Continuous Sensing on Intermittently-operating Sensors

Anonymous Author(s)

ABSTRACT

The main obstacles to achieve truly ubiquitous sensing are (i) the limitations of battery technology - batteries are short-lived, hazardous, bulky, and costly - and (ii) the unpredictability of ambient power. The latter causes sensors to operate intermittently, violating the availability requirements of many real-world applications.

In this paper, we present the *Coalesced Intermittent Sensor* (CIS), an intermittently powered "sensor" that senses continuously! Our key observation being that, the power cycles of energy-harvesting battery-less devices do not show correlation even when they are drawing energy from the same source, running the same application, and in close proximity. We challenged our observation using different real hardware and energy sources and showed that this observation holds.

Another important finding is that a CIS designed for certain (minimal) energy conditions requires no explicit spreading of awake times due to embedded randomness in the powering subsystem. However, when the available energy exceeds the design point, nodes employing a sleep mode (to extend their availability) do wake up collectively at the next event. This synchronization leads to problems as multiple responses will be generated, and -worse- subsequent events will be missed as nodes will now recharge at the same time. To counter this unwanted behavior we designed an algorithm to estimate the number of active neighbors and respond proportionally to an event. We show that when intermittent nodes randomize their responses to events, in favorable energy conditions, the CIS reduces the duplicated captured events by 50% and increases the percentage of capturing entire bursts above 90%.

CCS CONCEPTS

• **Human-centered computing** → *Empirical studies in ubiquitous and mobile computing*.

KEYWORDS

Embedded systems, Energy harvesting, Ubiquitous computing, Intermittent Systems

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1 INTRODUCTION

Batteries may compromise the viability of sensor nodes in various ways. Batteries are bulky, short-lived, hazardous, and expensive. To ameliorate the battery problem, researchers have been investigating different alternatives to extend lifetime and reduce costs and form factor. The reduction in power consumption of recent microcontrollers and the advances in energy-harvesting circuitry have enabled the emergence of battery-free energy-harvesting sensors. These sensors elide the constraints of batteries and extract power from ambient energy sources such as sunlight and RF emissions.

Ambient energy sources provide perpetual power. However, ambient power is usually too weak to directly power a sensor node [23]. Therefore, an energy-harvesting node first buffers the harvested energy until a usable amount has been accumulated; then it operates, for a short period of time, until the buffered energy has been exhausted [24]. Consequently, battery-less energy-harvest sensors operate intermittently (Figure 1).

Intermittent power introduces a set of new challenges that are under ongoing investigation. For example, [3, 8, 24, 32, 33] studied the intermittent computation problem, which is concerned with the preservation of application progress and data consistency under frequent power failures; Hester et al. [16] investigated the timely operation challenge, which is concerned with data freshness after a power interrupt; and Yıldırım et al. [43] introduced event-driven execution for the intermittent domain, which deals with input and output operations under arbitrarily-timed power loss.

Despite these notable advances, intermittently-powered sensors suffer from a new fundamental shortcoming: *the intermittent availability of the system.* Being frequently off charging compromises the value of these devices. For example, a sensor that has a low probability (e.g., 10% [**?**]) to be available (on) when an event of interest occurs has no value. Overcoming the intermittent availability challenge without changing the size of the device or re-including batteries requires a novel approach that explores new design dimensions.

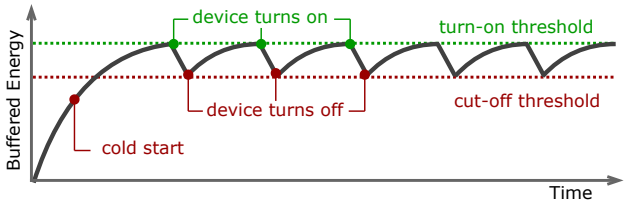


Figure 1: Harvested-energy profile. Ambient power is weak; therefore, it is usually buffered. The buffered energy is then consumed to operate the device. The operation period is often short as power consumption is much higher than the energy harvesting rate.

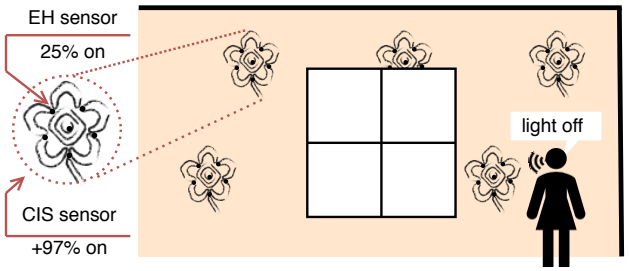


Figure 2: A Coalesced Intermittent Sensor (CIS) is a group of intermittently-powered nodes that sense continuously despite the intermittent power supply. CIS exploits the inherent randomization of energy harvesting systems, if available, and introduces artificial randomization, when needed, to preserve continuous sensing.

1.1 Vision and Application

Battery-powered sensors are reliable, but they are short-lived; energy-harvesting are long-lived, but they operate intermittently. Our goal is to combine the desirable features of these two types of sensors to create a new "sensor" that operates permanently (no batteries) and reliably (continuously available)—the Coalesced Intermittent Sensor (CIS).

Sensors with such characteristics would allow us to add a cheap and maintenance-free sensing layer to many objects, making them smart and interactive. For example, one can imagine developing smart wallpaper that users can interact with. Smart wallpaper with embedded microphones can enable direct in-building human-to-object communication (Figure 2). Such a permanently operating sensor can be deployed, for example, in kids' playgrounds to monitor their occupancy. These battery-less sensors can enable interactive and safe-to-dispose sports rugs (that count how many times a person has jumped on them) or play rugs for kids. In short, we would like to develop small sensors with permanent and continuous sensing capabilities.

1.2 Research Challenges

Many sensing applications require the sensor to be available when there is a change in the monitored environment. Energy-harvesting battery-less sensors can provide cheap and maintenance-free sensing, but the do not meet the availability requirements of many real-world applications.

C1-Approach continuous availability on intermittent power: An energy-harvesting battery-less sensor is frequently off, spending most of its time charging. One way to increase the system availability is by using multiple nodes. However, coordinating the nodes' awake times using communication may introduce prohibitive overhead as a scattering algorithm must be regularly executed, and messages for synchronizing nodes' clocks and reserving time slots need to be repeatedly exchanged. Thus, the challenge is *can we exploit some of the inherent characteristics of energy-harvesting battery-less sensors to distribute nodes' awake times without the need for communication?*

C2-Continuous sensing on intermittently powered sensors: Even when the collective availability of intermittent sensors approaches 100%, the emerging overall sensing behavior may still be intermittent. Event-trigger sensors sleep in low-power mode waiting for an event to wake them up. When ambient energy rises, the energy-harvesting rates of these sensors may equal (or approximate) their sleeping mode power consumption. Under such energy conditions, these sensors become available for and an extended period of time. Therefore, when an external event arrives, nodes respond collectively, which exhausts their energy buffers, making them unavailable for the next set of events. This is, particularly, a significant problem when events arrive in burst like a command of a few words (e.g., light on). Thus, the challenge is, *how to prevent energy-harvesting battery-less sensors from synchronizing their power cycles on some of the incoming events?*

C3-Efficient sensing on intermittent sensors: One of the main factors that determine the intermittency pattern of an energy-harvesting battery-less sensor is the richness of ambient energy. For example, at mid-noon under direct sunlight, even a small solar panel can power a sensor node continuously. In such conditions (favorable energy conditions), using plenty of intermittent sensors would only result in duplicated work that leads to duplicated messages, when the data is being communicated to a sink node: a continuously-powered node acts as a gateway for such sensors to communicate with other layers of the Internet of Things. These messages will collide as they will be generated at approximately the same time, and if some of them are received by the sink, then they waste energy as they carry the same information.

1.3 Contributions

In this paper, we tackle the paradox of continuous sensing on intermittently-powered sensors. We studied the inter-relationship between the power cycles of energy-harvesting battery-less devices, the emerging collective behavior, and the effect of changes in ambient energy levels on the sensors collective behavior. In particular, this paper makes the following key contributions:

- We show how to approach continuous sensing using multiple intermittently-powered sensors. For that, we **modeled** the collective effective availability—the system availability that leads to successful sensing—of a group of intermittent sensors and **validated** our models using simulation and on real hardware against different ambient energy sources.
- We introduce a new type of virtual sensor, showing its capabilities and limitations. This **Coalesced Intermittent Sensor (CIS)** is the abstraction of a group of intermittently-powered sensors that achieves maximum statistical availability by exploiting (inherent) randomization to spread nodes' awake times uniformly.
- Contrary to common sense, we show how favorable energy conditions can deteriorate the performance of a CIS. We, therefore, equipped the CIS with **an new algorithm** that makes it ambient-energy aware. This algorithm enables the nodes to determine their own duty cycles (without requiring additional hardware), and the average number of alive nodes (without requiring communication). This information can effectively be used by the nodes to decide when to back off

to avoid duplicated event detection and availability interruptions (implicit synchronization in favorable harvesting conditions).
- We prototype, evaluate, and demonstrate the feasibility of the Coalesced Intermittent Sensor concept in the form of voice-control commands recognizer, the **Coalesced Intermittent Command Recognizer** (**CICR**). The CICR is a group of solar-powered intermittent sensor nodes equipped with a microphone.

1.4 Motivation

Here we would like to motivate some of our design decisions.

Why does this work focus on miniaturized battery-less sensors? Small sensors are less intrusive devices than bigger ones. Therefore, they can be embedded in new locations that are not suited for the others. Powering small sensors with small batteries is problematic as small batteries severely limit sensor lifetime: even rechargeable batteries wear out after after a few hundreds of charging cycles [1]. Thus, this work researches battery-free energy-harvesting sensors as they have the potential to operate for decades-long without regular maintenance.

Why did we choose to develop a word recognizer? Voice is a natural way for human to interact with small devices. Moreover, Words allow us to easily experiment with individual events arrival and events that arrive in bursts. However, the goal of this paper is *not* to present a new and novel word recognition technique. Instead, it adopts a classical words recognition algorithm, making it power failure immune, to safely running on intermittently-powered devices.

2 COALESCED INTERMITTENT SENSOR

The Coalesced Intermittent Sensor (CIS) is the abstraction of a group of energy-harvesting battery-less sensor nodes seeking to approximate the continuous sensing availability characteristic of a battery-powered sensor. The design of a CIS needs to consider four main aspects: (i) how the nodes' awake time is distributed; (ii) the consequence of emulating continuous sensing availability by chaining multiple short on-times; (iii) the effect of the environment on the CIS's availability; and (iv) the spacial coverage of the event of interest, which determines the diameter of the CIS.

However, let us first characterize the power cycle of an energy-harvesting battery-less device. An energy-harvesting intermittent node frequently switches between off and on, charging energy and operating. We can characterize, from a time perspective, this charge-discharge (or power) cycle using the following notation, (t_{on}, t_p), where t_{on} is the node's uptime interval, and $t_p := t_{on} + t_{off}$, where t_{off} is the node's charging time interval.

2.1 Sensing

The ability of a CIS to sense depends on the availability of its intermittent nodes and on the characteristics of the event of interest.

2.1.1 Coalesced availability. The CIS's availability is the projection of its underlying intermittent nodes' on-times on the time axis. To determine the expected availability of a CIS, the strategy being employed to distribute its nodes' on-times must be specified first.

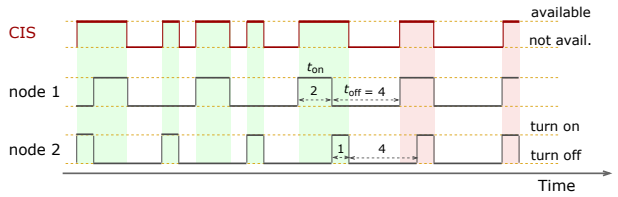


Figure 3: A Coalesced Intermittent Sensor's availability is the emerging collective on-time of its intermittent nodes' on-times. The difference between the power cycles leads to a constant relative shift between the nodes duty cycles. This, in turn, causes their on-times to be uniformly distributed on the overall power cycle. The red bars indicate a minimum CIS time span—CIS's nodes are overlapping—whereas the green bars show the maximum time span of the CIS.

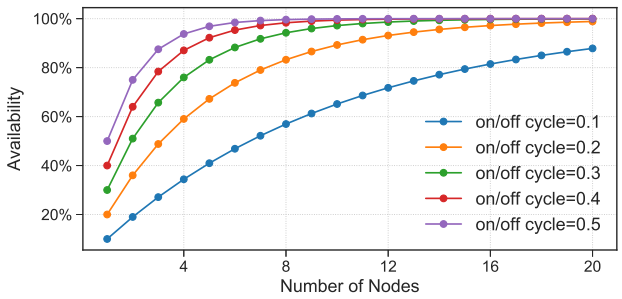


Figure 4: Coalesced Intermittent Sensor availability percentage for a different number of nodes and different duty cycles. The nodes are uniformly distributed and the CIS on-time evolves, when adding new nodes, according to the equation 1.

Explicit on-time division strategy. A CIS can build on top of the recent advancements in passive (light or RF) communication [23**?**] and ultra-low-power timers [16] to apply a time-division multiplexing strategy to minimize on-times overlapping. For example, a node calculates its average on-time $\overline{t_{on}}$ and off-time $\overline{t_{off}}$ for N power cycles. Then, it encodes the information $(\overline{t_{off}}, \overline{t_{on}})$ in a message and broadcasts it at the beginning of its power cycle. When a node receives this message it will have full knowledge about the transmitting node's power cycle. It can then alter its power cycle, relative to the transmitting nodes cycle, by either increasing (or decreasing) its power consumption to shorten (or lengthen) its on-time and subsequently shift its power cycle to a different time slot.

With such explicit on-times control strategy, a CIS of N nodes with on-time of $\overline{t_{on}}$ and off-time of $\overline{t_{off}}$ will have an availability $\approx N \times \frac{\overline{t_{on}}}{t_p} \pmod{100\%}$. However, we expect such an approach to introduce significant overhead as a scattering algorithm [13] must be frequently executed, messages need to be exchanged, and clocks should be synchronized. Therefore, we propose a different on-time spreading strategy.

Implicit on-time division strategy. With no information being exchanged between intermittent nodes, the best CIS can do is to uniformly distribute its node's on-times and maintaining this distribution over time. The key observation to approach uniform distribution is to ensure that the lengths of the node's power cycles are randomized, avoiding nodes being in lockstep indefinitely.

Let us start by assuming that we have a CIS of two nodes with idealized power cycles and those nodes have the same initial conditions. The availability of this CIS equals t_{on} as the nodes are in perfect synchronization (the two nodes wake up and power down together). To extend the availability of this CIS, one of the node should shift its on-time away from the other. If one of the nodes sleeps for t units of time, then the on-time of this power cycle will be $t_{\text{on}}+\Delta t$. Consequently, the length of the power cycle itself will be $t_{\text{p}}+\Delta t$, delaying the next awake time by Δt. If the node sleeps only once, then availability of the CIS will equal $\min(2\times t_{\text{on}}|t_{\text{on}}+\Delta t)$

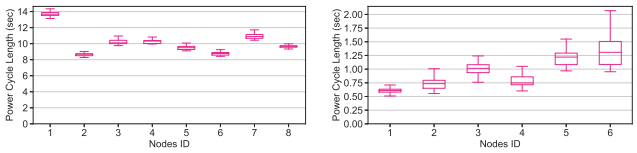
However, if the initial conditions are unknown, then shifting a node's on-time a constant number of times may cause the initially desynchronized nodes to become synchronized, collapsing the CIS's availability instead of extending it. Therefore, a safer option is to *constantly* shift the awake time of the node. In this case, the on-time will shift over the entire power cycle of the other node, spending $\frac{t_{\text{off}}}{t_{\text{p}}}$ and $\frac{t_{\text{on}}}{t_{\text{p}}}$ of the time overlapping with its off-time and on-time, respectively. This behavior is illustrated in Figure 3, where node 1 and node 2 have power cycles of (2,6) and (1,5). Following the time axis from the left to the right, we can observe that the position of the on-time of node 2 is shifted by -1 unit of time relative to the on-time of node 1 after each power cycle of node 1. This implies that the on-times of the two nodes are $\frac{1}{3}$ of the time cluster together and $\frac{2}{3}$ of the time they are apart (from an external event standpoint, the on-times are uniformly distributed over the longest power cycle, as they have the same probability to be anywhere when the event arrives). To model the availability of a CIS of N nodes, we first model the nodes' on-times and power cycles. If we represent the on-time of a node with a random variable R_{n} and find its expected value $E(R_{\text{n}})$ then we can approximate *any* CIS node's on-time with mean of the expected values of the nodes' on-times, i.e., $t_{\text{on}}=\frac{1}{N}\times\sum_{i=1}^{N}E(R_{\text{n}})^i$ (intuitively, since we are assume CIS's nodes have the same energy buffer, then, their expected on-times should be the same). Using a similar anology, we can define the mean of the expected values of the power cycles lengths as $t_{\text{p}}=\frac{1}{N}\times\sum_{i=1}^{N}E(R_{\text{p}})^i$. Now, we can model the availability of a CIS of N nodes as:

$$A_{\text{v}}(N)=A_{\text{v}}(N-1)+(1-A_{\text{v}}(N-1))\times\frac{t_{\text{on}}}{t_{\text{p}}}, \tag{1}$$

for the initial case where $N=1$ we define $A_{\text{v}}(0):=0$. Figure 4 shows the availability of CIS when $N\in\{1,2,..,20\}$ and nodes' duty cycles $\frac{t_{\text{on}}}{t_{\text{p}}}\in\{10\%,20\%,..,50\%\}$. We can conclude from the above discussion that to approach uniform distribution of nodes on-times, the lengths of the power cycles need to be randomized [1].

The power cycles of energy-harvesting battery-less devices are inherently randomized and different because the power source (ambient energy) is volatile and the harvesters are not perfect devices (notice that, even battery-powered wireless sensor nodes require a synchronization protocol to correct for the drift in their local clocks). Our own measurements on different energy-harvesting devices and different energy sources, i.e., solar and RF, also confirm that the power cycles of intermittent nodes are different and randomized, see Figure 5. Therefore, we expect their on-times to be uniformly distributed (we will challenge our expectation in Section 4).

[1]Note that, having power cycles of lengths that are multiples of each other is a very unlikely as nodes' energy buffers are assumed to be of the same size.



(a) Light **(b) RF**

Figure 5: Nodes' power cycles length for different energy sources, and different energy buffer sizes.

2.1.2 Events classification. The availability of a CIS is not a single stretched interval: it is a chain of short intervals. Therefore, it is important to classify, from a CIS perspective, which types of events the CIS is best suited for.

- *Short events*: are events that can be captured using single intermittent node. For example, a spoken word can be seen as a short event if the energy needed to recorded is less than what the energy buffer, i.e., the capacitor, can store.
- *Long events*: are events that need more energy to be completely captured than what the energy buffer can store. They can be subdivided into three categories:
  - *Simple*: is a long event that can be captured using single intermittent node—capturing part of it is sufficient to obtain all the information of interest—such as the sound produced by the friction between two moving parts of an engine.
  - *Burst*: is a group of short events that requires multiple intermittent nodes to be captured such as a command of a few words (e.g., room temperature up).
  - *Complex*: is a long event that must be fully captured to be recognized. For example, sampling a gyroscope attached to a moving device (e.g., a toothbrush).

Based on the above classification, we can argue that designing a CIS for long events is not like designing it for capturing short ones. While capturing a short event may require continuous CIS availability, capturing a long simple event that is longer than the power cycle t_{p} does not require extending the availability of a single intermittent node. Furthermore, capturing a long complex event may require data fusion and processing that require the CISs' nodes to communicate the raw data to a more powerful node, which may lead to significant overhead. However, this paper focuses on short and long bust events as they cover a wide range of applications (e.g., voice-controlled human-object interface).

2.1.3 Effective Availability. Approaching continuous availability does not mean that a CIS can successfully capture all events. It can happen that an event is being only partially captured by one or more nodes, which may lead to unsuccessful event detection. Therefore, it is important to specify the effective availability of a

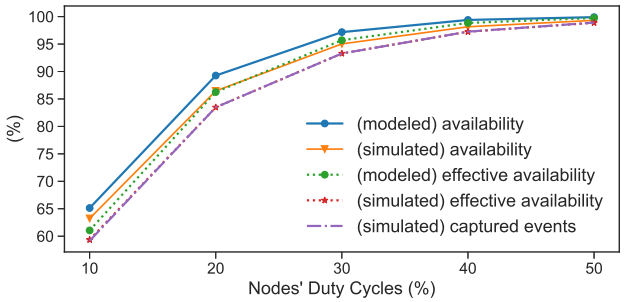


Figure 6: Simulating the availability, the effective availability, and successfully captured events of a CIS of 10 nodes with a node duty cycle $\in \{10\%, 20\%, ..., 50\%\}$.

CIS that leads to a successful event capturing (which we assume leads to successful sensing).

polling-based Sensing. Let us assume that we have a CIS of a single intermittent node monitors a short event of length t_e. For capturing the entire event, the event has to arrive within the interval, $t_{on} - t_e$, which we call, the effective on-time of an intermittent node. Therefore, the effective availability of a CIS of N nodes is the joined effective on-times of the underlying intermittent nodes, which can be modeled as,

$$A_v(N) = A_v(N-1) + (1 - A_v(N-1)) \times \frac{t_{on} - t_e}{t_p}, \quad (2)$$

Event-driven Sensing. An intermittent sensor has a limited energy budget per power cycle. When it is tasked with a polling-based sensing activity, its energy consumption, generally, switches between two levels: zero when charging and maximum when it activates its microcontroller for data acquisition and processing (Note that we assume that the microcontroller is the dominant energy consumer module of a node). However, in event-based sensing, a node puts its microcontroller into low-power mode and waits (or listens) for an external event to wake up the microcontroller. For example, in our prototype, a voice-controlled command recognizer, we exploit the microphone's wake-on-sound feature to send an interrupt to the microcontroller, which will then start recording the sound samples from the microphone. This wake-on-event style of operation is important as the minimal energy consumption during sleep significantly prolongs the period during which an event can be handled (for example, our prototype consumes 7 times less energy during sleep compared to being active). To model the effective CIS availability when it is tasked with event-based sensing the change in energy consumption between the sleep and active mode must be taken into account. Since the event itself times when the node changes its energy consumption, we can model the effective availability as,

$$A_v(N) = A_v(N-1) + (1 - A_v(N-1)) \times \frac{t_s - (t_e \times \frac{e_a}{e_s})}{t_p}, \quad (3)$$

[2]Notice that, there is a subtle point about equation 3 as when an event arrives the node wakes up, consuming more energy. Therefore, its uptime shirnks. We, for similicity, modeled this effect by extending the events time with same factor. This is sufficient to say if the event will be fully captured or not (effective availability). However, if too many events arrives then the nodes will spend significant time in the active mode which changes the total availability of the system.

where t_s is the expected sleep time of the CIS's nodes and $e_a and e_s$ are the energy consumption at active and sleeping modes, respectively.

2.1.4 Simulation. To do a first sanity check on our models, we simulated 10^5 power cycles of a CIS of 10 nodes (Figure 6). The duty cycles of the nodes range from 10% to 50%, while the event length is fixed at 3% of the power cycle length, t_p. The on-times and events arrivals were uniformly distributed over the power cycles. The results clearly confirm our models and support our argument about the distinction between CIS's availability and effective availability. The importance of this distinction is a function of the value $\frac{t_e}{t_{on}}$; observe the difference between availability and effective availability when nodes' duty cycle is 10% (large effect) and 50% (negligable effect).

2.2 Environment

Ambient energy controls the availability of a CIS's nodes. Consequently, it also controls their collective response to external events. When it rises, it extends nodes' on-times. Extended on-times may cause node's power cycles to be synchronized on events arrival, compromising the CIS's overall availability. To overcome this problem the CIS's nodes must be power-state aware and able to estimate the number of active nodes in the CIS.

2.2.1 Power States. A CIS can experience a wide range of ambient power intensities. For example, a solar-powered CIS may harvest no energy at night, modest energy from artificial light, and abundant energy from direct sunlight. Generally, we can identify four different CIS powering states:

- *Targeted power state*—These are the powering conditions that a CIS is designed for. In these conditions, the CIS should work intermittently and have sufficiently randomized power cycles to uniformly distribute its intermittent nodes on-times and meet the desired availability (Figure 4). In general, the targeted powering conditions should be near worst energy harvesting conditions to ensure that the system is properly functioning for the majority of the time.
- *Under-targeted power state*—Ultimately, the ambient energy is an uncontrollable power source, and it is not hard to imagine scenarios where a CIS will be under-powered or even comes to complete and long power down (for example, a solar CIS will come to a perpetual power down in the darkness). In general, for under-targeted energy conditions, the CIS behavior can be considered as undefined.
- *Hibernating power state*—In event-based sensing scenarios, the intermittent nodes of a CIS sleep in low-power mode waiting for an external event to wake them up. If the energy conditions are relatively higher than the targeted conditions, the nodes may not die and sustain their sleeping power consumption. This will cause them to synchronize their wake-ups on the first incoming event and their power down as the event capturing process depletes their energy buffers quickly. Consequently, the CIS may miss the next incoming events (specially if the events happens to arrive in bursts)

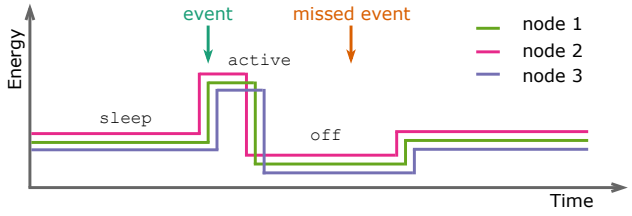


Figure 7: Coalesced Intermittent Sensor is in a hibernating power state when the energy harvesting rate approximates the energy consumption rate at the sleeping (or low-power) mode. In this state, the intermittent nodes lose the randomization in their power cycles. Thus, all the nodes capture the same event and power down shortly after missing the subsequent ones. Consequently, the CIS senses intermittently and does not take advantage of its redundant intermittent nodes to approach continuous sensing.

causing it to sense intermittently instead of continuously, see Figure 7.

- *Continuous power state*—Under direct mid-noon sun a tiny solar panel may provide sufficient power to run a sensor node continuously. In such conditions, the CIS will sense continuously without the need for randomization. Therefore, the job of a single node will be repeated N times, and instead of sending a single message to a battery-powered or tethered sink—to push the data to the Internet—N identical messages will be sent. These messages will collide as they are sent at about the same time, causing the information to be lost; if they arrive, however, they -except the first one- will waste energy of the sink as they carry the same information.

The inefficiencies highlighted in the hibernating and continuous power states can be mitigated by enforcing randomization on the response of intermittent nodes : when a node is woken up by an external event it responds to that event with a certain probability. However, if the randomized response is enforced all the time, then the CIS will have a lower probability of catching events during the targeted energy conditions state. Therefore, the CIS has to distinguish between the targeted and above-targeted energy conditions and randomize its response only during the hibernating and continuous power states.

Choosing a fixed response probability is an inefficient way of dealing with the over-powering problem as the number of active intermittent nodes at a given moment is a function of the total number of intermittent nodes and the power intensity at that time. Therefore, efficient randomization requires intermittent nodes to estimate the number of active nodes and respond proportionally. Our proposed algorithm for estimating the number of active nodes depends on the nodes ability of measuring their on-times and off-times.

2.2.2 Intermittent Timing. Timing is a key building block of sensing systems. It is, however, missing on intermittent nodes unless an additional dedicated (RC-based) timer is added to them [16]. Here we would like to propose an alternative that does not require

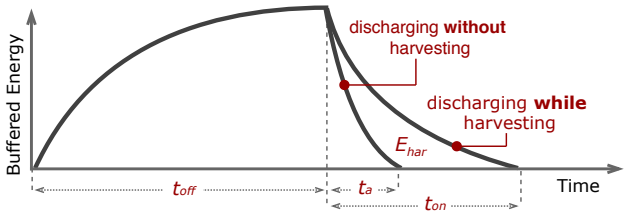


Figure 8: The difference in the time of discharging the energy buffer—a node's on-time—when an energy-harvesting device is allowed to charge while operating, and when it is not allowed.

Algorithm 1 off-time estimation

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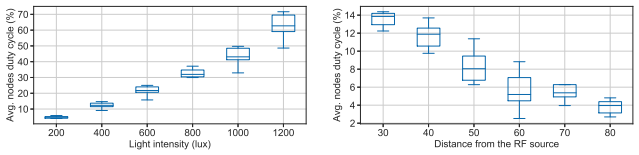
1:  R_cntr++                                   ▷ a persistent reboot counter
2:  E_buf                                      ▷ Size of energy buffer
3:  t_a                                        ▷ time of discharging E_buf at load a, no harvesting
4:  X_cy                                       ▷ time every X power cycles
    ▷ Code executed on each X power cycles
5:  if (R_cntr == X_cy) then
6:      R_cntr = −1
7:      f_LOAD(a)                              ▷ set node load to a
8:      t_on ← TIME()                          ▷ measure time until power down
9:  end if
    ▷ Code executed on each X + 1 power cycles
10: if (R_cntr == 0) then
11:     Δt = t_on − t_a                        ▷ time difference due to charging
12:     E_har ← E_buf × t_a/Δt                 ▷ harvested energy
13:     P_in ← E_har ÷ t_on                    ▷ incoming power
14:     t_off ← E_buf ÷ P_in
15: end if
```

additional hardware. This alternative does not only enable time estimation but also ambient energy richness, which is very important for estimating the number of a node's active neighbors. But, *how a node can time its own on/off cycle?*

Intermittent nodes fail abruptly; therefore, a persistent timer is needed. A simple way to emulate persistent timer is by using a persistent counter, or sampling the volatile built-in timers of the microcontroller and save the obtained values in the non-volatile memory. To estimate the off-time, t_{off} in Figure 8, a node needs to determine the incoming power (harvesting rate). The average harvesting rate can be induced from the on-time as follows. The node measures its on-time while harvesting, see t_{on} in Figure 8, and compares it to the time required to drain the energy buffer *without* charging, see t_{a} in Figure 8. The additional on-time, Δt, is the result of the energy accumulated while executing. If t_{on} and t_{a} are measured on the same load—thus, they have the same power consumption—then the amount of the energy harvested while the device is on can be calculated as in Line 12, Algorithm 1. And, the average input power can be found as in Line 13 that, in turn, enables the node to estimate its own t_{off} (Line 14). Since calculating the off-time requires constant load, the sensor cannot run arbitrary code during time measurement. Therefore, the sensor needs to sacrifice a certain percentage of its power cycles for time measurement,



(a) Light (b) RF

Figure 9: The average duty cycles of 8 solar-powered and 6 RF-powered intermittent nodes for different ambient energy sources and energy intensities. In general, the average duty cycle of a node is a good indicator of the average duty cycle of CIS's nodes.

Table 1: Measuring intermittent nodes overlapping of a CIS of 8 intermittent nodes for different light intensities.

light (lux)	N_{active}	std
300	1.01	0.85
500	1.63	0.98
800	2.88	1.50
1200	5.05	1.08

Line 1-8. Once the on-time and off-time are found the node's power cycle for load a is determined.

2.2.3 Nodes overlapping. Now, a CIS's node has all the information needed to estimate the number of active nodes in its CIS. Namely, it knows

In order for a CIS's node to estimate the number of active nodes at a given moment, it needs to determine the following information: (i) the size of the CIS it belongs to, which is a constant value that can be loaded to the memory; (ii) its own t_{on} and t_{off}; and (iii) how the CIS's nodes' on-times are distributed, Model 1. Figure 9 shows the average power cycles of solar- and RF-powered nodes. We can conclude from these measurements that a node power cycle approximates other CIS's nodes power cycles. This observation can be generalized by considering that the nodes of a CIS are assumed to have the same energy buffer size and they are in a close proximate, and therefore, they are expose to roughly the same energy conditions (this should not be confused with argument about the emerging uniform distribution of nodes' on-times as this distribution appears due to *small* differences between the power cycles).

Now, a node can estimate the maximum time span (t_{max}) of its CIS, which is the total duration of the nodes' on-times when they are aligned next to each other, as follows

$$t_{\text{max}} = N \times t_{\text{on}}. \tag{4}$$

Then, from Equation 1, the node calculates the CIS availability ($A_{\text{v}}(N)$). As we argued in Section 2.1.1, nodes on-times are uniformly distributed over the longest power cycle, $t_{\text{p}}^{\text{max}}$. Thus, the overlapping on-time is also uniformly distributed. Then, the node can calculate the average number of active intermittent nodes N_{active} using the following formula,

$$N_{\text{active}} = \frac{t_{\text{max}}}{t_{\text{p}}^{\text{max}} \times A_{\text{v}}(N)}. \tag{5}$$

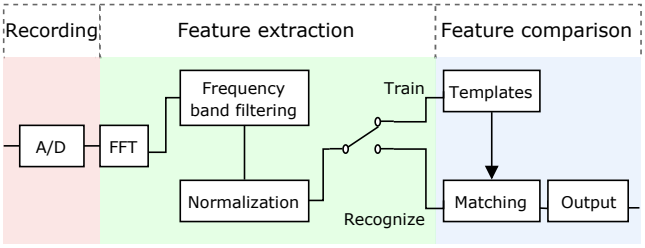


Figure 10: Coalesced Intermittent Command Recognizer: an instant of a Coalesced Intermittent Sensor. CICR features a power failure immune word recognition algorithm. First a word is recorded. Then, its spectral features are extracted. The resulting features vector is compared against previously-stored words' templates for recognition. The comparison is done using a liner distance matching algorithm

and choose the proper randomization factor. If a second event, however, happens shortly after the first one, a node needs to update N as follows,

$$N = N - (N_{\text{active}} - 1)$$

the -1 is because the node itself decided not to react on the first event.

Table 1 shows the average number of overlaps of an 8-nodes CIS for different light intensities. These measurements validate that nodes overlapping time is uniformly distributed over the CIS on-time. For example, at 1200 lux an individual node of our CIS has a duty cycle of $\approx 62\%$. If we multiply it by the number of nodes (Equation 4) we get about 500%. Figure 4 indicates that a CIS with eight nodes of duty cycles above 50% has near 100% availability. From equation 5, we find that the expected number of clustered nodes is 5 which is what Table 1 also shows.

3 IMPLEMENTATION—COALESCED INTERMITTENT COMMAND RECOGNIZER

We have developed a prototype of a coalesced intermittent command recognizer (CICR): an instant of a Coalesced Intermittent Sensor. The CICR consists of eight battery-less intermittent nodes. Each node is capable of performing isolated words recognition.

The reason behind developing a CICR is threefold: (i) voice is a natural and convenient way for human to interact with miniaturized devices; (ii) demonstrating *the world's first* battery-less intermittently-powered command recognizer, which shades light on the potential of battery-less intermittent systems; and (iii) facilitating testing with different sensing strategies and different type of external events arrival (i.e., regular or burst).

3.1 Hardware

A CICR node consists of thee main parts: a microphone, a microcontroller, and a harvester. MSP430RF5994 [39], an ultra-low-power microcontroller, is used for data acquisition and processing. This microcontroller has a 16-bit RISC processor running on 1 MHz, 8KB of SRAM (volatile), 256KB of FRAM (non-volatile), and a 12-bit analog to digital converter (ADC). It also features a Low Energy

Accelerator (LEA), which offloads the main CPU for specific operations, such as FFT. For recording we use the PMM-3738-VM1010-R piezoelectric MEMS microphone, which features Wake on Sound and ZeroPower listening technologies [31], allowing both the microcontroller and the microphone to sleep in a low-power mode until a sound wave is detected. The microcontroller and microphone are powered by a BQ25570 solar power harvester [38] connected to an IXYS SLMD121H04L solar cell [20] and a super-capacitor of 470 µF. For debugging we used the Saleae logic analyzer [35].

3.2 System Description

The CICR has a power interrupts immune command recognizer. The recognizer is capable of recognizing isolated-word type of speech. The main parts of the recognizer are illustrated in Figure 10 and explained below:

3.2.1 Data acquisition. The *Wake-on-Sound* feature of the microphone triggers the data acquisition process once the energy level in the sound signal crosses a certain level. The ADC, then, samples the output of the microphone at 8 kHz. This sampling rate is sufficient to cover most of the frequency range of the human voice. The recording length was set to be 285 ms, which suffices to get all the acostic features needed to recognize the words. By exploiting the Wake-on-Sound feature and using the minimum effective recording length, we eliminate the need for an endpoint detection algorithm, greatly improving the processing time and system efficiency from the energy perspective.

3.2.2 Feature Extraction. Once a recording has finished, framing and data processing begin. CICR divides the digitized signal into non-overlapping frames of 256 samples (≈ 33 milliseconds). This size is beneficial for doing a Fast Fourier Transform and short enough for the voice-features to be considered constant inside a frame.

To extract the spectral features of a frame, CICR divides the frequency of interest into 12 bands (as in [18]). The first five bands have a bandwidth of 200 Hz. The next three have a bandwidth of 300 Hz which are followed by two bands of 500 Hz. Finally, the last two bands have a 600 Hz bandwidth. This division is motivated by how the energy is concentrated in human speech [18]. Then, CICR computes the 256-point Fast Fourier Transform for each frame. The resulting feature vector contains the amount of energy concentrated in each frequency band defined earlier. This feature vector forms the basis for the words identifying process once it is normalized.

We normalize the feature vectors to reduce detection errors that result from differences in the amplitude of the speech input. To normalize a feature vector, CICR computes the binary logarithm of each entry of that vector. Then it computes the mean of the resulting vector. Finally, it subtracts the computed mean from each entry of the resulting vector. This is summarized in the following equation:

$$f_i = \log(\hat{f}_i) - \frac{\sum_{i=1}^{S} \log(\hat{f}_i)}{S}, \tag{6}$$

where f_i is the normalized output for the i^{th} spectral band of a feature vector, $\hat{f}_i$ is the energy in the i^{th} spectral band of the frame, and S is the number of spectral bands (12 in our case).

Table 2: Profiling of features matching algorithms: Dynamic Time Warping (DTW) and Linear Distance Matching (LDM).

Section	LDM (ms)	DTW (ms)
Recording	285	285
Feature extraction	501	501
Feature matching	99	1251
Total	885	2037

Table 3: Power usage

Section	Current (µA)	Voltage (V)	Power (µW)
Sleeping	64 ±20	2.008	128 ±40
Recording	423 ±20	2.008	849 ±40
Processing	282 ±20	2.008	566 ±40

3.2.3 Feature Matching. Feature matching is achieved by computing the distances between the normalized feature vectors of the recorded word and the feature vectors of the words stored during the training phase (templates). CICR computes the squared Euclidean distance between vectors as follows:

$$d_j = \sum_{i=1}^{S} (f_{s,i} - f_{r,i})^2, \tag{7}$$

where d_j is the distance between the j^{th} stored and recorded vectors. $f_{s,i}$ and $f_{r,i}$ are the normalized output of the i^{th} spectral band of a stored and recorded vector, respectively. The total distance between two words is calculated as follows:

$$D_k = \sum_{j=1}^{l} d(j) \tag{8}$$

where D_k is the distance between the k^{th} stored word and the recorded word, and l is the recording length measured in frames.

Once the recorded word has been compared to all CICR template words, the template with the smallest distance to the recorded word is considered the correct word. However, if the smallest distance is bigger the garbage threshold which we experimentally set, then the CICR will return "undefined word".

It should be emphasized that in the linear distance matching algorithm (LDM) the feature vectors of two words are compared successively, not accounting for differences in pronunciation speed. This is sufficient for our case as we are targeting isolated words and speaker dependent speech recognition type. We also implemented the Dynamic Time Warping algorithm which better handles the difference in the speed of speech. However, it is slower than the linear matching algorithm (Table 2) and the detection accuracy was comparable in our case. Therefore, we default our implementation to LDM.

3.2.4 Power Failure Protection. In order to preserve the progress state and to protect CICR data against randomly timed power failures, we manually split CICR program into 19 atomic regions. We ensured the each of these regions requires less energy than what the energy buffer can provide with a single charge. The program progress state is saved in the non-volatile memory (FRAM) on the transition between these regions. This prevents the program from

falling back to its starting point (`main()`) after each power failure. Data in the non-volatile memory with Write-After-Read dependency is double buffered to ensure data integrity when the power supply is interrupted.

3.3 Code profiling

The entire command recognition software was written in the `C` programming language. The total program consists of 973 lines of code, excluding the FFT function from the Texas Instrument DSP library. The memory footprint on the microcontroller is 20,064 bytes of FRAM and 1,134 bytes of SRAM. Execution times are shown in Table 2.

The power usage of a node differs according to it's activity. When a node is waiting for a voice event, it is in low-power mode. When data needs to be processed or recorded it is in active mode. When recording, the microphone and ADC consume additional power. The power consumption rates are determined by measuring the current with a Monsoon power monitor [27] and shown in Table 3.

4 EVALUATION

To evaluate the performance of the Coalesced Intermittent Sensor, we conducted several experiments in different energy conditions and with different event arrivals patterns.

4.1 Availability

In respective of the energy source (RF or light) we showed in Figure 5 that the power cycles of a CIS's nodes are different, which leads to uniform distribution of their on-times, as we argued in Section 2.1.1. We captured the expected joined availability of these nodes in Equation 1. Here, we challenge our arguement and model by comparing the modeled availability of a CIS against the measured ones under different powering conditions and with different hardware.

Figure 11 shows the availability of three CISs when they are powered by different energy sources (sunlight, artificial light, and RF) and for a different number of intermittent nodes. The results clearly confirm our expectation: when the power cycles are slightly different, the on-times are uniformly distributed. And they validate our model (the dashed lines represent the modeled availability when the nodes duty cycle is 15%).

4.2 Sensing

Table 4: Testing set

on	off	stop	clear	load
go	pause	resume	edit	cancel

4.2.1 Experiment setup. After validating our observation on different energy sources, we designed a testbed with controllable light intensity for clarity and results reproducible. To this end, we blocked uncontrollable light sources with a box of 60×40 cm. On the box ceiling, we attached a light strip of 2.5 m with 150 LEDs that can produce 15 different light intensities. On the bottom a Coalesced Intermittent Command Recognizer of 8 intermittent nodes is placed (see Section 3.1 for hardware description).

The events in our experiments are spoken words (Table 4). Short events (see events classification in Section 2.1.2) are represented with individual words, while long burst events are represented with phrases of a few words. We recorded different patterns of inter-event and inter-bust arriving time. We used a Bluetooth speaker [21] to replay a certain record. The data were collected using logic anaylyzer [35] and processed on a laptop running Ubuntu 16.04 LTS.

4.2.2 Events detection rate. Here we experiment with the behavior of a CIS when events arrive individually or in bursts *without* enabling randomized response in favorable energy conditions.

Individual events. Figure 12 shows the percentages of capturing duplicate and unique events when light intensity varies from 300 lux to 1400 lux and the inter-event arrival time from 1 sec to 6 sec. For each experimental trial 20 words were played, resulting in a total of 240 playbacks.

We can clearly see a positive correlation between light intensity and the number of detected events. In particular, the number of duplicate detections rises dramatically when light intensity increases, *demonstrating the overpowering problem* (Section 2.2.1). Moreover, increasing the inter-event arrival time also surges the number of duplicated events. The reason for this phenomenon is that when the time between events increases, the intermittent nodes get the chance to sleep longer in low-power mode, consuming less energy. Therefore, nodes' on-times expand, reducing their inherent randomization, which leads them to be in *hibernating power state* (Section 2.2.1).

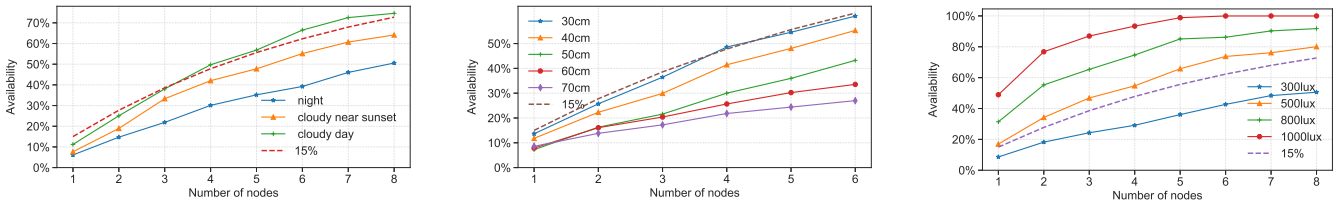
Bursty events. Figure 13 shows the capturing behavior of a CIS when the events arrive in bursts. a burst of four events with one second between the individual event was fired every 20 seconds. Each burst was repeated 10 times and under four different light intensities. The nodes sleep in a low-power mode when they finish processing an event, waiting for the next one.

In general, we observe that in favorable energy conditions (above 500 lux) intermittent nodes react to the first event of a burst and power down shortly after missing the rest of the burst. These results confirm our theory about the side effect of the *hibernating power state* of a CIS (Section 2.2.1). These results also demonstrate that the hibernating power problem happens on a wide range of power intensities, showing its significance. Next, we will show how randomizing the response can mitigate the problems generated when ambient energy exceeds the design point.

4.2.3 Events detection rate with randomization. Here, we examine the effect of enabling artificial randomization on the CIS's response.

Individual events. Table 5 compares the number of detected events when the CICR's response is randomized and not randomized. When the randomization is enabled, nodes were responding to events with a probability of 65% for the scenario of (800 lux, 6 seconds) and (1400 lux, 4 seconds), and for the highest energy level and the longest inter-event arrival time the responding probability was 30%.

We see that randomizing the response reduces duplicated events by an average of ≈50%, while only marginally lowers the number of the uniquely detected events.



(a) The CIS is powered by uncontrollable light sources—artificial light (night) and sunlight (day).

(b) The CIS is powered by an RF reader [19] located 30-70 cm aware from the RF tags (WISPs [36]).

(c) The CIS is powered by a controllable array of LEDs in a dark room.

Figure 11: Measuring Coalesced Intermittent Sensor availability for a differed number of intermittent nodes. Generally, adding a node increases the system availability. This increment, however, is proportional to the CIS off-time.

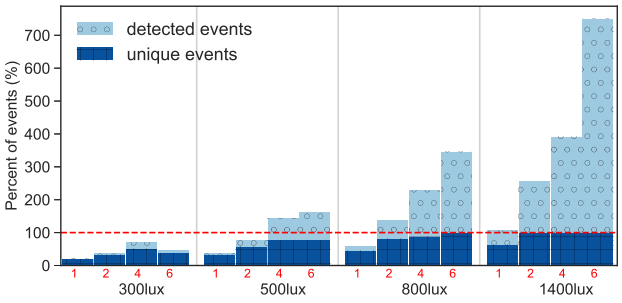


Figure 12: Duplicate and unique events captured by a coalesced intermittent command recognizer of eight solar-powered nodes. In general, we see that the number of captured events increases in tow case: when light intensity rises and when inter-event arrival time increases. Red numbers indicate events arrival interval in seconds.

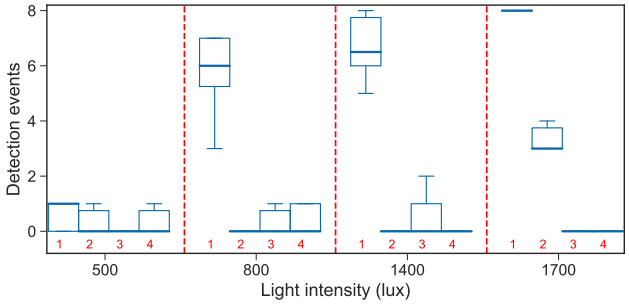


Figure 13: When capturing a burst of events without randomizing the response, the majority of the nodes react to the first event in the burst and power down shortly after, missing the rest of the burst. Red numbers indicate events index in a burst.

Bursty events. Figure 14 shows how randomizing the CIS response spreads the nodes' awake times–as compared to Figure 13–and enables the CIS to capture the entire burst with a high probability, i.e., above 85%. We also observe a positive impact of randomized response when the system is under-powered (500 lux).

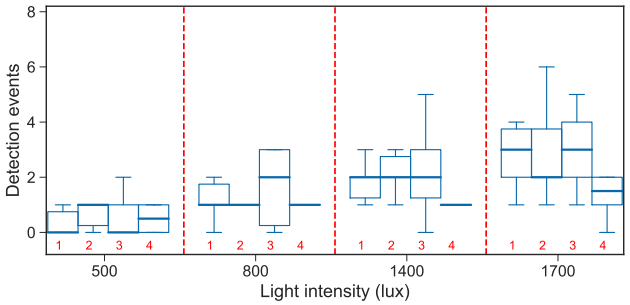


Figure 14: Response randomization enables a CIS to capture the entire burst of events with high capturing rates. It also reduces the number of duplicated events. Red numbers indicate events index in a burst.

(lux,second)	(800,6)	(1400,4)	(1400,6)
randomization	205/432	236/675	223/493
no randomization	240/831	240/938	240/1802

Table 5: These results are presented in the following format *unique/total* detected events. A CIS's node responds with a probability equals 65% in the first two scenarios,(800,6) and (1400,4), and 30% for the last one. We can see that Randomizing the response in this way reduces the number of duplicated events by 50% while losing only 7% of the unique events (if 7% is two high, a higher responding probability can be used).

To randomize during bursty events, a node reacts with a certain probability on a event. This probability is different for each event since the node become active after the last recharge. In order to spread the nodes over the events, the probabilities need to increase for subsequent events, since some nodes have reacted already on previous events, and therefore the number of nodes still available is smaller after each event. A node reacts with a probability of 40% on the first event, with 50% on the second event, 70% on the third event and 100% on the fourth event.

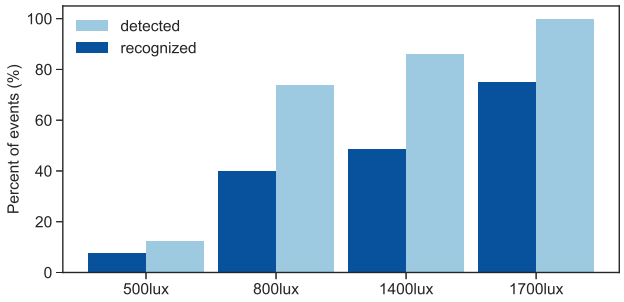


Figure 15: Average number of successfully recognized words per node and average number of detected words per node, as percentages of the total number of played words. Words are relatively long events and therefore some of their recordings do not complete due to insufficient harvested energy.

4.3 Coalesced intermittent command recognizer word detection accuracy

For evaluating the coalesced intermittent command recognizer accuracy, we used the word set in Table 4. Each word was pronounced by a single speaker 20 times and recorded on a PC. One of these recordings was stored as a template on the CICR, while the remaining 19 were played back through a Bluetooth speaker [31] for testing.

The ratio between detected events and successfully recognized events per node is shown in Figure 15 and it averages out at 76.7%. The difference between detection and capture is primarily caused by nodes that have insufficient buffered energy to finish recording.

5 RELATED WORK AND BACKGROUND

Recent advances in ultra-low-power microcontrollers along with the development of energy harvesters have enabled the creation of stand-alone battery-free sensors. These sensors operate intermittently as their energy sources are weak and volatile.

5.1 Energy-harvesting systems

Energy harvesters have the potential to power devices indefinitely as they collect energy from perpetual energy sources. Sunlight, vibration, and radio frequency (RF) waves are examples of such energy sources. The power harvested from these sources vary wildly, for example, RF harvestable power ranges from nW-scale when harvested from ambient signals to µW-scale when collected form a dedicated RF signal emitter, and solar power varies from tens of µW to tens of mW when it is harvested by a solar panels of a few cm^2 illumination surface [24, 34].

Many battery-less energy-harvesting platforms have been proposed. Some of them rely on dedicated external energy sources such as WISP -and its variants-, a general wireless sensing and identification platform [36, 44, 46]; WISPcam, an RF powered camera [28] and, the battery-free cellphone [37]. Others, harvest from ambient sources such as the ambient backscatter tag [23], and the solar-powered tag [26]. Platforms that facilitate the development of batteryless energy-harvesting systems have also been proposed. For instance, Fliker [15], a prototyping platform for batteryless devices; EDB [7] an energy-interference-free debugger for intermittent devices; and Capybara [9], a re-configurable energy storage architecture for energy-harvesting devices.

However, *there is no energy-harvesting platform that considers the abstraction of many intermittent sensors (or nodes) and exploits the statistical energy harvesting differences between them to provide reliable sensing.*

5.2 Intermittent execution

Intermittent execution models enable applications to progress despite frequent power failure [5, 8, 14, 25, 40]. To this end, they decompose an application into several small pieces and save the state of the computation progress on the transitions between these code segments. Therefore, intermittent applications do not return to the same execution point (e.g., `main()`) after each power failure—in contrast to the applications that assume continuous power supply—instead they resume execution from the last successfully saved state of execution.

Intermittent systems are regarded as the successor of energy-aware systems. Dewdrop [6] is an energy-aware runtime for (Computational) RFIDs such as WISP. Before executing a task, it goes into low-power mode until sufficient energy is accumulated. QuarkOS [45] divides the given task (i.e., sending a message) into small segments and sleeps after finishing a segment for energy recharge. However, these systems are not power disruption tolerant. In other words, if a system could not sustain the energy consumption of low-power mode and powers down, then all the computation progress will be lost.

Mementos [33] proposed a volatile memory *checkpointing-based* approach to enable long-running applications on intermittently powered devices. DINO [32] enables safe non-volatile memory access despite power failures. Chain [8] minimizes the amount of data need to be protected by introducing the concepts of *atomic tasks and data-channels*. Hibernus [2, 3] measures the voltage level in the energy buffer to reduce the number of checkpoints. Ratchet [41] uses compiler analysis to eliminate the need for programmer intervention or hardware support. HarvOS [5] uses both compiler and hardware support to optimize checkpoint placement and energy consumption. Mayfly [16] enables time-aware intermittent computing. InK [43] introduces event-driven intermittent execution. All the aforementioned studies focus their development on a single intermittent node. *Our system adopts a checkpoint-based approach to protect the computation progress from power failures.*

5.3 Speech recognition

Speech recognition consists of several steps. The basic steps are: *Speech recording and signal digitization*—a microphone records the sound waves and an ADC converts the microphone signal into a digital signal. A sampling rate of about 8 kHz is required to capture the frequencies of a human voice (100-4000Hz [4]). *Framing*—after that the digitized signal is divided into blocks of usually 10-30 ms [10–12] called frames. *Features extraction*—for each frame a feature vector is extracted containing all the relevant acoustic information. *Feature matching*—finally the extracted features are matched against features known to the recognizer.

The speech recognition problem has been tackled from many angles and has experienced many breakthroughs. For example, the dynamic time warping (DTW) algorithm enables matching voice signals with different speed (or time) [42]. Approaches based on Hidden Markov Models showed much better performance than DTW-based ones [22]. Hence, they became the standard techniques for general-purpose speech recognition until artificial intelligent algorithms [17], however, outperform them. Furthermore, many specialized hardware architectures for speech recognition have been proposed to, for instance, reduce energy consumption [29, 30].

Speech recognition algorithms can be classified based on the type of speech that they can recognize into *spontaneous speech, continuous speech, connected word,* and *isolated word* [12]. Systems with *continuous* or *spontaneous speech* recognition are the closest to natural speech, but are the most difficult to create because they need special methods to detect words boundaries [12]. This is less the case for the *connected word* type, where a minimum pause between the words is required. The type with the least complexity is the *isolated word* type. It requires a period of silence on both sides of a spoken word and accepts only single words.

Voice is a natural way for the human to interact with small devices. However, speech recognition on resources—memory, computation power, and energy—limited platforms is challenging, to say the least. Therefore, *Our command recognizer targets isolated words type of speech.*

6 DISCUSSION AND FUTURE WORK

Intermittent timing algorithm when the harvested power is very low the accuracy of inferring the charging time from the discharging degrades. However, for the Coalesced Intermittent Sensor this is not a serious problem as the intermittent nodes need to randomize their response to external events in favorable energy conditions.

Coalesced Intermittent Sensor Speech recognition on intermittent devices In this paper, we have shown the feasibility of speech recognition on intermittent power. We also demonstrated the possibility of recognizing burst of events (in our case four words). However, the type of speech we targeted is the simplest, isolated words. Next, we may attempt recognizing a more complicated type of speech and for a larger number of words than the number chosen for this study.

Additionally, the command recognition rate could further be improved by using an estimation of the energy left in the energy buffer, to start recharging early. This will prevent a detection when there is not enough harvested energy to record for a long enough time, letting a node recharge earlier and coming back with sufficient energy.

7 CONCLUSION

We presented the *Coalesced Intermittent Sensor* (CIS), an intermittently powered "sensor" that senses continuously! CIS is built around the observation that multiple intermittent nodes distribute themselves uniformly in time. This observation enables us to accurately model, and validate on real hardware, the CIS availability—the collective on-time of its intermittent nodes.

An important finding is that favorable energy conditions may cause sleeping intermittent nodes to synchronize their power cycles on the arrival of the first event. Consequently, they react to the same event, start recharging at the same time, and missing the next event. To counter this unwanted behavior we designed an algorithm to estimate the number of sleeping neighbors and respond proportionally to an event. We show that the Coalesced Intermittent Sensor is able to distribute bursts of events on its nodes "evenly" and capture the entire burst with above 90% detection accuracy.

Additionally, we prototype a battery-less coalesced intermittent command recognizer and show that it can successfully capture events of multiple words.

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