude and Hicks 2016]. A programmer can preserve idempotence by using intermittence-safe I/O programming patterns. Concretely, one programming pattern that avoids the problem in this example is to use a dedicated task to read and store both temp and pres, and to use another task to do the conditional updates to heaterOn and coolerOn. Alternatively, a programmer could avoid the problem by ensuring that both execution paths access the same set of memory locations: inserting coolerOn = false; on the if branch and inserting heaterOn = false; on else branch.

6.4 Forward Progress

Guaranteeing forward progress in an intermittent, energy-harvesting system is a difficult problem that is orthogonal to the problems solved by Alpaca. The key challenge is that a system buffers a fixed amount of energy before it begins operating and if the energy required by a task exceeds the buffered amount, the task will never complete executing, preventing progress. A task’s energy cost can be input dependent, adding further complexity. This progress issue is not unique to
Alpaca, afflicting prior task-based systems as well [Colin and Lucia 2016; Lucia and Ransford 2015; Mirhoseini et al. 2013; Ransford et al. 2011a; Van Der Woude and Hicks 2016].

Prior work has used ad hoc techniques that attempt to ensure progress, to the detriment of other system characteristics. Ratchet [Van Der Woude and Hicks 2016] inserts a dynamic checkpoint between static checkpoints after repeatedly failing to make progress. Other systems [Balsamo et al. 2016, 2015; Ransford et al. 2011b] dynamically checkpoint in response to an interrupt when energy is low. Dynamic checkpointing requires capturing enough state to restart from an arbitrary point, which can take a prohibitive amount of time [Colin and Lucia 2016], especially with hybrid volatile and non-volatile memory. Dynamic checkpointing may also violate I/O atomicity (see Section 6.3).

We opted not to include a dynamic checkpointing fall-back in Alpaca. Instead the programmer must ensure for sizing tasks such that tasks in their program do not require more energy than their target device can buffer. As long as this condition is satisfied, Alpaca always avoids atomicity violations and guarantees correctness. None of the tasks in our test programs have a forward progress problem. It would be straightforward to incorporate a dynamic checkpointing fall-back into our Alpaca prototype.

6.5 Reusability of Tasks
In a task-based programming model for intermittent execution, code reuse via functions is insufficient, because functionality that uses more energy than the device can buffer cannot be encapsulated in a single function. The programmer of Alpaca can reuse the sequence of tasks as a C programmer would reuse a function by passing arguments, return address, and return value manually through task-shared variables.

6.6 Prototype Limitations
Our Alpaca prototype supports a useful subset of the C language, handling most uses of pointers and complex data structures. Our prototype has a few implementation-specific limitations, which we emphasize are not fundamental limitations of Alpaca.

We implemented a limited pointer alias analysis and our prototype requires that a TS pointer only ever be assigned the address of a TS variable if that address is constant. Allowing TS pointers to constant variables permits the especially important case of function pointers. Our prototype requires the programmer to refer to array elements directly, i.e., writing A[30] instead of *(p + 30). Our prototype statically inserts code to maintain version-backed bitmasks on array accesses. Array indirection would require our prototype to use instrumentation that dynamically disambiguates pointers to arrays, to determine which bitmask to update. Our prototype makes the calculated choice to avoid this additional dynamic analysis cost by requiring direct array access. We note that this strategy is similar to DINO [Lucia and Ransford 2015].

7 BENCHMARKS AND METHODOLOGY
We evaluated Alpaca using a collection of applications taken from prior work running on real, energy-harvesting hardware. Our evaluation ran on a WISP5 [Sample et al. 2008] energy-harvesting platform that runs a TI MSP430FR5969 microprocessor with harvested RF energy. We used a Saleae Digital Logic Analyzer to measure the execution time by timing GPIO pulses generated at the end of each application. To power the WISP, we used the ThingMagic Astra-EX RFID reader as an RF energy source with its power parameter set to ~X 50, and a distance between the WISP and the power source of 20cm.

We evaluated Alpaca using applications ported to run on harvested energy using DINO [Lucia and Ransford 2015], Chain [Colin and Lucia 2016], Alpaca-redo, Alpaca-undo, and Ratchet [Van Der Woude and Hicks 2016], allowing for a thorough direct comparison. DINO and Chain versions
of four applications were provided by the authors of the Chain [Colin and Lucia 2016] paper: activity recognition (AR), cuckoo filter (CF), rsa encryption (RSA), and cold-chain equipment monitoring (CEM). We ported two additional applications from the MiBench [Guthaus et al. 2001] to run with DINO, Chain, and two versions of Alpaca.

DINO assumes precise pointer aliasing to work correctly [Lucia and Ransford 2015], and performs very poorly on conservative, practical pointer aliasing. Thus, the DINO code we obtained from the author of Chain [Colin and Lucia 2016] was hand-annotated assuming perfect pointer aliasing. Our evaluation shows that Alpaca even outperforms the hand-annotated oracle DINO. Alpaca does not assumes any perfect pointer aliasing as in DINO.

We ported Ratchet [Van Der Woude and Hicks 2016], which was originally targeted for ARM architecture, to run on TI MSP430 series. While doing so, we lack some of the ARM-specific optimizations suggested by the original work. According to the evaluation by the authors, omitting the optimizations can lead to around 1.6x slowdown [Van Der Woude and Hicks 2016].

We studied six applications, summarized in Table 2.

| App | Description |
|-----|-------------|
| CEM | LZW-compresses a random number stream using 512-entry dictionary. |
| CF  | Stores and retrieve a sequence of random numbers using 128-entry filter. |
| RSA | Encrypts a 11-byte string with 64 bit key using RSA encryption. |
| AR  | Collects 128 accelerometer samples and use nearest neighbor classification to detect movement. |
| BF  | Encrypts a 32-byte string using Blowfish encryption. |
| BC  | Counts the number of set bits in a given input stream. |

To ensure a fair comparison, applications use identical task definitions for Chain, Alpaca-redo, and Alpaca-undo, and we inserted task boundaries at equivalent code points for DINO. Since inserting boundaries automatically is part of the system for Ratchet, we did not manually inserted boundaries for Ratchet.
8 EVALUATION

Our evaluation compares directly to Chain, DINO, and Ratchet and illustrates several findings about Alpaca. The data show that both Alpaca-undo and Alpaca-redo outperforms existing systems while running natively on existing hardware both on harvested energy and running on continuous power. Our evaluation characterizes these findings, showing that Alpaca avoids the costliest time and memory overheads of prior approaches. We qualitatively and quantitatively show that programming with Alpaca is simple compared to other approaches. We also contrast our Alpaca-redo implementation with an alternative Alpaca-redo design that privatizes data to volatile memory, showing that our baseline design is usually more efficient because of additional overheads required by volatile privatization.

8.1 Run Time Performance

Figure 9 shows Alpaca’s run time performance, measured on real hardware on both continuous power and on harvested RF energy. Performance on continuous power is an upper bound on performance because it avoids reboot-related overhead. Performance on harvested energy includes all reboot-related overheads and is representative of a real-world deployment.

Figure 9a shows performance on continuous power for each system, normalized to a plain C implementation that implements each application without considering intermittence. As expected, Alpaca has an overhead compared to plain C code, with the average slowdown of 1.55x (Alpaca-undo) and 2.31x (Alpaca-redo), respectively. However, both Alpaca outperforms previous state-of-the-art systems Chain, DINO, and Ratchet. Also, Alpaca-undo consistently outperforms Alpaca-redo by 1.49x on average, exemplifying the optimization discussed in Section 5.1 to be useful. When compared to the previous state-of-the-arts, Alpaca-undo outperforms Chain, DINO, and Ratchet by 5.44x, 4.22x, and 2.99x on average.

Figure 9b shows performance on harvested energy. Here, we omit the plain C variant because it does not handle intermittence and cannot run correctly on harvested energy. Alpaca-undo again outperforms Alpaca-redo by 1.53x, and both Alpaca outperform all the other systems, by Alpaca-undo outperforming Chain, DINO, and Ratchet by 5.19x, 4.63x, and 4.00x on average. The performance gap is mostly larger on harvested energy because power failures introduce reboot-related overheads and Alpaca’s reboot overhead is extremely low.

8.2 Characterizing Alpaca’s Runtime Overhead

To better understand Alpaca’s performance, we made detailed measurements of each system’s major overheads. The two Alpaca’s main overheads are logging (undo-logging for Alpaca-undo, and redo-logging or privatization for Alpaca-redo) and task transitioning. Chain’s major overheads are channel manipulation and task transitioning. The task transitioning of the three systems are different: Alpaca-undo’s task transitioning simply clears the index of the backup list and some flags, whereas Alpaca-redo’s task transitions commit privatized state and Chain’s task transitions
commit all data written to “self”.channels. DINO and Ratchet’s major overheads are checkpointing and restoring the checkpoint on reboot.

We measured each system’s overheads by toggling GPIO at the beginning and at the end of each overhead and summing up the duration using Saleae Logic Analyzer. When measuring the overhead, we experimented on continuous power instead of harvested energy, since frequent GPIO toggling consumes non-negligible amount of energy. On continuous power, we used the microcontroller’s internel timer to periodically mimic power failure. Our measurements are not exact, and may over-estimate overheads whose resolutions are finer than what can be precisely captured by our method, such as Alpaca’s logging overhead which is only few instructions. Nonetheless, we expect the result to show the rough scale of each overhead without deviating too much from the truth.

Figure 10 shows overheads of each system. The data show that Alpaca has high performance because it imposes few overheads. Alpaca’s logging requires many fewer operations than Chain’s channel manipulations and Ratchet and DINO’s checkpointing. Also, the task transition overhead of Alpaca-undo is shown to be much less than the task transition overhead of Alpaca-redo. This is because Alpaca-redo needs to commit privatized values on transition, and is the main reason for the speedup of Alpaca-undo against Alpaca-redo.

8.3 Non-Volatile Memory Consumption

We measured the non-volatile memory consumption by inspecting each application binary. For Ratchet which uses FRAM as its main memory, we measured the size of the stack to measure the non-volatile memory consumption. For DINO which reserves double-buffered checkpointing space equal to twice the maximum stack size of 2KB, i.e., 4KB total, we added 4KB to the number from the binary. None of these applications dynamically allocates non-volatile memory, as is typical in embedded systems.

Figure 11 shows that Alpaca-undo and Alpaca-redo uses moderate non-volatile memory, using slightly more than Ratchet, but much less than Chain and DINO. Alpaca uses less non-volatile memory than Chain mainly because Chain creates multiple versions of variables that exist in different channels. Alpaca uses less non-volatile memory than DINO because DINO checkpoints all volatile state and versions some non-volatile state, while Alpaca never checkpoints and only selectively privatizes non-volatile state.

8.4 Privatizing Data to Volatile Memory

We evaluated an alternative implementation of Alpaca-redo, called Alpaca-VM that uses volatile memory to store privatized values, motivated by the fact that volatile memory accesses require less energy than non-volatile memory accesses. Unlike Alpaca-undo whose updates are made in-situ in FRAM, Alpaca-redo privatizes the W-A-R variable, making privatizing to volatile memory possible.

To ensure that volatile values commit atomically despite failures, Alpaca-VM must make a full copy of all privatized values to a non-volatile commit buffer during pre-commit. Privatizing data to volatile memory is only a net benefit if the time and energy saved by using volatile memory in the task are more than the time and energy consumed by copying to the commit buffer.

We experimented with a microbenchmark which does fixed number of read-modify-write (RMU) operation to measure how many accesses to volatile privatized data are required to amortize the
increased pre-commit cost of using volatile privatization buffers. The experiment result implied that when the task contains more than around 110 RMWs, Alpaca-VM begins to outperform Alpaca-redo.

We quantified the number of read and writes per each task in our real applications. Our tasks had 2.1 reads and 1.05 writes to a privatized variables on average. The numbers are much smaller than the “tipping point” which was around 110 RMWs, suggesting that volatile privatization is unlikely to pay off.

We implemented Alpaca-VM and the result showed that the performance is often worse than, or negligibly different from Alpaca-redo’s performance, which is consistent with our “tipping point” characterization. Alpaca-VM is only likely to be viable and beneficial in a system with a much larger energy buffering capacitor that accommodates more (i.e., hundreds of) reads and writes in each task.

8.5 Comparing Programmer Effort

We compared the programming effort required by Alpaca to the effort required by Chain, DINO, and Ratchet and found that Alpaca requires reasonable code changes compared to Ratchet and DINO code, but requires less change than writing Chain code. Like Alpaca, Chain also requires the programmer to decompose code into tasks, which is different from writing typical C code and we characterize task sizing next. Unlike Alpaca, Chain also requires additional effort to re-write memory access code in terms of channel operations, which is different from a typical C programming. Alpaca instead allows code to manipulate task-shared variables like ordinary C variables using loads and stores.

Table 3. Lines of code and number of keywords.

| App | Alpaca LoC | # Bnd. | # Decl. | Chain LoC | # Bnd. | # Decl. | # R/W | DINO LoC | # Bnd. | Ratchet LoC |
|-----|------------|--------|---------|-----------|--------|---------|-------|---------|--------|-------------|
| CEM | 372        | 19     | 28      | 721       | 19     | 40      | 63    | 338     | 13     | 325         |
| CF  | 397        | 19     | 29      | 707       | 19     | 41      | 72    | 335     | 11     | 324         |
| RSA | 765        | 27     | 40      | 1197      | 27     | 53      | 123   | 722     | 35     | 687         |
| AR  | 466        | 19     | 26      | 713       | 19     | 34      | 57    | 439     | 8      | 431         |
| BF  | 614        | 18     | 24      | 740       | 18     | 29      | 75    | 556     | 9      | 547         |
| BC  | 313        | 23     | 26      | 588       | 23     | 26      | 57    | 276     | 10     | 266         |

8.5.1 Quantifying Programmer Effort. We quantified the difference in programmer effort between systems by comparing the differences in the number of lines of code (LoC) and the number of keywords by each system. Keywords are divided into three types: boundary, declaration, and read/write. Boundary keywords (Bnd) represent task boundaries (i.e., transition_to) in Alpaca and Chain, and checkpoints in DINO. Declaration keywords (Decl) modify function and data declarations: task and TS for Alpaca, and task and channel declaration for Chain. Read/Write keywords (R/W) access memory and only occur in Chain (channel in and channel out), because Alpaca and DINO use a standard C read/write memory interface. Ratchet does not require any additional keywords.

Table 3 summarizes the data. On average, the number of lines of Alpaca code is 11% higher than DINO code and 14% higher than Ratchet, but Alpaca requires 39% fewer lines then Chain. The number of keywords used by Alpaca code is 240% more than the number used by DINO code, but is only 27% of the number used by Chain code. Although these data are only a rough indicator of programming complexity, the data suggest that Alpaca’s complexity lies somewhere between Chain and DINO.
8.5.2 Choosing a Task’s Size. Dividing a program into tasks is a key part of Alpaca development, and we experimentally characterize the process to show that it is reasonable. Alpaca preserves forward progress at the granularity of a task assuming the system eventually buffers sufficient energy to complete each task. However, a real, energy-harvesting system with a fixed-size energy buffer, may never be able to buffer sufficient energy for a very long task to complete, preventing progress. If a task is too short, its privatization, commit, and transition overhead will be relatively very high, impeding performance. Based on knowledge of the device and the energy cost of program tasks, the programmer must assign work to an Alpaca task.

While it is a non-trivial programming task, defining the extents of Alpaca tasks requires only modest programmer effort. We observed that on today’s energy-harvesting hardware, the task decomposition problem is independent of input power and depends only on the device’s energy buffer size. Figure 12a shows data for a microbenchmark that runs a loop on a WISP5 [Sample et al. 2008] device harvesting energy from an RF power supply. The x-axis shows the distance to the RF power supply, which corresponds to input power. The y-axis shows the distance to the RF power supply, which corresponds to input power. The y-axis shows the distance to the first brown out, at which point the device has exhausted energy accumulated in its capacitor and must slowly recharge. Except for distances so small that the RF supply effectively continuously powers the device (~10cm), the amount of work that the system can execute before browning out is invariant to input power; the energy buffer is constant. Forming Alpaca tasks is thus a reasonable (albeit non-trivial) task because the programmer need only reason about the total energy cost of a task. The programmer need not reason about instantaneous input power, nor the power envelope of particular hardware operations, which would be difficult.

We also experimentally observed that choosing a task size that amortizes privatization, commit, and transition costs is not overly challenging. On a WISP5 device, we studied the effect of task size on the run time of a microbenchmark that executes a fixed amount of work across a varying size of tasks. The microbenchmark executes a fixed total number of read-modify-write operations on entries in an array. We varied the number of accesses per task, and Figure 12b shows the relationship between task size and total run time. Run time decreases as task size grows because tasks better amortize commit and transition cost. However, the effect saturates as tasks grow, revealing that even relatively small tasks of around 100 read-modify-write amortize Alpaca’s overheads well.
The data suggest that choosing a task size that amortizes task overheads will not be prohibitively challenging to a programmer.

9 RELATED WORK

Alpaca relates to prior work in several areas. Most related are prior efforts studying intermittent computing, some of which discussed in Section 2. We also relate Alpaca to work on idempotent compilation, systems with non-volatile memory, transactions and transactional memory.

9.1 Energy-Harvesting and Intermittent Computing

There is a large body of work on intermittent execution and other support for intermittent systems. Some work [Maeng and Lucia 2018; Mirhoseini et al. 2013; Ransford et al. 2011a; Van Der Woude and Hicks 2016] preserves progress and keep memory consistent by placing checkpoint automatically that copies the volatile state. Alpaca avoids the overhead of volatile state checkpointing and conservatism of the checkpoint placed by the compiler.

Other work [Colin and Lucia 2016; Lucia and Ransford 2015] versions non-volatile memory either manually [Colin and Lucia 2016] or automatically [Lucia and Ransford 2015] to support systems with mixed-volatility [Ransford and Lucia 2014; Sample et al. 2008; Zhang et al. 2011a]. Alpaca’s non-volatile memory protection is more efficient than the prior systems (see Section 8).

Some systems [Baghsorkhi and Margiolas 2018; Bhatti and Mottola 2017; Colin and Lucia 2018] tries to statically estimate energy use of a code and optimize checkpoint placement. However, estimating energy use in arbitrary code is difficult and error prone. Alpaca asks the programmer to place the boundaries of the task.

QuickRecall [Ransford et al. 2011b], Hibernus [Balsamo et al. 2015], and Hibernus++ [Balsamo et al. 2016] do on-demand checkpointing of volatile state when supply voltage is below a threshold. This approach is effective, but requires continuous supply voltage measurement hardware, which is not typically available [Sample et al. 2008; Zhang et al. 2011a]. Also, choosing a threshold voltage is not straightforward. Too high a threshold makes the system checkpoint and wait for energy, even if there is ample energy to continue. Too low a threshold may fail to guarantee that checkpointing completes, which is especially problematic with a variable size call stack and arbitrary global variables. Alpaca is energy agnostic, avoiding hardware requirements and threshold voltage assignment issues.

Non-volatile processors [Ma et al. 2015] and Clank [Hicks 2017] propose architectural support making intermittent software simple, but precluding the use of an existing hardware and imposing a performance and complexity overhead. Dewdrop [Buettner et al. 2011] runs small, “one-shot” tasks on intermittent hardware, optimizing task scheduling to maximize task completion likelihood given limited energy. Dewrop, however, does not support computations that span failures.

Other work addresses intermittent computation, like Alpaca, but unlike Alpaca, these efforts are not programming or execution models. Incidental computing [Ma et al. 2017] and NEOFog [Ma et al. 2018] optimize specific applications on top of the non-volatile processor. Wisent [Aantjes et al. 2017; Tan et al. 2016] addresses intermittence, but is not a computing model, instead enabling reliable software updating of in situ intermittent devices. Ekho [Zhang et al. 2011b] helps test intermittent devices with support to collect and replay representative power traces from a realistic environment. EDB [Colin et al. 2016] is a hardware/software tool that allows programmers to profile and debug intermittent devices without interfering with their energy level. Federated energy [Hester et al. 2015] is a disaggregated energy buffering mechanism that decouples the energy storage of different hardware components. Flicker [Hester and Sorber 2017] eases the design of an energy-harvesting hardware platform by modularized peripherals and harvesters. TARDIS and CusTARD [Hester et al. 2016] keeps time on power failure and Mayfly [Hester et al. 2017] ensure timeliness of the data.
Capybara [Colin et al. 2018] enables changing the energy buffer size on-the-fly to support variety of application demands. Some earlier work addresses computing using harvested energy, but unlike Alpaca, these systems to not explicitly address intermittent computation. Eon [Sorber et al. 2007] is one of the earliest efforts to target harvested-energy computation, scheduling prioritized tasks based on energy availability. ZebraNet [Juang et al. 2002] dealt with the challenges of solar energy in an adversarial environment.

9.2 Idempotent Code Compilation
Several prior efforts [De Kruijf and Sankaralingam 2013; de Kruijf et al. 2012; Zhang et al. 2013] noted that a program decomposed into idempotent sections is robust to a number of failure modes because idempotent sections can be safely re-executed. Idempotence systems break W-A-R dependences by dividing dependent operations with a checkpoint (or section boundary). Like these systems, Alpaca leverages the fact that eliminating W-A-R dependences makes tasks idempotently re-executable. Unlike other systems, however, Alpaca does not make code sections idempotent by inserting checkpoints. Instead Alpaca ensures task atomicity by using task-based execution to avoid the need for volatile state checkpoints, and privatization of non-volatile data involved in W-A-R dependences to make tasks idempotently restartable.

As discussed in Section 2, Ratchet [Van Der Woude and Hicks 2016] uses compiler idempotence analysis to insert checkpoints to make inter-checkpoint regions idempotent, assuming main memory is entirely non-volatile. Alpaca makes no assumption about memory volatility making it applicable to more varied hardware, and its tasks’ sizes are free from idempotence analysis, unlike Ratchet.

9.3 Memory Persistency and Non-Volatile Memory Systems
The increasing availability of non-volatile memory creates a need for models defining the allowable reorderings of non-volatile memory updates and persist actions, which ensure data become persistent [Pelley et al. 2014, 2015]. Relaxing the ordering of updates and persist actions to different locations may expose a re-ordering to code resuming execution after a failure and persistency models describe which of these re-orderings are valid. Other, earlier work developed mechanisms for managing data structures in non-volatile memory, and for building consistent memory and file systems out of byte-addressable non-volatile memory [Coburn et al. 2011; Condit et al. 2009; Doshi and Varman 2012; Dulloor et al. 2014; Moraru et al. 2013; Narayanan and Hodson 2012; Venkataraman et al. 2011; Volos et al. 2011]. Alpaca relates to these efforts because both aim to keep non-volatile memory consistent across power failures. The prior work differs from Alpaca, however, in purpose and mechanism. Alpaca is programming model and run-time implementation that keeps data consistent across extremely frequent failures in intermittent executions. These prior efforts focused on large-scale systems and are only peripherally applicable to intermittent devices.

9.4 Transactions and Transactional Memory
Transactions [Gray and Reuter 1992] and, in particular, transactional memory [Hammond et al. 2004; Harris et al. 2005; Herlihy and Moss 1993; Shavit and Touitou 1995] (TM) systems are also related to Alpaca. Transactional memory targets multi-threading systems. A transaction speculatively updates memory until a (usually) statically defined atomic region ends. Transactions commit when they complete execution, updating globally visible state, or aborting their speculative updates due to a conflicting access in another thread, and beginning execution again. Transactions are similar to Alpaca because Alpaca buffers a task’s updates privately, committing them to global memory when a task ends. Moreover, when a power failure interrupts a task, its privatized updates are aborted and it begins again from its start. However, Alpaca differs in that it targets intermittent systems
with potentially extremely frequent failures. Unlike TM, Alpaca does not target multi-threaded programs, instead aiming to keep memory consistent between re-executions across power failures.

10 CONCLUSION AND FUTURE WORK

This work proposed Alpaca, a programming model for low-overhead intermittent computing that does not require checkpointing, using a task-based execution model and a logging scheme built on idempotence analysis. Compared to competitive systems from prior work, our Alpaca prototype achieves significant performance improvement compared to a variety of systems from the literature. Looking to the future, Alpaca emphasizes a need raised by Chain and DINO for a system to aid, or automate the decomposition of a program into tasks, which is currently a reasonable task, but mostly a manual process.

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