STeC: Exploiting Spatial and Temporal Correlation for Event-based Communication in WSNs

Andreas Biri
ETH Zurich
abiri@ethz.ch

Reto Da Forno
ETH Zurich
rdaforno@ethz.ch

Tonio Gsell
ETH Zurich
tgsell@ethz.ch

Tobias Gatschet
ETH Zurich

Jan Beutel
University of Innsbruck
jan.beutel@uibk.ac.at

Lothar Thiele
ETH Zurich
thiele@ethz.ch

ABSTRACT

Low-power wireless sensor networks have demonstrated their potential for the detection of rare events such as rockfalls and wildfires, where rapid reporting as well as long-term energy-efficient operation is vital. However, current systems require periodic synchronization to maintain network coordination, heavily rely on node placement or use costly long-range links to infrastructure. We present STeC, a novel wireless communication design that directly exploits the spatial and temporal correlation of signals from the sensed phenomenon to orchestrate event-based communication. We leverage the locality of a co-detection, where a physical event triggers multiple sensors quasi-simultaneously, to efficiently collect, characterize and report sensor data. This eliminates the overhead of periodic network activity and centralized control, resulting in more energy-efficient communication with a lower, more consistent detection latency. In doing so, we propose a fundamentally new approach to avoid the elementary conflict between duty cycle and latency requirements immanent to synchronous protocols by exploiting correlated sensor signals for networking. Experiments using real-world traces of a natural hazard detection application show that STeC reduces the detection latency by up to 87 % compared to standard single-hop communication and outperforms traditional schedule-based methods by up to $58.4 \times$ in energy efficiency.

CCS CONCEPTS

• **Networks** → **Cross-layer protocols**; *Topology analysis and generation*; • **Computer systems organization** → *Sensor networks*.

KEYWORDS

Event-based sensing, correlation, wireless sensor networks

ACM Reference Format:

Andreas Biri, Reto Da Forno, Tonio Gsell, Tobias Gatschet, Jan Beutel, and Lothar Thiele. 2021. STeC: Exploiting Spatial and Temporal Correlation for Event-based Communication in WSNs. In *The 19th ACM Conference on Embedded Networked Sensor Systems (SenSys '21)*, November 15–17, 2021, Coimbra, Portugal. ACM, New York, NY, USA, 14 pages. <https://doi.org/10.1145/3485730.3485951>

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

SenSys '21, November 15–17, 2021, Coimbra, Portugal

© 2021 Copyright held by the owner/author(s).

ACM ISBN 978-1-4503-9097-2/21/11.

<https://doi.org/10.1145/3485730.3485951>

Figure 1: A physical event σ generates sensor events σ_m at triggered sensors m , which form an ad-hoc network of size N_σ for sensor events arriving within an interval ΔT . Physical events are locally filtered and only reported if they fulfill application-specific requirements. For event α , N_α reached a threshold of 3 nodes per co-detection and is reported to the data sink, while β is suppressed.

1 INTRODUCTION

Motivation. Wireless sensor networks (WSNs) are inherently suited for long-term observations with rare activity and have been employed for intruder [60] and sniper detection [44], wildfire alerts [21, 33, 61], and volcano monitoring [56, 57]. In these scenarios, a physical event originates at a source and propagates through the environment until it reaches individual sensors with variable propagation delays and signal intensities, where it triggers a sensor event. This location dependency complicates the subsequent data analysis, as the distinction between a close physical event with small magnitude and a far-off but large physical event requires the relative interpretation of data inside the network. Therefore, including the correlation of spatial and temporal patterns is essential for data interpretation: The *co-detection* of multiple sensor events that are in proximity and occur within a bounded time frame permits conclusions on the intensity and location of the physical event [54]. These characteristics motivate event-based data collection that incorporates application-specific needs and adapts to events by filtering irrelevant data as shown in Figure 1. In this paper, we leverage the physical characteristics of signals propagating to distributed sensors for i) *establishing an ad-hoc network without prior coordination* and ii) *efficient local processing and filtering*. While not all WSNs and observed phenomena show the above signal pattern, some do. We exemplify them with a case study of seismic event detection on an alpine rock glacier, in which we demonstrate the benefits of exploiting the spatial and temporal correlation of signals originating from a single source for synchronization and data aggregation.

In the last two decades, WSNs have greatly benefited from more efficient sensing and communication hardware as well as advances in the protocol design for reliable multi-hop networks. However, the majority of these efforts has focused on continuous sampling and leverages extensive duty cycling in-between active phases to prolong system lifetime. While classical environmental monitoring applications such as bedrock [22, 55], structural [2], and agricultural [58] monitoring are well-suited for regular measurements, ephemeral and sporadic events such as sudden shifts in river sediments [14] or rockfalls [36] demand more reactive protocols. This is of particular importance for rare events occurring after months or years of operation, for which classical solutions such as over-sampling or event-triggered adaptation [49] quickly deplete the available energy resources of battery-powered devices.

Challenges. A communication scheme targeted at rare event detection must solve four individual challenges. First, such protocols are primarily focused on optimizing detection probability and delay [24] while maximizing lifetime. The latter requirement fundamentally contradicts traditional duty-cycled approaches, where an inherent trade-off between the reactivity and system lifetime is unavoidable. To achieve both simultaneously, we propose to refrain from any periodic activity and purely communicate event-driven. Second, as sensor events in our scenario occur quasi-simultaneously due to the synchrony of event detections [24, 47, 60], previous asynchronous protocols have suffered from decreased performance due to packet collisions. In contrast, we leverage the temporal correlation of events to coordinate data collection and permit relative, local filtering of events. Third, complete network activation following a sensor trigger, either time-triggered [27, 49] or through wake-up circuitry [38, 48], is highly inefficient for events that predominantly concern a small subset of nodes within proximity of the physical event. By inherently restricting activity to nodes that have received a sensor trigger, we exclude nodes which are not involved in the co-detection of events, thereby making energy consumption exclusively dependent on a node's local activity. Fourth, as only a subset of sensor nodes is activated by an event, short-range links can be insufficient to reach a distant data sink for reporting. We solve this by leveraging the capabilities of modern radios to support both short- and long-range links within a single chip set.

Approach. We propose to incorporate event detection based on distributed sensors as an integral part of orchestrating WSN communication. If events are received by multiple sensors in close proximity w.r.t. space and time, nodes can leverage the sensor signal for synchronization. Following an event trigger, nodes activate their radios and form an ad-hoc network that enables the characterization and reporting of co-detections with minimum overhead. Communication only occurs as events appear and is bounded by their physical characteristics, effectively alleviating the elementary conflict between duty cycle and latency inherent to other reactive schemes. Through local processing and filtering, irrelevant events are suppressed by an application-specific filter, such as a threshold on the number of nodes or the signal intensity. Only events of interest are compressed and reported to the data sink. Our scheme ensures that at each step (synchronization, local aggregation, and reporting), energy is only spent on events deemed relevant, and that such critical events are detected with minimal delay.

With STeC, we make the following core contributions:

- We show that local aggregation of information in short-range ad-hoc networks enables us to filter the majority of events and improves energy efficiency, discussed in [Section 3.1](#).
- We present a unique design for low-power communication protocols to reduce detection latency through a symbiosis of short- and long-range radio links in [Section 3.2](#).
- We demonstrate that exploiting the correlation of physical events both in the spatial and temporal domain can benefit communication schemes greatly, as shown in [Section 3.3](#).
- We develop methods to reliably discover and synchronize active sensor nodes in [Section 4](#). A novel scheme is introduced to efficiently establish an ad-hoc network and leverage this knowledge to suppress futile data acquisition.

In [Section 5](#), we present our open-source hard- and software implementation which we thereafter use for proof-of-concept testing. Based on real-world traces from a WSN deployment as well as synthetic events, we evaluate STeC in a variety of settings and validate its efficacy in a 7-month deployment for rock glacier monitoring in alpine environments, presented in detail in [Section 6](#).

2 RELATED WORK

Duty-cycled wireless networking. Synchronous low-power wireless protocols have proven their utility in countless applications for long-term monitoring with recurring traffic patterns [9, 25, 37, 58]. Initiated by Glossy [20], synchronous transmissions (ST) leverage topology-agnostic, low-latency, and highly reliable network floods to efficiently disseminate data to all nodes [19, 62]. While this concept has shown to work well for one-to-many [49] and convergencast networks [27, 52], it still requires periodic network synchronization and scheduling, thereby inherently trading off communication latency and energy consumption. STeC uses ST to quickly establish ad-hoc networks, aggregate data with low latency, and spread energy costs, but eliminates the dominating scheduling overhead.

Event-based communication. Previous efforts to avoid this trade-off have employed wake-up radios and leverage their extraordinarily low idle listening costs for long-term event-based communication [48, 50]. Similarly, a combination of wake-up radios and LoRa radios has been proposed to reduce the costs of long-range links [40], whereby local clusters remain synchronized to the data sink. While this concept has been applied to environmental monitoring and has shown to significantly reduce communication overhead, the requirement for additional, highly specialized hardware as well as the frequent erroneous wake-ups and the severely restrictive range of 45 m [39, 46] with and 15 m [10, 48] without line-of-sight limits its applicability. Schemes such as CTP-WUR [6], which combine secondary wake-up radios with primary radios to extend this range, depend on up-to-date topology information and hence also require periodic activation of the entire network. Without the additional cost and complexity of dedicated hardware, protocols have been mostly constricted to reducing communication overhead in times of inactivity [35, 45, 49]. Local collaboration to prevent the high energy costs of long-distance communication by removing a false positive event detection early on has been investigated for monitoring applications [24]. The formation of a local network for

each event has been shown to benefit area surveillance through a distributed evaluation algorithm [59]. This prompt suppression of superfluous data is beneficial for reliability and robustness and permits significant energy and latency savings. In particular, the partial information of aggregate queries is gaining interest for low-power wide-area networks (LP-WANs) [21]. Instead of introducing additional system complexity and costs, STeC's novel sensing-based coordination directly leverages the underlying physical events to synchronize local ad-hoc networks and suppress events that do not match given criteria before transmitting them on LP-WANs. This permits us to both eliminate scheduled communication overhead and reduce event detection latency.

Sensing for environmental monitoring. While continuous digital sensing has been shown to achieve hundreds of hours of lifetime [15], such devices have idle sensing costs in the order of multiple mW. To avoid this, analog trigger front-ends have been previously introduced to discover seismic events more efficiently using geophones [28, 36] and a variety of other sensors [34]. However, in these cases communication was disregarded and data was assumed to be collected opportunistically or in periodic batches. Previous work on structural monitoring using seismic events requires periodic low-power listening [41] and leverages a transmitter with unrestricted power to wake up the network on demand [31]. In contrast, STeC's communication design is inherently coupled to its sensor triggers and reveals a mutual symbiosis of both reducing communication costs based on sensor input as well as limiting sensing costs if local network traffic identifies an irrelevant event.

3 DESIGN GOALS AND PRINCIPLES

While only co-occurring events are relevant in the considered application scenarios, traditional protocols either spend excessive energy on directly reporting all events to the data sink for processing or regularly collect data with a high detection latency. With STeC, we develop an event-driven protocol that aggregates events in ad-hoc networks and forwards the joint co-detection to a central entity. We thereby exploit the spatial and temporal correlation of sensor triggers originating from a single physical event to efficiently co-detect events. In this section, we give an overview of STeC and its six protocol stages and introduce a formal model of event co-detection, which we illustrate in a real-world case study of seismic events.

Setting. We target a set of M resource-constrained sensor nodes which can locally communicate over *short-range* links within the propagation radius of the physical event. Each sensor node m is equipped with a sensing system that can trigger further processing of samples as well as communication upon detection of a sensor event. We suppose an event-driven hard- and software architecture, i.e., the node is primarily in a low-power mode but is activated by the occurrence of an event to characterize it. In addition, physical events that fit application-specific patterns must be reported with minimal detection latency to a data sink kilometers away that is only accessible via a *long-range* link. This data sink is placed at a location where resources are unconstrained and can serve multiple sensor networks in the vicinity. In summary, sensor nodes are sensor-triggered and support two kinds of wireless links, namely *short-range* between themselves and *long-range* to a data sink.

3.1 Local Event-based Aggregation

To efficiently detect co-occurring events, we leverage three key insights: First, a communication scheme which exploits correlated sensor-initiated triggers instead of timers can inherently confine its activity to locally involved sensors and does not require periodic activation of the entire network. Second, because of the restricted time window during which a physical event causes sensor events, we can limit communication to a brief interval directly after a sensor event and return to sleep thereafter. Third, co-detections of multiple sensors are rare and therefore incentivize a scheme that quickly detects lone wake-ups of a single sensor node. Early termination enables us to abort sensing and communication for irrelevant sensor events which do not fulfill filtering criteria. STeC integrates these insights to achieve energy-efficient co-detection and low-latency event reporting. While we give a detailed description in Section 4, we briefly sketch the short- and long-range communication scheme as depicted in Figure 3.

Nodes remain in their low-power mode and are exclusively activated if their sensor detects an event. Through analog trigger front-ends, this can be achieved with a power draw in the order of μ W. After the physical event has occurred, its signal propagates through the media and arrives at sensor m with a propagation delay of δ_m . As nodes are triggered depending on their individual distance to the source, this results in a *staggered wake-up* throughout the network; while some nodes might already be synchronized, others receive the trigger with varying delays. We resolve this correlated but asynchronous activation through a technique inspired by Low-Power Probing [37]. As soon as the sensor receives an event, the node enables its radio and starts listening. Simultaneously, a timer is set, which causes the node that first received the event to be activated earliest and flood a wake-up signal after a maximal propagation delay ΔT , thereby ensuring that all nodes within reach of the physical event have been triggered. Listening nodes directly synchronize to the wake-up and can immediately join the ongoing network flood without requiring further coordination. To quickly detect a lone sensor trigger and avoid futile protocol stages, a node sends multiple packets according to a unique pattern as described in Section 4.1 so active sensor nodes mutually *discover* each other.

As each physical event can generate a different ad-hoc network, it must always be bootstrapped from scratch. To do so, nodes perform *leader election* by exchanging packets based on their ID as shown in Section 4.2. The leader then announces a schedule containing a slot per node in the network to tightly synchronize the ad-hoc network and *aggregate data*. After activated nodes have exchanged their sensor events, an application-specific filter determines whether the co-detected physical event should be *reported* to a data sink.

3.2 Ensuring Connectivity to the Data Sink

As a data sink is typically situated in a location with Internet access and sufficient energy to support continuous listening, reachability from all remote sensor nodes via short-range links is not guaranteed. Furthermore, multi-hop connectivity cannot be assumed even if the data sink is in vicinity of the sensor network as the ad-hoc network only consists of a subset of sensor nodes. To resolve this, we make use of the ability of modern radios to transmit with modulations for both short- and long-range links using a single chip set [43].

Algorithm 1: Partition of a set of sensor events into sets of co-occurring events.

Input : Set of events $\sigma_m \in \Sigma$ with $\sigma_m = (m, f, t_m)$; number of sensors M ; maximal propagation delay ΔT .

Output: Sets of co-occurring events Σ_d of degree $1 \leq d \leq M$.

$\Sigma_d := \{\}$ for all $1 \leq d \leq M$;

$t_0 := -\infty$; $d := 1$; $C := \{\}$;

while $\Sigma \neq \{\}$ **do**

 determine event σ_{next} with smallest t_{next} in Σ ;

$\Sigma := \Sigma \setminus \{\sigma_{next}\}$;

if $t_{next} \leq t_0 + \Delta T$ **then**

$C := C \cup \{\sigma_{next}\}$; $d := d + 1$;

else

$\Sigma_d := \Sigma_d \cup C$;

$C = \{\sigma_{next}\}$; $d := 1$; $t_0 := t_{next}$;

end

end

$\Sigma_d := \Sigma_d \cup C$;

In case the co-detected event has not been filtered following data aggregation, a node assigned by the leader reports the compressed event information to the data sink, as described in Section 4.3. This occurs on the long-range link with single-hop connectivity. Because STeC primarily uses the short-range links and as most events are locally filtered, congestion on the long-range link is minimized. An acknowledgment from the data sink ensures successful reception of a critical event and allows for retransmissions if needed.

3.3 Exploiting Spatial and Temporal Correlation of Events

In order to exploit the spatial and temporal correlation of sensor events, protocol parameters need to be adjusted accordingly. In our application scenario, each one originates from a physical event σ occurring at time t_σ . A sensor event σ_m can be described by a tuple

$$\sigma_m = (m, f, t_m)$$

where m denotes the detecting sensor, f the associated features (such as duration and signal intensity) and t_m the time when the event was triggered at sensor m . As the sensors are within proximity of the physical event, we assume a maximal propagation delay $\delta_m = t_m - t_\sigma \leq \Delta T$ and hence $|\delta_i - \delta_j| \leq \Delta T$ for all $i, j \in M$.

We suppose that a set of sensor events is relevant if they occur close in time and space, as they are highly likely to originate from the same physical event. In such a case, we talk about *co-occurring* events. Given a set of sensor events Σ , we distinguish between co-occurring events of degrees d , where d corresponds to the number of nodes detecting a single physical event. Informally speaking, a set of d sensor events are co-occurring if they happen within a time interval ΔT , after which a physical event has reached all sensors. More formally, the set of all sensor events $\sigma_m \in \Sigma$ can be partitioned into subsets Σ_d for $1 \leq d \leq M$ using Algorithm 1, where each element of Σ_d is a set of exactly d co-occurring events.

d	1	2	3	4	5	6	7	8	9+
$ \Sigma_d $	4044	253	79	34	12	8	3	7	4
$ \Sigma_d / \Sigma [\%]$	91.0	5.7	1.8	0.8	0.3	0.2	0.1	0.2	0.1

Table 1: Most physical events are only received by a single sensor. Co-occurring events with a high degree are rare, as they require a physical event with a large magnitude to trigger multiple sensors.

Figure 2: The co-detection degree d varies significantly over time for our case study, with up to 13 nodes being activated by a single physical event. We find that events frequently appear in clusters, with 50 % of physical events occurring with an event interval of less than 3.35 s after a previous one. 23 % of physical events are separated by more than 20 min and show long periods of inactivity.

The purpose of the sensor network is to focus on and report such co-occurring events to a data sink, where a high degree d corresponds to a major event of critical importance. As our application requirement is to report co-occurring events of degrees larger or equal to the reporting threshold D , subsets Σ_d for all $d \geq D$ must be detected. STeC's goal is to efficiently and reliably report all relevant subsets above the threshold to the data sink. To achieve this, we aim for an energy-efficient and low-latency *distributed* implementation of Algorithm 1 directly inside the sensor network. Note that the distributed algorithm does not distinguish between multiple simultaneous physical events and a single large physical event. Since in both cases, multiple sensors could be triggered at the same time, the root cause must be analyzed during post-processing.

Co-detection. If a set $C_d \in \Sigma_d$ is successfully communicated to the data sink, co-detection has occurred. To obtain such a set of sensor events that are associated with a single physical event σ , we exploit two sensing properties. First, as σ propagates, it triggers sensors in increasing order of their distance to the source. It therefore usually only activates a connected multi-hop network of sensor nodes and inherently leverages the *spatial correlation* of sensors. In case of blocked signal paths without line-of-sight, this assumption might be constricted to physical events within the range of wireless communication. Second, it does so with a propagation delay δ_m depending on its propagation velocity and distance to sensor m . This allows us to upper-bound the maximal delay ΔT based on the spacing of sensors and utilize the *temporal correlation* of sensor events. STeC's location- and time-based communication permits us to inherently focus on co-detections and filter out irrelevant events.

Figure 3: STeC consists of six protocol stages: After a physical event has occurred, a sensor event σ_m is triggered at each sensor m with propagation delay δ_m . (1) The node which receives a trigger with the shortest δ_m listens for the delay τ_{prop} before sending a wake-up signal for initial synchronization. (2) Nodes efficiently detect whether there are other neighbors nearby and (3) elect a local leader. (4) After having sampled the event for at least τ_{sample} , the sensor events are aggregated in the ad-hoc network. (5) If deemed relevant, the assigned reporter finally sends the co-detection to the data sink and (6) optionally distributes returned commands and timestamping information.

Case study: Seismic event detection. As a real-world example of co-detections, Table 1 contains seismic events that have been collected by a network of $M = 32$ seismic sensors on a rock glacier at Dirruhorn, Switzerland, over a period of 17 months through a traditional schedule-based solution [49]. A maximal propagation delay $\Delta T = 100$ ms [18] and $|\Sigma| = \sum_{d=1}^M d \cdot |\Sigma_d| = 5154$ sensor events result in a total number of $\sum_{d=1}^M |\Sigma_d| = 4444$ detected physical events. Previous work [18, 36] has demonstrated that event co-detection is essential for the recognition of imminent catastrophic failure of the underlying rocks and hence critical for early warning systems. In this scenario, gravitational slope failure high above the valley floor must be reported with minimal detection latency to installations further below that can then restrict access to roads and rail lines or initiate the evacuation of populated areas.

Status quo. As shown in Figure 2, a co-detection with high degree occurs sporadically and does not require the periodic activation of the complete network, as many sensors experience long intervals without receiving any sensor event. If traditional schedule-based data collection is employed, co-detections are only obtained retrospectively during the post-processing of all data, resulting in an inefficient over-reporting of events and significant delays due to the periodic data aggregation. This follows as current protocols are agnostic to the underlying event characteristics and do not exploit their spatial and temporal characteristics. As an example, with a reporting threshold $D = 6$, up to 99.5 % of all physical events could already be filtered through event-based local processing.

4 STEC IN DETAIL

After having presented the principles behind STeC in Section 3, the following section dives into the details of the scheme as shown in Figure 3. We first demonstrate how to obtain coarse-grained synchronization from asynchronous triggers and efficiently detect lone wake-ups. Thereafter, we present a time-efficient bootstrapping method for an ad-hoc network and illustrate how to reliably exchange sensor data and efficiently report it to a central entity.

4.1 Synchronization and Mutual Discovery

Staggered wake-up. STeC exploits sensor triggers for asynchronous wake-ups. The individual propagation delays δ_m result in a *staggered wake-up* with sensor nodes receiving triggers one after another. To sufficiently synchronize for network communication, we must first obtain a common time reference. As the maximal propagation delay ΔT depends both on the spacing of the network and the propagation velocity of the media, this value is deployment-specific. While some events such as smoke spread (5 m/s [4, 29]) or explosions (343 m/s [44]) are relatively slow, even seismic waves propagating through rock at up to 4000 m/s [16, 23] still result in maximal propagation delays up to 100 ms [18]. For wireless communication, which requires ms-accuracy to efficiently exchange packets, directly synchronizing on sensor triggers is insufficient.

Therefore, STeC uses an additional radio wake-up signal to obtain timing accuracy in the order of single milliseconds independent of the event type. When a node receives a sensor trigger, it starts listening on its radio. In parallel, a timer is set to initiate the transmission of a wake-up signal after a delay $\tau_{prop} = \Delta T$. This ensures that even if a sensor is co-located with the physical event source, all nodes within event reach have already been activated before a wake-up signal is sent. If a node receives a wake-up, it cancels its local timer and synchronizes to the packet. The maximal time uncertainty within the ad-hoc network at this step is solely determined by the radio-specific switching time t_{switch} from listening to preamble transmission, with $t_{switch} = 1.15$ ms for our implementation. This follows as multiple nodes can be close together and start their own signal transmission just before being able to receive the one of others. Notice that as only the detection of a preamble is needed, the wake-up signal can still be recognized even if packets are sent concurrently. After this stage, active nodes have reduced the timing uncertainty due to the asynchronous wake-up to single milliseconds. However, as multiple nodes can detect an event quasi-simultaneously, the wake-up signal itself does not yet provide a unique time reference for reliable synchronous data aggregation and leaves sending nodes uncertain whether others are also active.

Figure 4: DiscoSync uses a balanced number of Tx and Rx slots to maximize the probability of mutual detection, enabling nodes to efficiently discover that a co-detection is occurring. If no successful reception occurs in any slot, a lone wake-up has been detected.

Discovery. Because 91 % of physical events only trigger a single sensor (Table 1), most data exchanges can be preemptively terminated if a lone wake-up is detected. Therefore, we seek to quickly assert the presence of other nodes, as subsequent protocol stages are otherwise executed in vain. Additionally, a single wake-up transmission only permits time synchronization for single-hop networks. However, multi-hop communication must be supported due to challenging environments with non-line-of-sight links as sensors are close to the ground and are distributed over a large, diverse area.

To solve both issues, we propose a novel discovery mechanism called *DiscoSync*, shown in Figure 4. Instead of transmitting only a single wake-up signal, each activated node executes an individual pattern of signal transmissions and receptions. Because nodes synchronize their pattern based on received signals from others, the wake-up signal floods the network across multiple hops. As the Tx/Rx pattern is randomized based on the node ID and differs for each node, a node has a high chance of overlapping Rx slots with a Tx slot of activated neighbors and detects their presence. Through combinatorial analysis [8], we find that 9 slots reduce the probability that a node in our case study with $M = 32$ nodes incorrectly assesses a lone wake-up to less than 0.1 %, with the failure probability decreasing even further for larger networks. In case more false negatives are tolerable, 5 slots already provide a reliability of 99.0 % and significantly increase the energy efficiency of STeC. Transmission occurs in the middle of a slot after t_{switch} , ensuring that slots sufficiently overlap despite timing uncertainty. After *DiscoSync* has finished, sensor nodes have verified the existence of other activated nodes and synchronized to their transmissions with μ s-accuracy, a prerequisite for subsequent network communication.

4.2 Ad-hoc Network Communication

With all nodes synchronized, we can start the exchange of sensor events. To efficiently disseminate data in a multi-hop network, we leverage synchronous transmissions (ST), initially introduced by

Figure 5: As nodes 5 and 7 have their most significant bit set, they simultaneously start floods in the first slot. As node 2 is aware of a higher ID, it does not initiate a flood in the second slot. However, it is assigned as the reporter by node 7 during the schedule distribution.

Glossy [20]. ST use the principle of constructive interference, where the transmission of multiple equivalent packets can improve reception quality [62], as well as the capture effect [32], which allows receiving radios to switch to the strongest signal. STeC exploits ST's purely time-based mechanism to communicate instantaneously in an ad-hoc network. Unlike routing, ST does neither gather nor require neighbor relationships apart from an upper bound on the diameter of the overall network to propagate a packet to all sensor nodes. The fact that all nodes receive the complete set of data is later on leveraged to distribute the high energy costs of reporting over long-range links and increase system lifetime by avoiding overload on a single node.

Leader election. The use of ST requires both scheduling due to its TDMA nature as well as tight time synchronization so nodes can utilize their floods efficiently. A naive synchronization approach based directly on the wake-up signal would be fragile, as nodes might synchronize to different references, thereby preventing reliable data aggregation. To deterministically provide a unique time reference, the activated nodes in STeC first elect the node with the highest ID as the leader of the ad-hoc network, as shown in Figure 5. We efficiently achieve this through a binary search [11–13] by initiating synchronous floods of the multi-hop network based on the unique node IDs. This enables us to agree on a single reference in a multi-hop network with deterministic latency, in contrast to most leader election algorithms which either only work locally or terminate with a significant and often variable delay. To swiftly determine the highest active ID, $\lceil \log(M) \rceil$ slots are utilized, where M is the number of nodes in the network. In the first slot, all nodes whose most significant bit is set initiate a flood. Other nodes whose current bit is not set relay the flood but withdraw themselves from ever starting future slots, as they know that they do not themselves possess the highest ID. With the relevant bit for initiating a flood shifting each slot towards the least significant bit, nodes start to gradually drop out until only the highest ID remains active.

Data aggregation. With a known leader, the ad-hoc network based on ST is now established. However, the data aggregation stage in Figure 3 does not follow instantly after leader election has finished. As the sensor itself requires time to sample sufficient data for the ensuing feature extraction, the schedule distribution starts with a delay τ_{sample} after the initial wake-up signal. This delay depends on the demands on the application-specific features f , which can for example include a minimum sampling time.

In the schedule distributed by the elected leader, each potential node in the network is statically assigned a data slot, resulting in M slots. An activated sensor node then floods its sensor event σ_m to all other nodes in the ad-hoc network during its corresponding slot. While this schedule might initially seem inefficient, co-detection only occurs sporadically and the actual number of activated nodes is unknown. Furthermore, a contention-based scheme could result in non-deterministic detection latencies which quickly soar for the most critical cases where many nodes co-detect a major event.

Suppressing irrelevant events. While we have previously used the correlation of sensor events, STeC also applies local knowledge of all current sensor events to finally determine whether the event should be filtered or reported to a central entity. This enables nodes to refrain from using energy-intensive long-range links until a relevant physical event which passes the filter arises.

Filtering occurs based on application-specific requirements and can include features such as the co-detection degree d , the difference in propagation delays δ_m , as well as signal-specific characteristics such as event duration, number of consecutive triggers as well as extremal and averaged data points. As it has been shown that the co-detection degree is a viable surrogate for slope instability in our case study scenario of seismic events [18], STeC by default reports all events of degree d larger or equal to the reporting threshold D .

Exploiting communication for sample termination. The quick assertion of lone wake-ups and co-detections below the reporting threshold further allows us to reduce *sensing* costs. In the majority of cases where a physical event only triggers a single sensor, our implementation of DiscoSync determines within 138 ms that no further node is activated. If a co-detection occurs, STeC can aggregate data in a network of $M = 32$ nodes within 1.18 s in our implementation and afterwards directly terminate sampling if the physical event is irrelevant. Combining these principles, we show in Section 6.2 that sensing costs can be reduced by 76 % compared to traditional systems which continue sampling futile data.

4.3 Bridging the Gap to the Data Sink

To save energy and reduce detection latency, short-range links are used for all protocol stages except for the final *reporting*. Due to the large distance between sensor nodes and the data sink, a more resource-demanding long-range link is required to directly communicate over a single hop and is therefore only used for relevant co-detections. This long-range link is similarly dependent on the occurrence of sensor events and always initiated from the sensor network, as only the data sink with its unconstrained energy resources can afford to be continuously listening for incoming traffic. The following paragraphs describe how we spread reporting costs across an unknown set of nodes and support bi-directional communication despite one-sided contact initiation by a single node.

Reporting. In traditional cluster-based networks, a cluster lead gathers the data from all associated sensor nodes and forwards their aggregate to the data sink [3]. However, this significantly increases the energy consumption of the lead and results in a reduced lifetime. By exploiting that ST inherently disseminate the complete set of data to all nodes, we can delegate this communication overhead to any node in the just formed ad-hoc network. By randomly assigning a node per report which changes for each ad-hoc network, the energy overhead is distributed and the system lifetime significantly extended. While this works straightforward in persistent networks where the set of active nodes is known, the ad-hoc network differs with each physical event and therefore does not permit assignment to a node known in advance. On the other hand, if the leader transmits the assignment after data aggregation, crucial events could be lost if this single packet does not successfully reach the reporter.

STeC solves this issue by having the node which is *closest* to an ID contained in the schedule report the physical event. To do so, the leader randomly chooses an ID out of the set of known node IDs and already includes it in the schedule even before nodes have communicated their events. This ensures that the reporter is uniquely defined within the network and only shares data if it is aware of its assignment, having received the schedule. Thereafter, each active node computes its difference to the assigned reporter ID, whereby a cyclic computation is used that wraps around from the maximal to the minimal ID. This ensures that each node has the same probability to be elected if the reporter ID is chosen uniformly at random. A node then compares its own difference to all other active nodes and determines whether it is closest. This scheme guarantees that at least one node will identify as reporter even if not all packets are successfully received at each node, as the closest ID will never defer from reporting and nodes only participate if they successfully received the schedule containing the assignment.

Reaching sensor nodes. While long-range communication is only initiated by the sensor network in STeC, WSNs often also require bi-directional communication from the data sink to deliver information to the sensor network. The ability to adjust protocol parameters is indispensable for real-world WSN deployments [5], as optimal settings are hard to estimate a-priori and may change over time. Duty-cycled networks can schedule periodic communication to accommodate for these needs, but our purely event-driven scheme requires a more reactive approach. We utilize that acknowledgments are essential for LP-WANs to ensure that the reported data has been successfully received by the data sink, as the reporter must be able to detect the lack of a response from the data sink and retransmit the packet. STeC leverages this to send commands to sensor nodes by directly embedding them into the acknowledgment packet. In addition, the data sink also includes the current global time so nodes can synchronize their local clocks with each reported event.

Because only one node communicates with the data sink to reduce the energy consumption, the remaining ad-hoc network must be separately informed. In the last protocol stage, the *acknowledgment is distributed* as shown in Figure 3. All activated nodes wake up with a delay τ_{ack} after the data aggregation has terminated to receive the response flooded by the reporter. A contention slot permits nodes to exchange final information before the ad-hoc network disbands and each sensor node returns to its low-power mode.

Figure 6: The sensor node consists of a sensor (left), an application processor (middle) and a communication processor (right).

5 IMPLEMENTATION

To test STeC in realistic environments for a case study of natural hazard warning, we employ a wireless sensor platform consisting of a seismic sensor with integrated trigger and data acquisition front-end, a processor for sensor data and event processing as well as a dedicated processor to control radio communication (see Figure 6).

5.1 Prototype Hardware

The seismic sensor [36] consists of an ION SM-6 14 Hz Omni-tilt Geophone [26] which is connected both to MAX9019 comparators for dual-sided triggering as well as a MAX11214 ADC to convert the analog signal to digital samples at up to 1000 Hz. An STMicroelectronics STM32L496VG microcontroller unit (MCU) containing an ARM Cortex-M4F as well as 1 MB of Flash and 320 KB RAM is used as an application processor to interface with the trigger and perform the signal characterization. While the complete signal is logged onto an SD card, the extracted features are used to generate sensor event packets for a communication processor. To modularize and reduce system complexity, we follow the dual-processor paradigm [7, 51] and implement STeC separately on an STMicroelectronics STM32L433CC with 256 KB of Flash and 64 KB RAM. This MCU controls the heart of the wireless sensor, a Semtech SX1262 868 MHz LoRa transceiver [43]. Supporting both GFSK modulation for short-range links (< 1 km) as well as LoRa for long-range links and a high Tx power of up to +22 dBm, this radio provides the opportunity for both efficient local communication as well as long-range connectivity to a data sink. The complete sensor node fits into a water- and shockproof aluminium enclosure measuring $160 \times 100 \times 81$ mm and weighing 1552 g with a 13 Ah battery.

Research artifacts. We provide all our hard- and software products for STeC as open-source, including a custom discrete event simulator written in Python and all event traces used in the evaluation as introduced in Section 6.1. Access to our real-time network monitoring tools as well as all gathered sensor and communication data is publicly available at <https://gitlab.ethz.ch/tec/public/stec> [8].

5.2 Making STeC Work in Practice

Ensuring precise timing information. To report gathered sensor events to the data sink, data from all nodes is combined into a single packet. However, timestamps based on the local time reference of nodes are subject to individual clock drifts of up to 20 ppm and hence 1.7 s/d and strongly depend on environmental conditions such as temperature [17] as well as manufacturing tolerances [42]. In contrast to duty-cycled networks, which can synchronize clocks periodically, STeC remains inactive for prolonged periods of time if

events are rare. Therefore, it is inconclusive to compare local trigger timestamps as initially measured by each node. To avoid this, sensor nodes compute the time *difference* between their sensor trigger and the start of the data aggregation, as this is the first network-wide synchronized point in time. This extension of a concept introduced by the ETA algorithm [30] allows us to obtain relative propagation delays with sub-ms accuracy even if nodes have not been activated for days and have experienced significant clock drift since their last event. To still obtain absolute timestamps as a final data product, timestamps are then adjusted at the data sink, which has the ability to synchronize itself to global time through its Internet connection.

Supporting different propagation delays. While systems detecting events with a high propagation velocity such as light can benefit from a short staggered wake-up stage, some event types might incur longer propagation delays. To also support physical phenomena with different characteristics such as smoke spread or motion, we can leverage the available radio capabilities which provide carrier activity detection (CAD) instead of constant listening during the staggered wake-up stage for up to τ_{prop} . This specialized radio mode permits receivers to periodically poll whether a transmission is ongoing and avoid idle listening in-between, thereby leveraging the long preambles of modulations supporting long-range communication. We have seen in experiments that this technique would allow us to reduce listening costs by 75.2 %.

Requesting additional slots through contention. As sensor nodes only have a single opportunity to disseminate their event data, they are unable to communicate additional data after the data aggregation has started. As the latency of this stage increases with the network size and the ensuing reporting might take several seconds depending on the chosen modulation, nodes are temporally incapable of reacting to new sensor events. While we show in Section 6 that this only results in a minor detection loss of 8.8 % of physical events that should be reported, STeC caters to this problem through its optional contention slot. By allowing nodes that have received sensor events after their scheduled data slot to inform others, the ad-hoc network can be kept alive and additional data aggregation can be scheduled. While this does not involve re-synchronization based on the newly gathered sensor triggers, we thereby exploit the fact that subsequent physical events of event bursts often only activate a similar subset of nodes as is already part of the ad-hoc network. This contention slot essentially permits nodes to periodically schedule slots during bursts of activity. In addition, it can be used to retransmit and re-evaluate if a node detects that its packet was lost during the data aggregation stage.

6 EVALUATION

To demonstrate STeC's efficacy in detecting and reporting rare events, we first perform an extensive analysis of the communication scheme based on real-world traces from our deployment. Through simulation, we compare our method to both a standard single-hop protocol as well as a representative of state-of-the-art schedule-based multi-hop protocols for event-based WSNs w.r.t. i) the *energy per event* and ii) *detection latency*. The simulation is validated using synthetic traces on a wireless testbed in order to expose different detailed aspects of our implementation. Subsequently, we present results from our deployment case study where seismic events are

Figure 7: While some nodes gather up to 6351 sensor events over a period of 17 months on a rock glacier in alpine environments, others are primarily inactive and experience less than 100 triggers.

detected in an alpine natural hazard detection application over the course of 7 months. Since validation against ground truth in our case study deployment is difficult, we have implemented a shorter 15-week test deployment in an urban setting where ground truth data has been captured in parallel.

6.1 Experimental Setup

Trace-based simulation. In order to analyze and compare protocols that fit our application scenario of rare event detection, we use a custom trace-based discrete event simulation [8]. This setup enables us to evaluate months of protocol execution with various configurations. To correctly reproduce communication characteristics in simulation, we gather detailed energy and timing measurements of our hard- and software implementation (Section 5) using the FlockLab testbed [53]. While our simulation supports low-power mode costs, we exclude them for the rest of this evaluation as they equally affect all protocols. At $1.7 \mu\text{A}$, the low-power current draw of our implementation is comparable to the $1.4 \mu\text{A}$ that STeC uses on average with default settings. Our input trace consists of 80 675 physical events with a total of 92 803 sensor events over a period of 511 days from a deployment of $M = 32$ seismic sensors in the alpine setting presented in Section 3.3. This data set contains both days with and without rain to represent a realistic environment, as raindrops can trigger uncorrelated seismic sensors events. As shown in Figure 7, the number of events varies significantly between nodes and incentivizes a communication scheme which only requires the participation of active sensors to save energy.

Base lines. ALOHA [1] represents an event-based protocol that does not rely on the formation of a local network and serves as a simple reference for direct one-hop communication with a data sink. As it cannot filter events locally, nodes report each sensor event directly over the long-range link. To avoid packet collisions, we grant it the ability to perfectly detect ongoing transmissions and delay reporting until the channel is clear. To showcase how schedule-based schemes can use a local network for data aggregation, we choose eLWB [49]. This protocol is designed for event-based communication via a persistent network and relies on periodic schedules for nodes to request slots and exchange data. Similar to STeC, eLWB relies on synchronous transmissions to flood packets but requires the entire network to be activated with a default round period of 15 s, whose influence we investigate later on, to remain synchronized and ensure adequate detection latencies. To simulate long-range reporting, we extend eLWB with STeC’s reporter assignment scheme.

Figure 8: While eLWB is an energy-efficient synchronous protocol, the rare occurrence of seismic events results in many unused rounds and a high energy consumption (notice the logarithmic scale). ALOHA cannot locally filter and must report each event, which results in high detection latencies during bursts of activity. Node 24 and 25 are not part of any co-detection and correctly filter their events locally with STeC and eLWB, but cannot for ALOHA.

Note that we compare higher layer protocols and do not include wake-up radio schemes to avoid restrictions on range and hardware.

STeC parameters. As for the other protocols, we simulate STeC based on a real-world deployment of $M = 32$ sensor nodes and extract its characteristics from our implementation. Short-range links employ GFSK at 250 kbps, while long-range links use LoRa with spreading factor 11 and a bandwidth of 125 kHz, with both links transmitting at +14 dBm for reliable communication despite non-line-of-sight. We use a delay $\tau_{prop} = 100$ ms according to our scenario in Section 3.3 and 9 DiscoSync slots to detect other nodes with a probability exceeding 99.9% and synchronize within 138 ms. A delay $\tau_{sample} = 100$ ms ensures that key signal features such as the peak intensity can be obtained. Thereafter, mirroring our implementation, we flood 65-byte sensor events using ST with three transmissions for robustness and compress each to 12 bytes for reporting after nodes finished data aggregation within 1.18 s.

Figure 9: The reporting threshold D primarily influences energy consumption for $D \leq 4$, as the long-range communication thereafter does not significantly impact the overall energy consumption anymore. However, the worst-case nodes in the network can still suffer from increased detection latencies with higher D .

6.2 Simulation-based Comparison

The main metrics of comparison between the protocols and their variants are the average energy spent for the communication of each observed sensor event and the detection latency defined as the time span between the first trigger in a set of co-occurring events and the time when the co-detection is reported to the data sink.

Default behavior. To see how the protocols fare, we simulate them in Figure 8 using default parameters as described above and a reporting threshold $D = 2$, i.e., each physical event detected by two or more sensors should be reported. We find that STeC enables nodes to spend 52 mJ for the communication of a sensed event, which is significantly less than the median communication costs of 308 mJ with ALOHA or 3087 mJ with eLWB by a factor of $5.83 \times$ and $58.4 \times$, respectively. The network-wide energy consumption throughout the deployment amounts to 5.04 kJ for STeC, compared to 28.10 kJ for ALOHA and 375.11 kJ for eLWB. In addition to event-driven local processing, STeC achieves its high energy efficiency by reducing costs by 37.9 % through using only 4.76 mJ on lone wake-ups with DiscoSync and terminating early. For the detection of reported events, eLWB takes a median 13.49 s through synchronous communication. While purely event-driven, ALOHA frequently suffers from strong contention and waits for a median 25.39 s until it can successfully report. STeC combines event-based communication with the efficiency of synchronous exchanges to achieve a low and highly deterministic median detection latency of 3.38 s. Through

Figure 10: As expected, STeC manages to reliably report the most important events, as they are sufficiently rare for the network to finish reporting all previous events. On the other hand, ALOHA drastically over-reports as it cannot filter any events locally.

local data aggregation, STeC can filter 79.1 % of events and avoid reporting them over the resource-demanding long-range link.

Parameter tuning. The reporting threshold D is the primary tuning knob of STeC, as it permits adjusting the severity of events which should be reported independently of event characteristics (affecting τ_{prop}) or data requirements (affecting τ_{sample}). With a high threshold, only a major event reaching many nodes due to its large magnitude is reported and others can be filtered. Therefore, we compare the protocol behavior depending on D in Figure 9. As eLWB spends an average 4016 mJ per sensed event for periodic scheduling overhead during the 511 days of the simulated deployment, the difference in reporting costs due to filtering is minimal. Simulations with increased round periods show that even with communication occurring every 5 min, this overhead of 365 mJ still exceeds ALOHA's energy costs. ALOHA is unable to leverage a raised reporting threshold, as processing occurs after reporting due to its lack of local communication. On the other hand, STeC can exploit thresholds and filter co-detections $d < D$, reducing communication costs from an average 54 mJ for $D = 2$ to 17 mJ for $D = 4$. However, as each report contains more data, the long-range link delay increases the average detection latency from 3.36 s to 4.34 s.

Next, we investigate how the reporting threshold influences the number of reported events in Figure 10. We find that STeC correctly reports 91.2 % of all co-detections with the default settings of $D = 2$ and spreading factor 11. In case only larger events are of interest, $D = 7$ increases reliability to 97.3 %. The considerable amount of missed co-detections is due to the long reporting duration with a spreading factor of 11, during which the radio cannot be used for synchronization to the next sensor trigger if event intervals

Figure 11: Even with consistent co-detections of 5 nodes, STeC outperforms all schedule-based variants if events occur rarer than every 7.5 h. For lone wake-ups, this already occurs after 46 s.

are small; apart from collisions, the simulated links themselves are assumed to be perfect. By requesting additional slots as described in Section 5.2, these missed sensor events could still be reported if desired. The use of a lower spreading factor 7 further mitigates this issue for deployments with frequent event bursts, boosting reliability to 99.89 % for $D = 2$ and 100 % for $D > 4$. However, this requires the data sink to be positioned closer to the sensor network to ensure that it is still within reach of the lower spreading factor. In our deployment, discussed in Section 6.5, spreading factors below 11 were inadequate for highly reliable communication to all nodes. On the other hand, ALOHA depletes its battery by sending all events and thereby reports more than 116 $\times$ the relevant packets for $D > 6$.

Event-driven communication exploits rarity. To observe how the sparsity of events affects energy consumption, we search the event interval beyond which STeC outperforms schedule-based protocols. For this, we compare it against eLWB with periods of 15 s (default), 1 min, 5 min, and 15 min in Figure 11 with a constant reporting threshold of $D = 2$. We run two synthetic traces of 500 physical events each with either only 1 sensor event per physical event or a high co-detection degree at 5 sensor events per physical event (occurring fewer than 1 % in our case study). Each physical event is separated by the event interval $\pm 25\%$ to avoid artifacts due to matching schedule periods. Sensor events have a uniformly distributed propagation delay $\delta_m = 0 - 100$ ms. While eLWB variants with high scheduling frequencies quickly lose their efficiency, the energy consumption of STeC is independent of the event interval. We find that even compared to an impractically long period of 15 min, STeC outperforms schedule-based protocols in energy efficiency while reporting events with a drastically shorter latency, especially if, as in our case study (Table 1), most physical events are only observed by a single sensor and co-detections are rare.

Sample termination. In contrast to other protocols, STeC can quickly determine whether an event is relevant and terminate sampling if the number of active nodes is below the reporting threshold. This enables us to reduce sampling costs by an average 76.4 % (Figure 12). Because sensing costs are significantly higher than communication costs of our event-based protocol for our implementation, this results in an effective median lifetime improvement of 3.25 $\times$.

Figure 12: The termination of irrelevant events allows sensors to eliminate excessive sampling and reduce sensing costs by an average 76.4 %, with some sensors saving as much as 95.6 %.

Figure 13: Comparisons between our simulation and testbed experiments demonstrate that the simulator correctly predicts both energy and latency metrics. However, occasional packet loss leads to a slightly increased energy consumption. STeC's reporter assignment successfully spreads costs across nodes in larger networks.

6.3 Testbed Validation

To validate our simulation results, we use synthetic traces, which we run both through our simulator as well as on the FlockLab testbed [53]. We simulate 50 physical events with a spreading factor of 11 and an ad-hoc network of 2 – 9 nodes, where each node in the network receives one sensor trigger per physical event. Additionally, we set $\tau_{sample} = 1000$ ms to represent the impact of longer sampling. As demonstrated in Section 6.2, the event interval has no influence on STeC and is hence set to 20 s for all events to reduce testing time. To emulate sensor events, we use the GPIO actuation feature of FlockLab, which permits us to individually trigger sensor nodes at sub-ms granularity while running the same software as our deployment implementation used in Section 6.4 and Section 6.5.

Network size. We find that our simulator accurately predicts experimental results of both energy per event and detection latency for various network sizes (Figure 13). As expected based on our simulations, we observe that an increased network size can be effectively used by our reporter assignment scheme, as presented in Section 4.3, to distribute reporting across a larger set of nodes. This enables us to decrease average energy costs, a dynamic which the testbed runs confirm. Notice that because each synthetic event needs to be reported, protocol execution cannot be terminated early,

Figure 14: In our test deployment, nodes correctly report most co-detections (Report) compared to ground truth based on logged events (GT), which our simulation (Sim) reliably predicts.

resulting in a higher average energy consumption compared to the real-world traces. Out of 2200 sensor events, STeC successfully reports 99.22 % to the data sink in our experiments. Due to the indoor location of the testbed with non-line-of-sight, sensor nodes occasionally experience packet loss and are forced to retransmit, resulting in a slightly higher energy consumption than expected.

Event accuracy. As the triggers are known, we further investigate the accuracy of reported event timestamps. We find that STeC obtains absolute timestamps with a median accuracy of 185 μ s and a maximum of 493 μ s for the 2200 sensor events. For example, this precision would enable us to determine distances to a seismic event source with sub-meter accuracy and potentially triangulate it.

6.4 Test Deployment

In a first phase, we deploy 9 nodes as described in Section 5.1 at a local urban location which is easy to reach and permits us to retrieve ground truth data by accessing the logs on the SD card of the nodes. We spread 6 of them across the rooftop of an office building, while three are situated within range on a lower floor to be unaffected by precipitation. Due to ongoing construction work, the sensor nodes regularly experience seismic triggers. This allows us to verify that STeC can correctly detect and aggregate physical events in realistic settings. For comparison, ground truth is computed with Algorithm 1 on the gathered logged sensor events. Figure 14 shows that the sensors receive up to 43 825 triggers per node over a 15-week period and a total of 19 334 co-detections. We observe that STeC correctly represents the dynamics compared to the ground truth and reliably reports major events to the data sink. Using the logged sensor events as an input trace for our simulator, we find that STeC successfully reports 75.2 % of events despite a noisy environment, including rain on 40 % of days, which causes frequent uncorrelated sensor triggers. During rain, STeC can misinterpret triggers by raindrops at multiple sensors for the co-detection of a single physical event arriving at an event interval that is too short for events to be constantly reported. Physically protecting the sensor against precipitation could mitigate this issue. As only 7.62 % of events must be reported to the data sink, STeC performs well at an average energy cost of 21 mJ. In comparison, ALOHA would spend an average 313 mJ to report all events.

Figure 15: Increased detection rates are frequently correlated with precipitation events. The increased availability of liquid water strongly affects downslope kinematics of active rock glaciers [18].

6.5 Real-world Deployment

To test STeC under real-world conditions, we install 9 sensors for 7 months in mountainous terrain at 2500 m.a.s.l.. The sensors are situated in a cluster at the tongue of a rock glacier where material is continuously breaking off due to increased slope movement. Therefore, the data sink is located on the other side of the valley multiple kilometers away, where the necessary infrastructure can be supported. During our deployment, we have gathered 566 sensor events resulting in 275 co-detections, with 8 physical events being detected by 3 up to 6 nodes (see Figure 15). As the main ground motion dynamics are happening in the summer months and not in winter, the low detection numbers meet expectations. However, in the last deployment weeks, STeC has detected increasing event activity, e.g., following heavy rain on March 11, 2021 which resulted in 31 co-detections reported on March 13 and 14 on March 14.

7 CONCLUSION

With STeC, we develop a novel communication scheme that exploits the spatial and temporal correlation of sensed signals to effectively construct and control an ad-hoc communication network. This is the first time that a network is structured from the ground up by events as they appear. As such, this approach alleviates the elementary conflict of synchronous systems between optimizing either for duty cycle or latency. STeC achieves fast and energy-efficient bootstrapping of a connected network of nodes, minimizing overhead and idle listening times. We show that this technique permits a drastic reduction in energy costs and detection latency, especially effective for applications where events are rare. Furthermore, we demonstrate that further optimization techniques, e.g., local data aggregation and filtering of events as well as long-range reporting to a data sink, can be integrated without affecting the fundamental event-driven wake-up based on sensor events. Our implementation shows that STeC works well and reliably in practice in both a test deployment as well as a real-world case study.

ACKNOWLEDGMENTS

This research was supported by the Swiss National Science Foundation under NCCR Automation, grant agreement 51NF40_180545, as well as the Swiss Federal Office for the Environment.

REFERENCES

- [1] Norman Abramson. 1970. The ALOHA system: Another Alternative for Computer Communications. In *Proceedings of the November 17-19, 1970, Fall Joint Computer Conference* (Houston, TX, USA) (AFIPS '70). Association for Computing Machinery, New York, NY, USA, 281–285. <https://doi.org/10.1145/1478462.1478502>
- [2] Mikhail Afanasov, Naveed Anwar Bhatti, Dennis Campagna, Giacomo Caslini, Fabio Massimo Centonze, Koustabh Dolui, Andrea Maioli, Erica Barone, Muhammad Hamad Alizai, Junaid Haroon Siddiqui, and Luca Mottola. 2020. Battery-Less Zero-Maintenance Embedded Sensing at the Mithraeum of Circus Maximus. In *Proceedings of the 18th Conference on Embedded Networked Sensor Systems* (Virtual Event, Japan) (SenSys '20). Association for Computing Machinery, New York, NY, USA, 368–381. <https://doi.org/10.1145/3384419.3430722>
- [3] Mohammad Mehdi Afsar and Mohammad Tayarani-N. 2014. Clustering in sensor networks: A literature survey. *Journal of Network and Computer Applications* 46 (2014), 198–226. <https://doi.org/10.1016/j.jnca.2014.09.005>
- [4] Chan-Sol Ahn, Boo-Hyoung Bang, Min-Woo Kim, Scott James, Alexander Yarin, and Sam Yoon. 2019. Theoretical, numerical, and experimental investigation of smoke dynamics in high-rise buildings. *International Journal of Heat and Mass Transfer* 135 (2019), 604–613. <https://doi.org/10.1016/j.ijheatmasstransfer.2018.12.093>
- [5] Guillermo Barrenetxea, François Ingelrest, Gunnar Schaefer, and Martin Vetterli. 2008. The Hitchhiker's Guide to Successful Wireless Sensor Network Deployments. In *Proceedings of the 6th ACM Conference on Embedded Network Sensor Systems* (Raleigh, NC, USA) (SenSys '08). Association for Computing Machinery, New York, NY, USA, 43–56. <https://doi.org/10.1145/1460412.1460418>
- [6] Stefano Basagni, Chiara Petrioli, and Dora Spenza. 2016. CTP-WUR: The collection tree protocol in wake-up radio WSNs for critical applications. In *2016 International Conference on Computing, Networking and Communications*. IEEE, 1–6. <https://doi.org/10.1109/ICCNC.2016.7440687>
- [7] Jan Beutel, Roman Trüb, Reto Da Forno, Markus Wegmann, Tonio Gsell, Romain Jacob, Michael Keller, Felix Sutton, and Lothar Thiele. 2019. The dual processor platform architecture: Demo abstract. In *Proceedings of the 18th ACM/IEEE International Conference on Information Processing in Sensor Networks* (Montreal, QC, Canada) (IPSN '19). Association for Computing Machinery, New York, NY, USA, 335–336. <https://doi.org/10.1145/3302506.3312481>
- [8] Andreas Biri, Reto Da Forno, Tobias Gatschet, and Tonio Gsell. Accessed: 2021-09-29. Software repository for STeC - GitLab. <https://gitlab.ethz.ch/tec/public/stec>
- [9] Nicolas Burri, Pascal von Rickenbach, and Roger Wattenhofer. 2007. Dozer: Ultra-Low Power Data Gathering in Sensor Networks. In *Proceedings of the 6th IEEE International Conference on Information Processing in Sensor Networks* (Cambridge, Massachusetts, USA) (IPSN '07). Association for Computing Machinery, New York, NY, USA, 450–459. <https://doi.org/10.1145/1236360.1236417>
- [10] Li Chen, Stephen Cool, He Ba, Wendi Heinzelman, Ilker Demirkol, Ufuk Muncuk, Kaushik Chowdhury, and Stefano Basagni. 2013. Range extension of passive wake-up radio systems through energy harvesting. In *2013 IEEE International Conference on Communications*. IEEE, 1549–1554. <https://doi.org/10.1109/ICC.2013.6654734>
- [11] Bogdan Chlebus, Dariusz Kowalski, and Andrzej Pelc. 2012. Electing a Leader in Multi-hop Radio Networks. In *International Conference On Principles Of Distributed Systems*. Springer, Berlin, Heidelberg, 106–120. https://doi.org/10.1007/978-3-642-35476-2_8
- [12] Marek Chrobak, Leszek Gasieniec, and Wojciech Rytter. 2002. Fast broadcasting and gossiping in radio networks. *Journal of Algorithms* 43, 2 (2002), 177–189. [https://doi.org/10.1016/S0196-6774\(02\)00004-4](https://doi.org/10.1016/S0196-6774(02)00004-4)
- [13] Artur Czumaj and Peter Davies. 2019. Communicating with beeps. *J. Parallel and Distrib. Comput.* 130 (2019), 98–109. <https://doi.org/10.1016/j.jpdc.2019.03.020>
- [14] Michael Dietze, James Losee, Lina Polvi, and Daniel Palm. 2020. A seismic monitoring approach to detect and quantify river sediment mobilization by steelhead redd-building activity. *Earth Surface Processes and Landforms* 45, 12 (2020), 2840–2849. <https://doi.org/10.1002/esp.4933>
- [15] Prabal Dutta, Mike Grimmer, Anish Arora, Steven Bibyk, and David Culler. 2005. Design of a wireless sensor network platform for detecting rare, random, and ephemeral events. In *4th International Symposium on Information Processing in Sensor Networks* (Piscataway, NJ, USA) (IPSN '05). IEEE, 497–502. <https://doi.org/10.1109/IPSN.2005.1440983>
- [16] Darwin V Ellis and Julian M Singer. 2007. Acoustic Waves in Porous Rocks and Boreholes. In *Well Logging for Earth Scientists*. Springer, 499–530. https://doi.org/10.1007/978-1-4020-4602-5_18
- [17] Atis Elsts, Xenofon Fafoutis, Simon Duquennoy, George Oikonomou, Robert Piechocki, and Ian Craddock. 2018. Temperature-Resilient Time Synchronization for the Internet of Things. *IEEE Transactions on Industrial Informatics* 14, 5 (2018), 2241–2250. <https://doi.org/10.1109/TII.2017.2778746>
- [18] Jérôme Faillietaz, Martin Funk, Jan Beutel, and Andreas Vieli. 2019. Towards early warning of gravitational slope failure with co-detection of microseismic activity: the case of an active rock glacier. *Natural Hazards and Earth System Sciences* 19, 7 (2019), 1399–1413. <https://doi.org/10.5194/nhess-19-1399-2019>
- [19] Federico Ferrari, Marco Zimmerling, Luca Mottola, and Lothar Thiele. 2012. Low-Power Wireless Bus. In *Proceedings of the 10th ACM Conference on Embedded Network Sensor Systems* (Toronto, Ontario, Canada) (SenSys '12). Association for Computing Machinery, New York, NY, USA, 1–14. <https://doi.org/10.1145/2426656.2426658>
- [20] Federico Ferrari, Marco Zimmerling, Lothar Thiele, and Olga Saukh. 2011. Efficient network flooding and time synchronization with Glossy. In *Proceedings of the 10th ACM/IEEE International Conference on Information Processing in Sensor Networks* (Chicago, IL, USA) (IPSN '11). Association for Computing Machinery, New York, NY, USA, 73–84. <https://ieeexplore.ieee.org/abstract/document/5779066>
- [21] Akshay Gadre, Fan Yi, Anthony Rowe, Bob Iannucci, and Swarun Kumar. 2020. Quick (and Dirty) Aggregate Queries on Low-Power WSNs. In *Proceedings of the 19th ACM/IEEE International Conference on Information Processing in Sensor Networks* (Sydney, NSW, Australia) (IPSN '20). Association for Computing Machinery, New York, NY, USA, 277–288. <https://doi.org/10.1109/IPSN48719.2020.00031>
- [22] Antoine Guillemot, Laurent Baillet, Stéphane Garambois, Xavier Bodin, Agnès Helmstetter, Raphaël Mayoraz, and Eric Larose. 2021. Modal sensitivity of rock glaciers to elastic changes from spectral seismic noise monitoring and modeling. *The Cryosphere* 15, 2 (2021), 501–529. <https://doi.org/10.5194/tc-15-501-2021>
- [23] Antoine Guillemot, Agnès Helmstetter, Eric Larose, Laurent Baillet, Stéphane Garambois, Raphaël Mayoraz, and Reynald Delaloye. 2020. Seismic monitoring in the Gugla rock glacier (Switzerland): ambient noise correlation, microseismicity and modelling. *Geophysical Journal International* 221, 3 (March 2020), 1719–1735. <https://doi.org/10.1093/gji/ggaa097>
- [24] David Harrison, Winston Seah, and Ramesh Rayudu. 2016. Rare Event Detection and Propagation in Wireless Sensor Networks. *Comput. Surveys* 48, 4, Article 58 (March 2016), 22 pages. <https://doi.org/10.1145/2885508>
- [25] François Ingelrest, Guillermo Barrenetxea, Gunnar Schaefer, Martin Vetterli, Olivier Couch, and Marc Parlange. 2010. SensorScope: Application-Specific Sensor Network for Environmental Monitoring. *ACM Transactions on Sensor Networks* 6, 2, Article 17 (March 2010), 32 pages. <https://doi.org/10.1145/1689239.1689247>
- [26] ION Geophysical Corporation. Accessed: 2021-05-17. "SM-6 - Omni-directional geophones". <https://www.iongeo.com/technologies/hardware/seismic-equipment/precision-geophones/>
- [27] Timofei Istomin, Amy L. Murphy, Gian Pietro Picco, and Usman Raza. 2016. Data Prediction + Synchronous Transmissions = Ultra-Low Power Wireless Sensor Networks. In *Proceedings of the 14th ACM Conference on Embedded Network Sensor Systems* (Stanford, CA, USA) (SenSys '16). Association for Computing Machinery, New York, NY, USA, 83–95. <https://doi.org/10.1145/2994551.2994558>
- [28] Sasha Jevtic, Mathew Kotowsky, Robert Dick, Peter Dinda, and Charles Dowding. 2007. Lucid Dreaming: Reliable Analog Event Detection for Energy-Constrained Applications. In *Proceedings of the 6th IEEE International Conference on Information Processing in Sensor Networks* (Cambridge, Massachusetts, USA) (IPSN '07). Association for Computing Machinery, New York, NY, USA, 350–359. <https://doi.org/10.1145/1236360.1236405>
- [29] Myung Bae Kim, Yong Shik Han, and Myoung O. Yoon. 1998. Laser-assisted visualization and measurement of corridor smoke spread. *Fire Safety Journal* 31, 3 (1998), 239–251. [https://doi.org/10.1016/S0379-7112\(98\)00009-5](https://doi.org/10.1016/S0379-7112(98)00009-5)
- [30] Branislav Kusy, Prabal Dutta, Philip Levis, Miklos Maroti, Akos Ledeczi, and David Culler. 2006. Elapsed time on arrival: a simple and versatile primitive for canonical time synchronisation services. *International Journal of Ad Hoc and Ubiquitous Computing* 1, 4 (2006), 239–251. <https://doi.org/10.1504/IJAHUC.2006.010505>
- [31] Akos Ledeczi, Thomas Hay, Péter Volgyesi, D. Robert Hay, András Nadas, and Subash Jayaraman. 2009. Wireless Acoustic Emission Sensor Network for Structural Monitoring. *IEEE Sensors Journal* 9, 11 (2009), 1370–1377. <https://doi.org/10.1109/JSEN.2009.2019315>
- [32] Krijn Leentvaar and Jan Flint. 1976. The capture effect in FM receivers. *IEEE Transactions on Communications* 24, 5 (1976), 531–539. <https://doi.org/10.1109/TCOM.1976.1093327>
- [33] Yanjun Li, Zhi Wang, and Yeqiong Song. 2006. Wireless Sensor Network Design for Wildfire Monitoring. In *6th World Congress on Intelligent Control and Automation*, Vol. 1. IEEE, 109–113. <https://doi.org/10.1109/WCICA.2006.1712372>
- [34] Mateusz Malinowski, Matthew Moskwa, Mark Feldmeier, Mathew Laibowitz, and Joseph Paradiso. 2007. CargoNet: A Low-Cost Micropower Sensor Node Exploiting Quasi-Passive Wakeup for Adaptive Asynchronous Monitoring of Exceptional Events. In *Proceedings of the 5th International Conference on Embedded Networked Sensor Systems* (Sydney, Australia) (SenSys '07). Association for Computing Machinery, New York, NY, USA, 145–159. <https://doi.org/10.1145/1322263.1322278>
- [35] Zaher Merhi, Mohamed Elgamel, and Magdy Bayoumi. 2009. EB-MAC: An event based medium access control for wireless sensor networks. In *IEEE International Conference on Pervasive Computing and Communications*. IEEE, 1–6. <https://doi.org/10.1109/PERCOM.2009.4912863>
- [36] Matthias Meyer, Timo Farei-Campagna, Akos Pasztor, Reto Da Forno, Tonio Gsell, Jérôme Faillietaz, Andreas Vieli, Samuel Weber, Jan Beutel, and Lothar Thiele. 2019. Event-triggered Natural Hazard Monitoring with Convolutional Neural Networks on the Edge. In *Proceedings of the 18th ACM/IEEE International Conference on Information Processing in Sensor Networks* (Montreal, QC, Canada) (IPSN '19). Association for Computing Machinery, New York, NY, USA, 73–84. <https://doi.org/10.1145/3302506.3310390>

- [37] Razvan Musaloiu-E., Chieh-Jan Liang, and Andreas Terzis. 2008. Koala: Ultra-Low Power Data Retrieval in Wireless Sensor Networks. In *Proceedings of the 7th IEEE International Conference on Information Processing in Sensor Networks (IPSN '08)*. IEEE, 421–432. <https://doi.org/10.1109/IPSN.2008.10>
- [38] Rajeev Piyare, Timofei Istomin, and Amy L. Murphy. 2017. WaCo: A Wake-Up Radio COOJA Extension for Simulating Ultra Low Power Radios. In *Proceedings of the 2017 International Conference on Embedded Wireless Systems and Networks (Uppsala, Sweden) (EWSN '17)*. Junction Publishing, USA, 48–53. <https://dl.acm.org/doi/abs/10.5555/3108009.3108016>
- [39] Rajeev Piyare, Amy L. Murphy, Csaba Kiraly, Pietro Tosato, and Davide Brunelli. 2017. Ultra Low Power Wake-Up Radios: A Hardware and Networking Survey. *IEEE Communications Surveys and Tutorials* 19, 4 (2017), 2117–2157. <https://doi.org/10.1109/COMST.2017.2728092>
- [40] Rajeev Piyare, Amy L. Murphy, Michele Magno, and Luca Benini. 2018. On-Demand LoRa: Asynchronous TDMA for Energy Efficient and Low Latency Communication in IoT. *Sensors* 18, 11 (2018), 3718. <https://doi.org/10.3390/s18113718>
- [41] Joseph Polastre, Jason Hill, and David Culler. 2004. Versatile Low Power Media Access for Wireless Sensor Networks. In *Proceedings of the 2nd International Conference on Embedded Networked Sensor Systems (Baltimore, MD, USA) (SenSys '04)*. Association for Computing Machinery, New York, NY, USA, 95–107. <https://doi.org/10.1145/1031495.1031508>
- [42] Thomas Schmid, Zainul Charbiwala, Jonathan Friedman, Young Cho, and Mani Srivastava. 2008. Exploiting Manufacturing Variations for Compensating Environment-Induced Clock Drift in Time Synchronization. In *Proceedings of the 2008 ACM SIGMETRICS International Conference on Measurement and Modeling of Computer Systems (Annapolis, MD, USA) (SIGMETRICS '08)*. Association for Computing Machinery, New York, NY, USA, 97–108. <https://doi.org/10.1145/1375457.1375469>
- [43] Semtech. Accessed: 2021-05-13. "Semtech SX1262 - LoRa Core Long Range Low Power LoRa Transceiver". <https://www.semtech.com/products/wireless-rf/loracore/sx1262>
- [44] Gyula Simon, Miklós Maróti, Ákos Lédeczi, György Balogh, Branislav Kusy, András Nádas, Gábor Pap, János Sallai, and Ken Frampton. 2004. Sensor Network-Based Countersniper System. In *Proceedings of the 2nd International Conference on Embedded Networked Sensor Systems (Baltimore, MD, USA) (SenSys '04)*. Association for Computing Machinery, New York, NY, USA, 1–12. <https://doi.org/10.1145/1031495.1031497>
- [45] Lanny Sitanayah, Cormac Sreenan, and Kenneth Brown. 2010. ER-MAC: A Hybrid MAC Protocol for Emergency Response Wireless Sensor Networks. In *4th International Conference on Sensor Technologies and Applications*. IEEE, 244–249. <https://doi.org/10.1109/SENSORCOMM.2010.45>
- [46] Dora Spenza, Michele Magno, Stefano Basagni, Luca Benini, Mario Paoli, and Chiara Petrioli. 2015. Beyond duty cycling: Wake-up radio with selective awakenings for long-lived wireless sensing systems. In *IEEE Conference on Computer Communications*. IEEE, 522–530. <https://doi.org/10.1109/INFOCOM.2015.7218419>
- [47] Yanjun Sun, Shu Du, Omer Gurewitz, and David Johnson. 2008. DW-MAC: A Low Latency, Energy Efficient Demand-Wakeup MAC Protocol for Wireless Sensor Networks. In *Proceedings of the 9th ACM International Symposium on Mobile Ad Hoc Networking and Computing (Hong Kong, Hong Kong, China) (MobiHoc '08)*. Association for Computing Machinery, New York, NY, USA, 53–62. <https://doi.org/10.1145/1374618.1374627>
- [48] Felix Sutton, Bernhard Buchli, Jan Beutel, and Lothar Thiele. 2015. Zippy: On-Demand Network Flooding. In *Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems (Seoul, South Korea) (SenSys '15)*. Association for Computing Machinery, New York, NY, USA, 45–58. <https://doi.org/10.1145/2809695.2809705>
- [49] Felix Sutton, Reto Da Forno, David Gschwend, Tonio Gsell, Roman Lim, Jan Beutel, and Lothar Thiele. 2017. The Design of a Responsive and Energy-Efficient Event-Triggered Wireless Sensing System. In *Proceedings of the 2017 International Conference on Embedded Wireless Systems and Networks (Uppsala, Sweden) (EWSN '17)*. Junction Publishing, USA, 144–155. <https://dl.acm.org/doi/abs/10.5555/3108009.3108028>
- [50] Felix Sutton, Reto Da Forno, Jan Beutel, and Lothar Thiele. 2019. BLITZ: Low Latency and Energy-Efficient Communication for Event-Triggered Wireless Sensing Systems. *ACM Transactions on Sensor Networks (TOSN)* 15, 2, Article 25 (2019), 38 pages. <https://doi.org/10.1145/3309702>
- [51] Felix Sutton, Marco Zimmerling, Reto Da Forno, Roman Lim, Tonio Gsell, Georgia Giannopoulou, Federico Ferrari, Jan Beutel, and Lothar Thiele. 2015. Bolt: A Stateful Processor Interconnect. In *Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems (Seoul, South Korea) (SenSys '15)*. Association for Computing Machinery, New York, NY, USA, 267–280. <https://doi.org/10.1145/2809695.2809706>
- [52] Matteo Trobinger, Davide Vecchia, Diego Lobba, Timofei Istomin, and Gian Pietro Picco. 2020. One Flood to Route Them All: Ultra-Fast Convergecast of Concurrent Flows over UWB. In *Proceedings of the 18th Conference on Embedded Networked Sensor Systems (Virtual Event, Japan) (SenSys '20)*. Association for Computing Machinery, New York, NY, USA, 179–191. <https://doi.org/10.1145/3384419.3430715>
- [53] Roman Trüb, Reto Da Forno, Lukas Sigrüst, Lorin Mühlebach, Andreas Biri, Jan Beutel, and Lothar Thiele. 2020. FlockLab 2: Multi-Modal Testing and Validation for Wireless IoT. In *3rd Workshop on Benchmarking Cyber-Physical Systems and Internet of Things (CPS-IoTBench 2020)*. 7. <https://doi.org/10.3929/ethz-b-000442038>
- [54] Fabian Walter, Arnaud Burtin, Brian McArdell, Niels Hovius, Bianca Weder, and Jens Turowski. 2017. Testing seismic amplitude source location for fast debris-flow detection at Illgraben, Switzerland. *Natural Hazards and Earth System Sciences* 17, 6 (2017), 939–955. <https://doi.org/10.5194/nhess-17-939-2017>
- [55] Samuel Weber, Jan Beutel, Reto Da Forno, Alain Geiger, Stephan Gruber, Tonio Gsell, Andreas Hasler, Matthias Keller, Roman Lim, Philippe Limpach, Matthias Meyer, Igor Talzi, Lothar Thiele, Christian Tschudin, Andreas Vieli, Daniel Vonder Mühll, and Mustafa Yücel. 2019. A decade of detailed observations (2008–2018) in steep bedrock permafrost at the Matterhorn Hörnli-grat (Zermatt, CH). *Earth System Science Data* 11, 3 (2019), 1203–1237. <https://doi.org/10.5194/essd-11-1203-2019>
- [56] Geoff Werner-Allen, Jeff Johnson, Mario Ruiz, Jonathan Lees, and Matt Welsh. 2005. Monitoring volcanic eruptions with a wireless sensor network. In *Proceedings of the Second European Workshop on Wireless Sensor Networks (EWSN '05)*. IEEE, 108–120. <https://doi.org/10.1109/EWSN.2005.1462003>
- [57] Geoff Werner-Allen, Konrad Lorincz, Jeff Johnson, Jonathan Lees, and Matt Welsh. 2006. Fidelity and Yield in a Volcano Monitoring Sensor Network. In *Proceedings of the 7th Symposium on Operating Systems Design and Implementation (Seattle, WA, USA) (OSDI '06)*. USENIX Association, USA, 381–396. <https://dl.acm.org/doi/abs/10.5555/1298455.1298491>
- [58] Daniel Winkler and Alberto Cerpa. 2019. WISDOM: Watering Intelligently at Scale with Distributed Optimization and Modeling. In *Proceedings of the 17th Conference on Embedded Networked Sensor Systems (New York, New York) (SenSys '19)*. Association for Computing Machinery, New York, NY, USA, 219–231. <https://doi.org/10.1145/3356250.3360023>
- [59] Georg Wittenburg, Norman Dziengel, Stephan Adler, Zakaria Kasmi, Marco Ziegert, and Jochen Schiller. 2012. Cooperative event detection in wireless sensor networks. *IEEE Communications Magazine* 50, 12 (2012), 124–131. <https://doi.org/10.1109/MCOM.2012.6384461>
- [60] Georg Wittenburg, Norman Dziengel, Christian Wartenburger, and Jochen Schiller. 2010. A System for Distributed Event Detection in Wireless Sensor Networks. In *Proceedings of the 9th ACM/IEEE International Conference on Information Processing in Sensor Networks (Stockholm, Sweden) (IPSN '10)*. Association for Computing Machinery, New York, NY, USA, 94–104. <https://doi.org/10.1145/1791212.1791225>
- [61] Ilkjun Yoon, Dong Kun Noh, Dongun Lee, Rony Teguh, Toshihisa Honma, and Heonshik Shin. 2012. Reliable Wildfire Monitoring with Sparsely Deployed Wireless Sensor Networks. In *IEEE 26th International Conference on Advanced Information Networking and Applications*. IEEE, 460–466. <https://doi.org/10.1109/AINA.2012.107>
- [62] Marco Zimmerling, Luca Mottola, and Silvia Santini. 2020. Synchronous Transmissions in Low-Power Wireless: A Survey of Communication Protocols and Network Services. *Comput. Surveys* 53, 6, Article 121 (Dec. 2020), 39 pages. <https://doi.org/10.1145/3410159>