Lance: Optimizing High-Resolution Signal Collection in Wireless Sensor Networks

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Abstract

An emerging class of sensor networks focuses on reliable collection of high-resolution signals from across the network. In these applications, the system is capable of acquiring more data than can be delivered to the base station, due to severe limits on radio bandwidth and energy. Moreover, these systems are unable to take advantage of conventional approaches to in-network data aggregation, given the high data rates and need for raw signals. These systems face an important challenge: how to maximize the overall value of the collected data, subject to resource constraints.

In this paper, we describe *Lance*, a general approach to bandwidth and energy management for reliable data collection in wireless sensor networks. Lance couples the use of optimized, data-driven reliable data collection with a model of energy cost for extracting data from the network. Lance's design decouples resource allocation mechanisms from application-specific policies, enabling flexible customization of the system's optimization metrics.

We describe the Lance architecture in detail, demonstrating its use through a range of target applications and resource management policies. We present an extensive study driven by both real and synthetic data distributions, through simulations and runs on a large sensor testbed. We show that Lance maximizes the value of the collected data under a range of resource constraints, achieving near-optimal allocation of radio bandwidth and energy. Finally, we present results from a real sensor network deployment at Tungurahua volcano, Ecuador, in which Lance was used to drive data collection for an eight-node network collecting seismic and acoustic signals from the active volcano.

Categories and Subject Descriptors

C.2.4 [**Distributed Systems**]; C.3 [**Special-Purpose and Application-Based Systems**]: Real-time and embedded systems

General Terms

Design

Keywords

Wireless Sensor Networks, Data Collection, Resource Management

SenSys'08, November 5–7, 2008, Raleigh, North Carolina, USA.

1. INTRODUCTION

Many sensor network applications involve the acquisition of high-resolution signals using low-power wireless sensor nodes. Examples include monitoring acoustic, seismic, and vibration waveforms in bridges [13], industrial equipment [14], volcanoes [26], and animal habitats [3, 16]. These systems all attempt to acquire high data-rate (100 Hz or higher), high-fidelity data across the network, subject to severe constraints on radio bandwidth and energy usage.

Given these constraints, it is typically not possible to acquire continuous waveforms from all nodes. As a result, applications strive to acquire the most "interesting" signals, such as a marmot call or earthquake, and avoid wasting resources on "uninteresting" signals. Currently, these resource-management decisions are made on an *ad hoc* basis for each application, often resulting in suboptimal solutions that can consume excessive bandwidth or lose data. We argue that all of these applications would benefit from a general approach to managing resources that optimizes the application-specific value of the data acquired by the network.

Optimizing reliable data acquisition requires a coordinated approach to managing both limited energy capacity and severely constrained radio bandwidth. Depending on the sampling rate and resolution, downloading signals may take longer than real time; while low-power sensor node radios obtain single-hop throughput of about 100 Kbps, the the best reliable protocols achieve less than 8 Kbps for a single transfer over multiple hops [12]. Likewise, to achieve long lifetimes in the field, the energy cost of downloading a signal from the network must be carefully considered. The fundamental challenge is how to best direct these limited network resources to acquire the most valuable data to the application.

This paper presents *Lance*, a general approach to bandwidth and energy management for reliable signal collection in wireless sensor networks. In Lance, each node acquires data at potentially high rates. For each application data unit (ADU), each node generates a concise ADU *summary*, which is periodically sent to the base station and used to compute a ADU *value*. Lance computes an ADU *download schedule* based on these values, and uses a reliable transfer protocol to download ADUs according to this schedule.

Energy usage and battery lifetime are major concerns for long-term sensor network deployments. Lance incorporates a *cost estimator* that predicts the energy cost for reliably downloading each ADU from the network. We describe a novel energy cost estimation algorithm that uses information on the network topology to determine the energy cost at the sensor node hosting the ADU as well as intermediate nodes impacted by the multihop transfer protocol. Information from the cost estimator is used to adjust the download schedule for ADUs, allowing Lance to target a battery lifetime for the network by load-balancing download operations in a manner that adheres to an energy schedule.

Lance incorporates a general framework for managing bandwidth and energy that decouples the mechanism for prioritizing resource allocation from the application-specific policies used to assign ADU values. This is accomplished through user-supplied *policy modules* that permit a range of sophisticated prioritization policies to be tailored for specific applications. Policy modules allow Lance to target a broad range of optimization metrics, including node-local and network-wide value maximization, lifetime targeting, and acquiring temporally- or spatially-correlated data from across the network. Policy modules allow the network's behavior to be significantly altered at the base station, without reprogramming the sensor nodes themselves.

The contributions of this paper are as follows. First, we present the Lance architecture in detail, which is the first system to provide a value-driven bandwidth and energy management framework for high-data-rate sensor networks. Second, we describe Lance's policy modules, which offer a clean separation of policy and mechanism that allows the system to be tailored to a broad range of applications. We focus on one application in detail: using Lance to maximize data quality for a network of seismic and acoustic sensors deployed at an active volcano. Third, we show through detailed simulation measurements that Lance achieves *near optimal* efficiency (greater than 96% in most cases) under a range of data distributions and resource limitations. Fourth, we present results from an eight-node field deployment of Lance at Tungurahua Volcano, Ecuador, demonstrating the system's performance in a real field setting and the flexibility of policy modules for altering the network's operation following deployment.

The rest of this paper is organized as follows. Section 2 presents motivation and related work. We describe the architecture of Lance in detail in Section 3 and discuss the use of application-specific policy modules in Section 4. Section 5 presents a case study of several applications that can make use of the Lance architecture. We briefly describe our prototype in Section 6. Section 7 presents a detailed evaluation while Section 8 presents results from our field deployment. Finally, Section 9 discusses future work and concludes.

2. BACKGROUND AND MOTIVATION

Wireless sensor networks are becoming more common for applications that focus on reliable collection of raw signals at relatively high sampling rates, as opposed to in-network aggregation of low-data-rate samples. These applications generally make use of extensive offline analysis to study the collected data, and it is often infeasible or impossible to perform this computation within the network itself. Even in cases where it is possible to shift computation to the network, a system designer may wish to extract raw data occasionally for calibration or testing. Examples of such applications include structural health monitoring [5, 13, 17], acoustic sensing [6, 7, 3, 16], distributed camera networks [23], and geophysical monitoring [26].

These systems typically record data to flash at each sensor node and make use of a reliable bulk-transfer protocol to collect data at a base station. Given that the network is capable of sampling data at a higher rate than it can be downloaded, it is not possible to collect the complete signal from all nodes. The system is therefore forced to make a decision about what data to collect and what to throw away. In most cases this decision is application-specific: for example, a volcanologist may be chiefly interested in a specific type of seismic tremor, and a biologist may be looking for acoustic signatures of a specific species of marmot [3]. The implication is that the system must be able to determine the intrinsic *value* of a given signal to determine whether resources should be devoted to storing and downloading that signal.

Previous approaches have involved simple mechanisms tailored for specific applications. For example, in the NetSHM [5, 21] structural monitoring system, data collection is triggered manually following an excitation of the structure. Sentri [13] has been used for vibration monitoring at the Golden Gate Bridge; it is unclear from the paper how sampling and communication are triggered, but reported experimental results suggest manual operation. The Reventador volcano monitoring system [26] used a simple triggering algorithm to detect seismic events and initiate reliable transfer to the base station. The Intel Predictive Maintenance system [14] performs high-data-rate sampling staggered over infrequent, periodic collection periods to extend system lifetime. All of these systems involve a tight binding of the *mechanisms* used to manage storage and bandwidth with their respective application-specific *policies*.

The typical approach to download management is a FIFO model where downloads occur in a round-robin fashion across the network once a trigger occurs. In general, new data may be sampled and stored to flash while a download is taking place. Therefore, the trigger frequency, download cycle duration and the number of nodes in the network all effect the amount of data captured by such an approach. For example, the Flush [12] protocol achieves only 8 Kbps for a reliable transfer over multiple hops; the Fetch [26] and Straw [13] protocols fare somewhat worse. The RCRT protocol [22] is designed for a case where all nodes are transmitting simultaneously to the sink, although this approach severely limits the obtained per-node throughput. As a result, when incoming data rates exceed download capacity, FIFO download management can produce excessive delays between data acquisition and retrieval.

Lance assumes that sensor nodes contain adequate flash storage to buffer signals prior to download. While the popular TMote Sky platform supports a relatively small 1 MB flash, more recent sensor designs [11] have several GB of flash, and we expect this trend to continue. Rather than focusing on per-node storage, our primary concern is with limitations on bandwidth and energy.

Our goal is to develop a general-purpose approach to bandwidth and energy management that complements a reliable data-collection protocol. Such a system should have several key properties. First, it should be *customizable*, allowing different applications to specify their own policies for storage management and bandwidth prioritization. Second, the system should target a range of optimization goals. Examples include maximizing overall data priority, bounding energy consumption, maximizing temporal or spatial coverage of the collected data, or achieving fairness across sensor nodes. Third, the system should be decoupled from a specific routing protocol, reliable collection protocol, or sensor node platform, making it possible to leverage the system in different settings.

Related work: Several systems are related to Lance but differ substantially in their goals and assumptions. EnviroMic [16] is a system designed to support distributed acoustic recording by leveraging the collective storage resources of multiple sensor nodes. EnviroMic focuses on storage management and load balancing, and assumes that data will be manually retrieved from sensor nodes following the deployment. Unlike Lance, EnviroMic is not intended for applications with real-time data needs.

ICEDB [28] supplies a delay-tolerant and priority-driven query processor for the CarTel [1] system. While ICEDB considers bandwidth limitations, it does not consider energy as a constraint. ICEDB provides SQL extensions allowing queries to assign both inter- and intra-stream priorities, which are used by the query processor to manage bandwidth and storage resources. ICEDB also uses a similar node-level summarization technique to that used by Lance.

VanGo [6] provides an architecture for collecting and processing high-resolution sensor data on resource-constrained nodes. VanGo

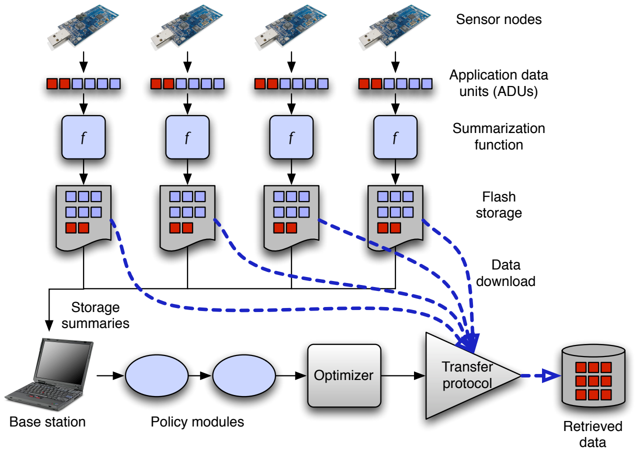


Figure 1: **The Lance system architecture.** *The summarization portions are provided by the application; all other components are generic.*

focuses on a programming model based on a linear filter chain and implementing efficient signal-processing operations with limited computational power. WaveScope [4] and Flask [18] are languages for stream processing applications. These systems are largely complementary to Lance, and could be used to process signal data prior to collection, although our focus is on collecting *raw* sensor data from large networks. These systems do not attempt to optimize data collection under varying energy and bandwidth constraints.

3. LANCE SYSTEM ARCHITECTURE

This section describes the Lance architecture, introducing a formal problem definition, design principles, and major system components. Section 6 covers implementation details omitted here.

3.1 Problem definition

In Lance, the network consists of a set of sensor nodes that continuously sample and store sensor data into *application data units (ADUs)*, which are the unit of data storage and retrieval. Each unique ADU a_i consists of a tuple $\{i, n_i, t_i, d_i, v_i, \bar{c}_i\}$, where i is a unique ADU identifier, n_i is the node storing the ADU, t_i is a timestamp, and d_i is the raw sensor data. We assume that ADUs are of uniform size and that nodes have sufficient flash storage to buffer collected signals, so an ADU is only evicted from a node's flash once it has been downloaded. We define the *universe* U as the set of all ADUs sampled by the network over time.

Every ADU is assigned an application-specific *value* v_i that represents the application's intrinsic "utility" for the data contained within the ADU. We make no assumptions about how ADU values are assigned; the value could be a function of the data itself, the time the data was acquired, which node sampled the data, data being sampled by other nodes, and so forth. Lance provides a flexible infrastructure for applications to define their own value functions through policy modules.

Each ADU has an associated cost $\bar{c}_i$ that represents the energy requirement to download the ADU from the network. $\bar{c}_i$ is a vector $\{c_i^1, c_i^2, \ldots, c_i^n\}$ where c_i^j represents the estimated energy expenditure of node j when ADU i is retrieved. The key idea is that we explicitly model both the energy cost for downloading the ADU from its "host" node n_i and the energy cost for each node along the routing path from n_i to the base station which must forward packets during the transfer. In addition, we also model the energy cost to nodes that overhear transmissions by nodes participating in the transfer. This energy cost on intermediate nodes is non-negligible, since reliable transfer protocols involve a potentially large number of retransmission. However, the overhearing cost is typically small, since modern low-power MAC protocols quickly return to sleep when overhearing transmissions to another node. The cost vector $\bar{c}_i$ therefore depends on the network topology.

We assume that each node has a battery with a fixed capacity of C joules, and no energy harvesting is performed in the field. Without loss of generality, let us assume that C is identical for all nodes in the network and is known *a priori*. We define the *lifetime target* L as the desired lifetime of each node in the network. To meet the lifetime target, nodes should strive to consume no more than C/L joules per unit time on average; we call this the *discharge rate* of the node.

The high-level goal of Lance is to download the set of ADUs that maximizes the total value, subject to the lifetime target. Abstractly, we define an *epoch duration* Δ. Over each epoch, the energy consumption of each node must be less than the discharge rate, that is, $\sum_i \sum_j c_i^j \leq \Delta \times C/L$. Determining the optimal set of ADUs to download can be determined by solving a multidimensional knapsack problem in which each ADU represents an item to place in the knapsack with value v_i and cost $\bar{c}_i$. The knapsack has N dimensions (where N is the number of nodes in the network), each of size $\Delta \times C/L$ representing the energy availability over an epoch. However, calculating the optimal solution requires *a priori* knowledge of all ADUs generated by the network over time. Clearly, any real system must make use of an online, heuristic algorithm to approximate the optimal solution. We discuss and evaluate several different approaches, presenting results with respect to the optimal offline solution.

3.2 Design principles

Before describing Lance in detail, we first outline several principles that guide its design.

Decouple mechanism from policy. We wish to make it easy to adapt Lance to different application domains by providing a simple set of underlying mechanisms for weighing cost and data value that can be tailored for different end-user goals. These core mechanisms should not be tied to any interpretation of the data stored in an ADU. This approach leads to a clean separation of concerns between Lance's resource management layer and the higher-level policies informing its operation.

Simplicity through centralized control. In a field deployment setting, it is highly desirable for the sensor network to be as simple as possible, to prevent failures or unexpected behavior due to bugs. Past deployment experiences have taught us, and others, that introducing complex dynamics within the network can lead to a system that is difficult to understand, debug, or fix in the field [26, 25]. To maximize the chances of a successful deployment, Lance places most of the control logic at the base station, treating sensor nodes as slave devices. This principle makes it easy to change the behavior of the network at the base station and allows nodes to fail independently without affecting the rest of the system. Conventional replication and failover techniques can be used to bolster the reliability of the base station itself.

Low cost for maintenance traffic. Given limited node energy, we wish to reserve as much capacity as possible to support data collection. This implies that the system should strive to limit control messages between the base station and the sensor nodes, as well as internal traffic within the network, as transmitting packets unnecessarily consumes valuable energy. This is somewhat at odds with the need for central control, as the latter could require extensive coordination between sensor nodes and the base station; we wish to strike a good balance between these two conflicting goals.

3.3 System overview

Figure 1 provides an overview of the Lance architecture. Sensor nodes sample sensor data, storing the data to local flash storage. Each application data unit (ADU) consists of some amount of raw sensor data, a unique *ADU identifier*, and a *timestamp* indicating the time that the first sample in the ADU was sampled. ADU timestamps can either be based on local clocks at each node, or tied to a global timebase using a time synchronization protocol such as FTSP [19]. The size of an ADU should be chosen to balance the granularity of data storage and download with the overhead for maintaining the per-ADU metadata. In the applications we have studied, an ADU stores several seconds or minutes of sensor data, not an individual sample. ADUs are stored locally in flash, which is treated as a circular buffer.

Ideally, nodes would be able to compute the value v_i of an ADU locally, as the data is sampled. However, since the value might depend on factors other than the ADU's data, such as data computed at other nodes. Lance assigns values v_i at the base station, based on global knowledge of the state of the network. However, this requires nodes to communicate some low-bandwidth information on the ADU contents to the base station. For this purpose, each node applies an application-supplied *summarization function*, computing a concise summary s_i of the contents of the ADU as it is sampled. Nodes periodically send *ADU summary* messages to the base station, providing information on the ADUs they have sampled, their summaries, timestamps, and other metadata. As a special case, if a node is able to assign the ADU's initial value directly, this is used as the summary.

The Lance *controller* receives ADU summaries from the network. The controller also estimates the download cost $\bar{c}_i$ for each ADU, based on information on network topology as well as a model of energy consumption for download operations. The ADU summaries and cost are passed through a series of *policy modules*, which provide application-specific logic to assign the value v_i to each ADU. The resulting values are passed to the Lance *download manager* which is responsible for performing downloads, using a reliable data-collection protocol, such as Flush [12].

3.4 Summarization functions

Lance computes ADU values using two application-provided components. The first is the summarization function, described above. The second component is a chain of *policy modules* executed at the base station which, by modifying the value for each ADU, can implement a range of application-specific policies. Since the base station receives ADU summaries from every node, the policy modules can use global information not available to individual nodes to make informed bandwidth and energy allocation decisions.

Lance places two constraints on the on the summarization function. First, we require that the summary be small (typically a few bytes) to limit the overhead for storing and transmitting these values. Second, the function must be able to run efficiently on the sensor node as ADUs are being sampled. Otherwise, the exact form of the function is entirely application-specific.

As a concrete example, consider a network for downloading seismic events from an earthquake zone. One commonly-used measure of overall seismicity during a time period is the Real-Time Seismic Amplitude Measurement (RSAM) [20], which computes the average amplitude of a seismic signal over some time window (typically 1 to 10 minutes). This function is simple to compute and reduces a complex seismic waveform to a single scalar value, with higher values indicating greater seismic activity.

Another form of summarization is an event detector, which would produce a nonzero value whenever an event of interest is contained within the ADU; the summary might also represent the strength or confidence of the event detection. For example, an acoustic animal tracking system [3] or countersniper localization system [24] might use a simple trigger-based summarization function, indicating the detection of a marmot call or gunshot in the ADU.

3.5 Cost estimation

Lance estimates the download energy cost vector $\bar{c}_i$ for each ADU sampled by the network. We assume that nodes are organized into a spanning tree topology rooted at the base station. The cost is a function of many factors, including the reliable transport protocol, each node's position in the routing tree, radio link quality characteristics, and the MAC protocol.

Given the complex dynamics that can arise during a sensor network's operation, we opt to use a simple conservative estimate of the energy cost to download an ADU from a node. Our approach is based on an empirical model that captures three primitive energy costs involved in downloading an ADU. The first, E_d, represents the energy used to download an ADU from a given node which includes the energy cost for reading data from flash and sending multiple radio packets (including any retransmissions) to the next hop in the routing tree. The second, E_r, represents the energy cost at intermediate nodes to forward messages during the ADU transfer. The third, E_o, represents the energy cost to nodes that overhear transmissions during a transfer. For simplicity, we assume ADUs of fixed size and compute E_d, E_r, and E_o based on the time necessary to download an ADU from the target node.

Using this simple model, we set the elements of the cost vector $\bar{c}_i$ as follows. $c_i^n = E_d$ for the node n hosting the ADU, and $c_i^m = E_r$ for nodes m along the routing path from n to the base station. We set $c_i^o = E_o$ for nodes that are assumed to be within one radio hop of any of the nodes involved in the transfer. Estimating $\bar{c}_i$ therefore requires knowledge of the current routing topology. This information is readily available: the periodic summary messages, sent to the base station by every node, include the node's radio neighbors and parent in the routing tree. Cost vectors can be easily recomputed whenever the routing topology changes.

To ensure that all nodes meet the lifetime target L, Lance models the energy availability at each node using a token bucket with depth D and fill rate C/L, corresponding to the mean discharge rate. D is determined by the target lifetime L, the battery capacity B and the background drain rate R. In general, $D = B - L * R$, so D represents the energy remaining after the node reserves enough to ensure it can meet its target lifetime at the background level.

3.6 Lance optimizer

The Lance optimizer is responsible for scheduling ADUs for download, based on knowledge of the set of ADUs currently stored by the network, their associated values, and costs. ADU download itself is accomplished using a reliable transfer protocol such as Fetch [26] or Flush [12]. In our design, Lance attempts to download a single ADU at a time, in order to prevent network congestion, although it may be possible to download multiple ADUs simultaneously, depending on the network topology. A download completes either when the entire ADU has been received or a timeout occurs.

Lance's optimization process attempts to maximize the value of the ADUs retrieved while adhering to the lifetime target L. In essence, we seek a greedy heuristic approximation of the multidimensional knapsack solution that would be used by an oracle with complete knowledge of the ADUs sampled by the network over all time. The optimizer first excludes ADUs that would involve nodes without enough energy to perform a download. That is, if the token bucket for a given node m has $E(m)$ joules, ADUs for which

$E(m) < c_i^m$ are excluded from consideration. Note that as the bucket fills, the ADU may become available for download at a later time. We call these ADUs *infeasible*, and the remaining *feasible*.

To determine the next ADU to download, the optimizer considers the value v_i of each ADU and the its associated cost $\bar{c}_i$. We consider three *scoring functions* that assign a download score to each feasible ADU; the ADU with the highest download score is downloaded next. In the case of ties, an arbitrary ADU is chosen.

The first scoring function, *value-only*, simply downloads the feasible ADU with the highest value v_i. Note that *value-only* will meet the network's lifetime target (since only feasible ADUs are considered) but does not rank ADUs according to cost. The second scoring function, *cost-total*, assigns the score $\hat{v}_i$ by scaling the value of the ADU by its total cost: $\hat{v}_i = v_i / \sum_j c_i^j$. The feasible ADU with the highest score is then downloaded from the network. This approach penalizes ADUs stored deep in the routing tree, which have a higher overall cost than those located near the base station.

The third scoring function, *cost-bottleneck*, scales the ADU value v_i by the cost to the node that is an energy bottleneck for downloading this ADU. That is, let b represent the node with the minimum value of $E(b)$ such that $c_i^b > 0$. *cost-bottleneck* sets the score $\hat{v}_i = v_i / c_i^b$. The intuition behind this scoring function is that the most energy-constrained node should be considered when scoring ADUs for download. We evaluate all three scoring functions in this paper and show that they yield very different results in terms of spatial distribution and energy efficiency.

4. POLICY MODULES

Policy modules provide an interface through which applications can tune the operation of the Lance optimizer. Since policy modules are loaded into the system at the base station, they can be modified at any time without necessitating reprogramming of the sensor nodes themselves. In this section we provide a general discussion of policy modules and provide a series of examples of various policies that can be implemented through this feature.

4.1 Definitions

A policy module is an application-supplied function that takes as input an ADU summary tuple $a_i = \{i, n_i, t_i, d_i, \bar{c}_i, s_i, v_i\}$ and produces a new tuple a_i' with a possibly modified value v_i'. Policy modules run at the base station, can maintain internal state, and operate with global knowledge of the ADUs stored in the network.

A series of policy modules $\{m_1, m_2, ...m_n\}$ are composed into a linear chain, which is passed the ADU information extracted from the ADU summary messages received at the base station. The first policy module in the chain is responsible for assigning the initial value v_i to the ADU based on the summary information s_i calculated by the sensor node. The final ADU value produced by the chain is used as input to Lance's optimizer for the purpose of scheduling ADUs for download.

Lance requires that policy modules be efficient in that they can process the stream of ADU summaries received from the network in real time. In practice this is not difficult to accomplish, as the rate of ADU summary reception is modest, and the base station (typically a PC or laptop) is assumed to have adequate resources. For example, a 100-node network with an ADU size of 60 sec would receive an ADU summary every 600 msec. Typical policy modules take a small fraction of this time to run.

One of the main benefits of policy modules is that they permit significant changes to the network's behavior *without requiring changes to the node-level summarization function*. Changing the latter would typically involve reprogramming sensor nodes. In the field, it is often undesirable to reprogram the network except when absolutely necessary, and in many cases it is difficult to reach sensor nodes physically once deployed. Although systems such as Deluge [9] permit over-the-air reprogramming, any changes to the sensor node software could result in unexpected failures that can be very difficult to debug without manual intervention. On the other hand, introducing new policy modules at the base station is relatively straightforward, and can be quickly reversed without risking sensor node failures.

Policy module	*Description*
`filter`	Set ADUs below threshold to zero value
`boost`	Set ADUs above threshold to max value
`timespread`	Dilate ADU values across time
`spacespread`	Dilate ADU values across space
`adjust`	Add or subtract offset to ADU value
`smooth`	Apply low-pass filter to remove noise
`debias`	Median filter DC debiasing
`correlated`	Boost values for correlated events
`costfilter`	Filter ADUs above cost threshold

Figure 2: **Standard policy modules provided by Lance.**

4.2 Example policy modules

Policy modules can be used to encapsulate a wide range of data collection goals, and make it easy to customize Lance's behavior for specific applications. We provide a standard toolkit of general-purpose policy modules, summarized in Figure 2. Application developers are free to implement their own modules as well. By composing modules in a linear chain, it is easy to implement various behaviors without requiring a general-purpose "policy language."

Value thresholding: `filter` is perhaps the simplest example of a policy module that filters out ADUs with a value below a given threshold T by setting their values to zero. Setting $v_i' = 0$ prevents an ADU from being considered for download by the optimizer. This type of filtering can be used to force a drop of low-valued data. Conversely, the `boost` policy module sets the value for an ADU above a given threshold to the maximum value, ensuring it will be downloaded as soon as it is feasible.

Value adjustment and noise removal: Policy modules can be used to remove the effects of noise or correct for node-level value bias, for example, based on poor sensor calibration or differences in site response. Moreover, since each node computes the ADU summary based only on local sensor data, it may be necessary to normalize the ADU values in order to compare values across nodes.

`adjust` adds or subtracts a node-specific offset to each ADU value to correct for differences in sensor calibration.`smooth` applies a simple low-pass filter on the raw ADU values to remove spikes caused by spurious sensor noise. Likewise, `debias` is intended to remove sensor-specific DC bias from the ADU values. `debias` computes the median ADU value for a given node over a time window. It then subtracts the median from each ADU value before passing it along to the next module in the chain.

Likewise, when a sensor network contains multiple sensors with varying sensitivity, it is natural to prioritize data from more sensitive instruments. In cases where networks are deployed to monitor fixed physical phenomena, it may be desirable to prioritize data from nodes located close to the phenomena being observed. The `adjust` module can be used to scale raw ADU values based on a sensor's location, SNR, or other attributes.

Value dilation: Another useful policy is to dilate a high (or low) ADU value observed in one ADU across different ADUs sampled at different times or different nodes. This can be used to achieve greater spatial or temporal coverage of an interesting signal observed at one or more nodes. The `timespread` detects ADUs with a value above some threshold T and assigns the same value to those ADUs sampled just before and just after.

Likewise, the `spacespread` module groups ADUs from across multiple nodes into time windows and assigns the maximum ADU value to all ADUs in that window. Define a window $W(t, \delta)$ as the set of ADUs such that $t - \delta \leq t_i \leq t + \delta$ where t represents the center of the window and δ the window size. `spacespread` determines the maximum ADU in the window $v^* = \arg_{i \in W} \max v_i$ and sets $v'_i = v^*$ for each ADU in W.

Correlated event detection: The `correlated` module is used to select for ADUs that appear to represent a correlated event observed across the entire sensor network. `correlated` counts the number of ADUs within a time window $W(t, \delta)$ with a nonzero ADU value. If at least k ADUs meet this criterion, we assume that there is a correlated stimulus, and the values for all ADUs in the set are passed through. Otherwise, we filter out the ADUs in the window by setting $v'_i = 0$ for each ADU in W.

As an example of composing policy modules to implement an interesting behavior, consider the chain

$$\textit{filter}(T) \rightarrow \textit{correlated}(k) \rightarrow \textit{spacespread}$$

This policy filters incoming values, rejects time-correlated sets with fewer than k ADUs above the threshold, and assigns the max value across the set to all ADUs. This can be useful in systems that wish to perform collection of time-correlated data, but avoid spurious high-value data from just a few nodes. This policy is similar to the volcanic earthquake detector reported in [26], expressed as a simple policy module chain.

Cost-based filtering: Lance's optimizer considers both the cost of ADUs as well as their application-assigned values when making download scheduling decisions. The cost vector $\bar{c}_i$ is also available to the policy module chain, allowing policy modules to perform their own adjustments to the ADU value according to cost, permitting applications to augment Lance's own policies for energy scheduling. For example, the *costfilter* policy module filters out ADUs with a total energy cost $\sum_j c_i^j$ greater than some threshold; this ensures that the network avoids expending an arbitrary amount of energy to download a given ADU (regardless of its data value). Policy modules give applications a great deal of control over energy usage to complement Lance's own energy scheduling policy.

5. APPLICATION CASE STUDIES

In this section, we present several case studies of how Lance can benefit different application domains. We describe our use of Lance in a geophysical monitoring sensor network in detail, and discuss its use for limb motion analysis, structural monitoring, and animal habitat monitoring. All of these applications share the challenges that Lance was designed to address: the need for reliable data collection with limited bandwidth and storage.

5.1 Geophysical monitoring

Wireless sensor networks can greatly benefit geophysical monitoring applications, such as seismic and acoustic data collection at fault zones [10] and volcanoes [26]. Low-power wireless sensors are highly desirable in these settings, where sensors must be carried to a deployment site by hand and often cannot be manually serviced once deployed.

The goal is to deploy a wireless array of sensors for monitoring both seismic and infrasonic (low-frequency acoustic) signals, including earthquakes, tremor, and volcanic eruptions. Depending on the level of seismic or infrasonic activity, the network might record dozens of events an hour, with each event typically lasting less than 60 sec (although long-period tremor events can last minutes or hours).

As an example, in our previous work on volcano monitoring at Reventador [26], each sensor node continuously sampled two channels of seismic and acoustic data at 100 Hz per channel with a resolution of 24 bits/sample. Raw data was stored to the node's flash memory as a circular buffer. An event-detection algorithm running on each node would send an event report to the base station whenever an interesting seismic signal was detected. If the base station received enough event reports within a short time window, it would initiate a round-robin download of the last 60 sec of data from each node. Although this system was successfully deployed, it exhibited several deficiencies which led to a significant loss of data [26].

The first problem is that the decision used to download a given signal was based on a simplistic binary approach, based on the event-detection algorithm running on each node. As a result, the system could not prioritize certain events over others. The event-detector logic used a simple threshold scheme, and as reported in [26], the threshold was set too low, causing the network to trigger on less than 5% of the actual seismic events.

The second problem was that following each trigger, the network initiated a *nonpreemptive* download from every node in the network in a round-robin fashion. This policy caused the system to devote resources to downloading small precursor earthquakes that immediately preceded larger eruptions [26]. As a result, many such larger events were not captured.

Finally, our previous system made no attempt to manage energy. As a result, the expected lifetime of the network is only about a week (using D-cell batteries), necessitating frequent battery changes over a long deployment. Clearly, this system could benefit from a prioritized approach to download management that also considers energy costs to increase lifetime.

5.1.1 Adaptation to Lance

To address these problems, we reimplemented our previous volcano monitoring system using Lance. Many of the components of the original system, such as multihop routing, time synchronization, reliable download protocol, and flash storage interface, remained unchanged. The node-level event detector was replaced by an ADU summarization function, as described below. The base station code for responding to correlated events was replaced with Lance's optimizer and policy modules. Our deployment of the completed system at Tungurahua volcano in August 2007 is discussed in Section 8.

5.1.2 Summarization functions

The original system was intended to detect correlated seismic events from across the network and download data from all nodes, regardless of whether every node detected the event. This was based on a simple event detector that computes two exponentially-weighted moving averages (EWMA) of the seismic signal, with different gain settings; one EWMA represents the short-term average and the other the long-term average. When the ratio between these two averages exceeds a threshold, an event detection message is sent to the base station. Subsequent triggers are suppressed for a short duration afterwards.

This policy is straightforward to implement in Lance by using the "ratio of two averages" as the node-level summarization function. Rather than performing thresholding at the node level, we report the maximum ratio over the ADU as its value, allowing Lance to prioritize different events. The base station's policy modules are configured as shown in Section 4.2, using a chain of `filter`, `correlated`, and `spacespread` to implement the equivalent of the event triggering policy used in the original system. Note that the Lance version of the system differs from the original in that download management is value-driven rather than FIFO. Also, Lance can download ADUs from different events out of order, avoiding the nonpreemptive download problems of the earlier system.

While our original system was designed to capture short earthquakes, were also interested in determining whether Lance could be used to capture different types of volcanic activity. For this, we make use of the Real-Time Seismic Amplitude Measurement (RSAM) [20], which computes the average seismic amplitude over a given time window. Intuitively, RSAM measures the total amount of ground shaking caused by earthquakes and tremor, and is often used by volcano observatories to characterize the overall level of seismic activity.

Different summarization functions and policy modules can be used to implement a wide range of geophysical monitoring systems with Lance. For example, a hazard monitoring system could be configured to periodically report RSAM values for all sensor nodes and download only the strongest events for further analysis. By limiting downloads to those ADUs with RSAM above some threshold, energy can be saved. In contrast, a scientific study that wishes to perform earthquake localization [2] or tomographic inversion [15] would prefer to download only small earthquakes with clearly delineated onsets, which can be used to determine the velocities of seismic waves. Likewise, a researcher studying explosive events would prefer to download only seismic events with a corresponding infrasonic component, since non-explosive earthquakes should not generate any infrasound.

5.2 Other application domains

We believe that Lance can be used to benefit many applications that make use of high-resolution signals delivered over a bandwidth-limited wireless network. These applications require high data rates, precluding continuous data collection, and rely on classification techniques to determine which signals to download. Two examples are given below.

Structural monitoring: Structural monitoring systems collect vibration waveforms from a building, bridge, or other structure in order to study structural properties and seismic response. In previous systems [21, 13], data collection has been triggered manually or on a simple periodic schedule. Instead, Lance can be used to prioritize signals following an earthquake or forced excitation of the structure, similar to the EWMA and RSAM functions described earlier. To save energy, the system could choose a subset of nodes from which to download data to achieve a good spatial distribution across the structure. The size of the subset could be chosen depending on the strength of the excitation. In addition, policy modules can be used to perform periodic downloading of ADUs from each sensor for calibration, as well as to determine whether each sensor is still functioning properly.

Animal habitat monitoring: Habitat monitoring applications that deploy high-bandwidth sensors, such as microphones or cameras, are good candidates for prioritized data extraction. An example application may attempt to download interesting audio signals facilitating offline species classification or localization [3]. The summarization function could involve either a triggered event detector, an audio waveform classifier, or motion detector from a series of camera images [23].

At the base station, policy modules can use offline knowledge of node positions to modify the initial ADU value. One approach might enhance spatial coverage by prioritizing data collection from nodes nearby the source of the signal. Another could reject noise by deprioritizing signals detected by only one node. For example, if fewer than three nodes report an audio event, it is impossible to perform acoustic localization and Lance need not waste bandwidth on the signal. Policy modules can take other metrics into account as well, such as the SNR of the recorded signal or the time of day (e.g., reducing confidence in camera images taken at night).

6. PROTOTYPE IMPLEMENTATION

We have implemented Lance in TinyOS 2.x [8] for TMote Sky and iMote2 sensor nodes. The TMote Sky features a 1 MB flash memory (ST M25P80) divided into 16 sectors of 64 KB each. Our current prototype matches the ADU size to the sector size to simplify storage management, but this is not a fundamental limitation in the design. Sensor nodes participate in a multihop spanning-tree protocol rooted at the base station; we use the Collection Tree Protocol provided with TinyOS 2.0 for this purpose. Nodes send a periodic storage summary to the base station. To improve reliability, we use a sliding window approach in which each summary includes information on the last 5 ADUs recorded by the node. The node prioritization function is implemented as an application-supplied NesC component conforming to a simple API. Our prototype uses our own Fetch [26] reliable transfer protocol, although it would be straightforward to replace this with another protocol such as Flush [12].

The Lance download manager runs at the base station and receives data from the network via a "gateway node" connected to the base station by a serial cable or radio modem. The download manager is implemented in Perl and makes use of several external utilities for reading and parsing storage summary packets and sending download requests to the network. Policy modules are implemented as separate UNIX processes (which can be in any language; we typically use Perl) that read storage summaries on `stdin` and produce modified storage summaries on `stdout`. A simple configuration script is used to compose multiple policy modules into a pipe. We find that using standard scripting languages and UNIX utilities makes it very easy to implement a range of policy modules. A suite of Python utilities for logging, data visualization, and managing the network through a GUI are also provided.

7. EVALUATION

This section presents a careful evaluation of Lance conducted along several lines. Using a high-level system simulator and synthetic data sets, we evaluate the three scoring functions described in Section 3.6. We motivate our use of the *cost-bottleneck* scoring function and demonstrate that it performs better than simpler alternatives. Next, we look at the impact of varying parameters such as download bandwidth and network lifetime, as well as the impact of errors in the cost vectors. We also present results from experiments run on a 50-node sensor network testbed using realistic data sets.

7.1 Metrics and methodology

As stated in Section 3.1, the high-level goal of Lance is to download a set of ADUs maximizing the total value subject to energy and bandwidth constraints. The *optimal* solution is defined as the solution to the multidimensional knapsack problem, which yields a set of downloaded ADUs $\mathcal{O} = \{a_1, a_2, ...a_n\}$ that maximize data value subject to bandwidth and energy constraints. The total data value of the optimal solution $\hat{v}(\mathcal{O}) = \sum_{a_i \in \mathcal{O}} v_i$. Recall that computing the optimal solution requires *a priori* knowledge of all of the ADU values sampled by the network over time. We define *optimality* as the fraction of the data value downloaded by Lance compared to the optimal solution. That is, given a set of downloaded ADUs $\mathcal{L}$ with total data value $v(\mathcal{L})$, we define optimality as $v(\mathcal{L})/\hat{v}(\mathcal{O})$.

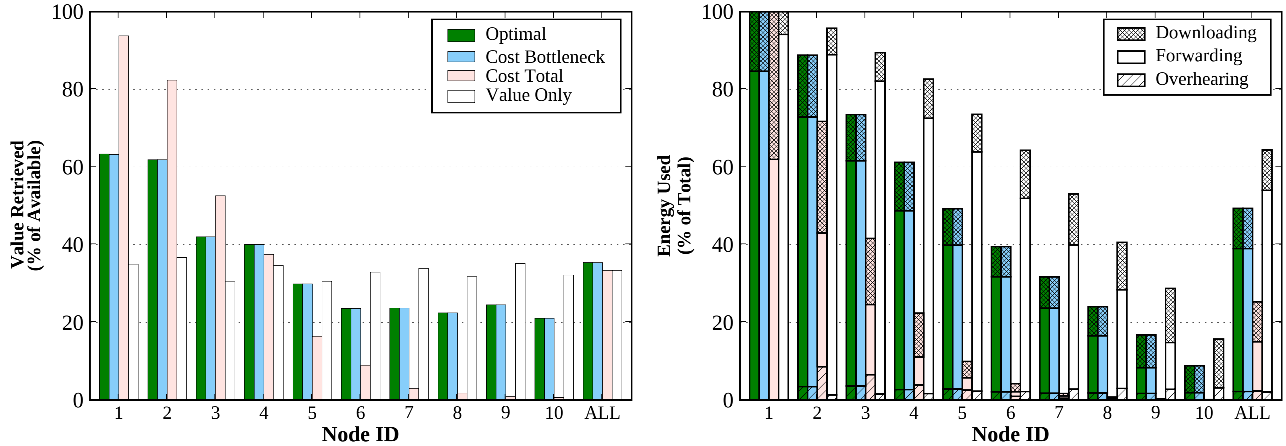


Figure 3: **Per-node distribution of ADU value and energy usage for the linear simulation experiment.** *The top graph shows the amount of data value downloaded from each node, while the bottom graph breaks down the amount of energy used by each node into the downloading, routing and overhearing components. Node 1 is closest to the base station.*

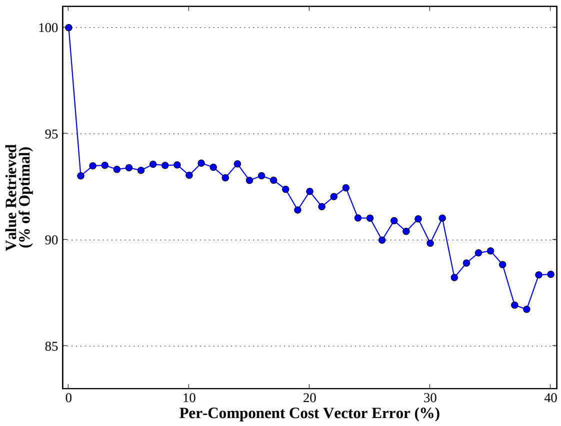


Figure 4: **Effect of cost vector error on optimality.** *The optimization process is guided by the cost vectors, but predicting the energy cost of operations before they are performed can be difficult. Here we show the impact of introducing a degree of error into the cost vectors used by the optimizer. As can be seen, we can tolerate a relatively high degree of error, as long as the shape of the cost vector does not change.*

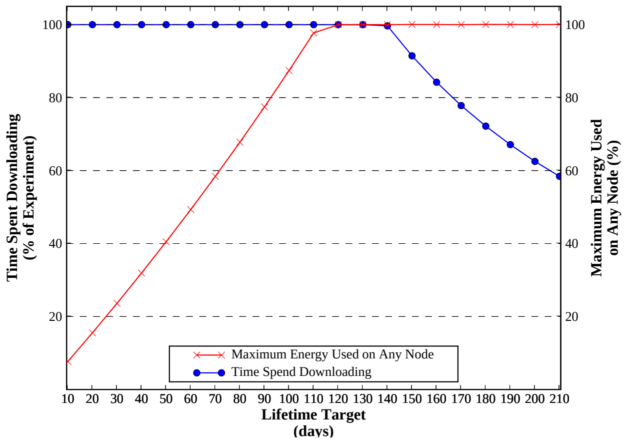


Figure 5: **Crossover between bandwidth and energy constraint dominance as lifetime is varied.** *This graph shows the transition between bandwidth and energy constrained regions for an optimal system. The right axis shows the percent of energy consumed by the most highly-drained node, and the left axis shows the amount of time spent downloading.*

We begin by presenting results based on a realistic system simulator that allows us to quickly vary parameters such as ADU data value distribution, network topologies, download speeds, energy costs, and target lifetimes. We also present results from Lance running on MoteLab [27], a sensor network testbed deployed over 3 floors of the Harvard EECS building. Our simulation experiments use a 10-node linear topology as well as a 25-node realistic tree topology shown in Figure 9(a). Both topologies use per-node ADU download speeds based on empirical measurements taken using the testbed. In our experiments, the ADU size is 36 KB and each node samples one ADU every 60 seconds (or 600 bytes/s of data).

We draw ADU values from several distributions in an attempt to understand Lance's behavior as the properties of the sampled data change. Three value distributions are used: uniform random, exponentially distributed, and Zipf with exponent $\alpha = 1$. We also make use of an ADU value distribution based on a 6 hour seismic signal collected at Reventador Volcano, Ecuador in 2005 [26].

The energy costs for various operations are modeled as follows. The background current drain of each node is set to 2 mA, based on empirical measurements of a TMote Sky sensor node performing high-data-rate sampling and storing to flash. We also measured the current consumption to download an ADU from a sensor node, and derived the energy costs for downloading ($E_d = 17.6$ mA/s), routing ($E_r = 16.9$ mA/s), and overhearing ($E_o = 2$ mA/s). Our experiments assume that each node can only overhear its parent in the routing tree; developing more detailed overhearing models is the subject of future work. Computing the components of the cost vector for a particular ADU is done by multiplying the current consumption by the ADU download time for each node either downloading, routing, or overhearing the transmission.

7.2 Effectiveness of scoring functions

We begin by evaluating the three scoring functions described Section 3.6. We want to see which is the most able to approximate the optimal solution across a range of target lifetimes and ADU distributions. As discussed earlier we expected the *value-only* scoring

		Scoring Functions		
Distribution	Lifetime	Value Only	Cost Total	Cost Bottleneck
Uniform	4 months	62.4%	90.5%	**93.2%**
	11 months	43.4%	68.0%	**96.9%**
	18 months	44.6%	49.0%	**90.0%**
Exponential	4 months	83.9%	85.1%	**88.0%**
	11 months	70.4%	82.0%	**93.0%**
	18 months	67.2%	72.8%	**91.2%**
Zipfian	4 months	84.7%	**91.4%**	87.1%
	11 months	63.8%	91.1%	**96.2%**
	18 months	53.1%	86.9%	**93.8%**

Figure 6: **Optimality of different scoring functions.** *This table summarizes simulation results evaluating the three different scoring functions. Results are shown for several different lifetime targets and value distributions.* cost-bottleneck *out-performs the others in almost all cases.*

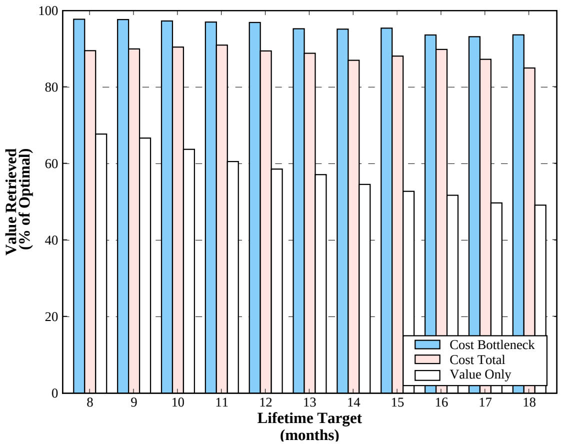


Figure 7: **Scoring function performance on Zipfian distribution.** *The* cost-bottleneck *scoring function outperforms the other two across a range of lifetime targets.*

function, without considering the energy or bandwidth overhead of downloading each ADU, to consume more energy downloading high-valued ADUs when it could have increased the total data value by downloading several slightly less-highly valued ADUs with lower costs. The *cost-total* scoring function incorporates a notion of cost, but will tend to favor nodes closer to the base station at the expense of high-valued ADUs that are more routing hops away. The *cost-bottleneck* scoring function should strike a balance between the two, since it considers only the most significant component of the cost vector when ranking ADUs.

Figure 3 shows simulation results using the 10-node linear topology with exponentially-distributed ADU values, and a target lifetime of 3 months. Nodes are numbered in increasing distance from the base station. The graph confirms the intuition behind the scoring function behavior. *value-only* downloads roughly equal value from each node, but fails to match the optimal performance. *cost-total* downloads more data from nodes near the sink. *cost-bottleneck* comes close to matching the optimal solution, retrieving over 99% of the value retrieved by the optimal solution.

Table 6 summarizes simulation results from a variety of different lifetimes and value distributions, run on the 25-node tree topology. The table shows that the *cost-bottleneck* scoring function outperforms the other two in most cases, with optimality values between 87.1% and 96.9%. The one exception is the 4-month Zipfian data set, where *cost-total* slightly outperforms *cost-bottleneck*. Figure 7 shows the effect of varying the network's target lifetime, using the

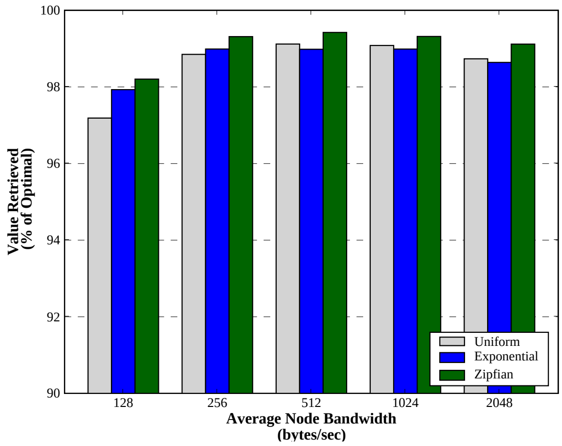


Figure 8: **Effect of varying download bandwidth.** *Lance maintains a high degree of optimality as the per-node download bandwidth is varied. Here results are shown for the three synthetic distributions across a 25 node tree topology and the* cost-bottleneck *scoring function. Note that the y-axis starts at 90%.*

25-node tree topology and a Zipfian data value distribution. As the figure shows, the *cost-bottleneck* scoring function maintains a high degree of optimality as the network bandwidth changes.

To illustrate the effect of varying lifetime targets in more detail, Figure 5 shows how the optimal solution transitions between bandwidth-dominant and energy-dominant constraints as the target lifetime increases. At low lifetime targets, the system is bandwidth constrained and cannot download data fast enough to exhaust the nodes' batteries. At high lifetime targets, the system is energy constrained and cannot download continuously without exhausting the nodes' batteries.

7.3 Bandwidth adaptation

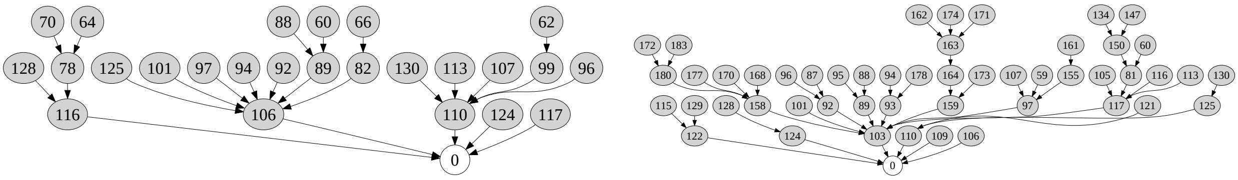
Next, we evaluate the impact of varying the download bandwidth in Figure 8, using the 25-node tree topology and the *cost-bottleneck* scoring function. We vary the per-node download bandwidth from 128 to 2048 bytes/s and peg the target lifetime at 8 months. As the figure shows, Lance performs very well across the range of bandwidths, with optimality greater than 97% in all cases.

7.4 Effect of cost vector error

Our last simulation study evaluates the effect of introducing errors into estimated download cost. This experiment uses the 25-node topology, *cost-bottleneck* scoring function, and an exponential data distribution. As described in Section 3.5, estimating the cost of performing different operations *a priori* can be difficult. As shown in Figure 4, even a 40% error in each component of the cost vector $\bar{c}_i$ for a given ADU only degrades optimality by approximately 15%. We conclude that accurate estimations of download costs are not strictly necessary to achieve good performance.

7.5 Testbed experiments

In this section, we present results from the Lance system running on the MoteLab testbed, in 25-node and 50-node configurations shown in Figure 9. These experiments stress the system in a realistic setting subject to radio interference and congestion, and exercise the multihop routing protocol, Fetch reliable data-collection protocol, and ADU summary traffic generated by the nodes. For these experiments, we injected artificial ADU values directly into each node rather than relying on the nodes sampling real sensor



(a) (b)

Figure 9: **Topologies for testbed experiments.** *This graph shows the 25 (a) and 50 (b) node topologies used for our testbed experiments.*

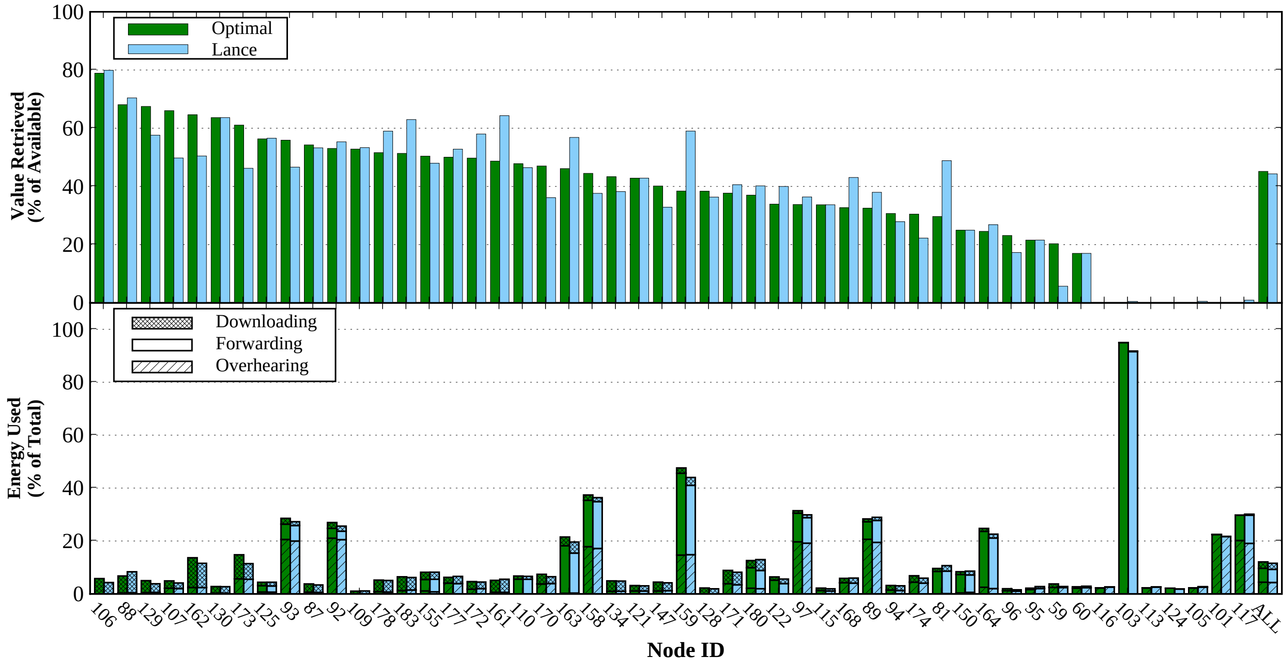


Figure 10: **Optimality and energy use in the 50-node testbed experiment.** *Lance achieved near-optimal performance during this 8-hour testbed experiment, retrieving 98% of the value obtained by the offline optimal algorithm.*

data; this approach allows us to perform repeatable experiments that explore a wider range of ADU value distributions. We use the *cost-bottleneck* scoring function.

Figure 10 shows the results of a 50-node testbed experiment using a Zipfian data distribution and a target lifetime of 6 months. The upper portion of the figure shows the amount of data value obtained by Lance from each node, compared to the optimal solution (which was computed offline). Nodes are sorted by decreasing optimal value. As the figure shows, Lance achieves very close to the optimal solution, with an optimality of 98% overall. In some cases, Lance incorrectly downloads more data from some nodes and less data from others; this is due to the inherent limitations of an online solution that cannot foresee future ADU values. The lower portion of the figure shows the energy breakdown for each node with downloading, forwarding, and overhearing costs shown. Some nodes consume more than others because of their location in the routing tree. For example, node 103 in uses a great deal of energy for routing packets as it is one hop from the base station, although no ADUs are ever downloaded from that node.

Finally, we demonstrate the use of Lance's policy modules. For this experiment, we use a distribution of ADU data values based on a 6-hour seismic trace collected at Reventador Volcano, Ecuador in 2005 [26]. The raw seismic data is divided into ADUs of 36 KB and ADU values v_i are assigned by computing the ratio of two EWMA filters on the data; this assigns greater value to ADUs that contain earthquakes, as described in Section 8.3. For each node in the 25-node topology, the ADU values from the seismic trace are attenuated based on a hypothetical signal source and assigned to each of the 25-nodes based on their location with respect to the signal source. We then enable a policy module chain, as described in Section 4, that assigns higher priority to ADUs that correspond to correlated seismic activity across the network.

Figure 11 shows the result of this experiment running on the MoteLab testbed. The upper portion of the figure shows the ADU values over time; the middle portion, the set of ADUs downloaded by the system with no policy modules in use; and the lower portion, the ADUs downloaded with the policy module chain in use. As the figure shows, the policy modules cause the network to prefer correlated seismic events and download an ADU from all nodes in the network when such an event is detected. Gaps in the set of ADUs downloaded are due to download timeouts. In one case, a single ADU is downloaded spuriously due to an incorrect value being reported by that node to the base station. This use of policy modules shows the drastic change in the system behavior that is affected without programming the sensor nodes themselves.

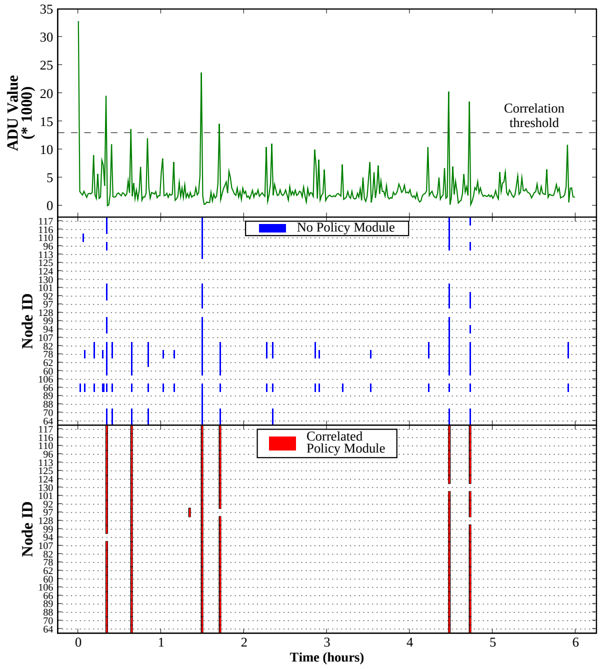


Figure 11: **Usage of policy modules to affect download distribution.** *Here we illustrate the use of policy modules in the context of the volcano-monitoring application. The graph compares the download behavior of the system with and without the policy module chain described in Section 8.3, which assign greater values to ADUs corresponding to correlated seismic activity. The graph is colored at a particular timestamp and node ID if we downloaded that signal from that node. The top graph shows the ADU values over time, with the threshold for the* `filter` *component of the policy module chain indicated.*

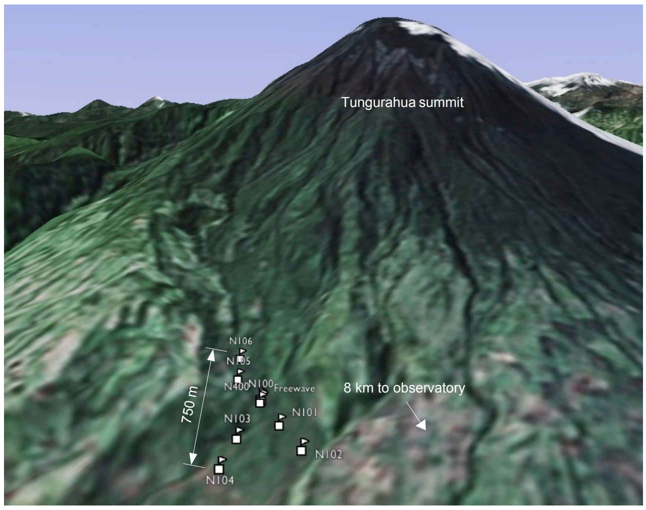


Figure 12: **Location of the Tungurahua sensor network deployment.**

Node	ADUs downloaded	Mean throughput
100	311	651.0 B/sec
101	131	446.8 B/sec
102	262	445.8 B/sec
103	292	424.4 B/sec
104	150	256.8 B/sec
105	66	453.7 B/sec
106	20	253.4 B/sec
Total	1232	431.5 B/sec

Figure 13: **Download performance during the deployment.**

8. FIELD DEPLOYMENT AT TUNGURAHUA VOLCANO

To evaluate the performance of Lance in a real field setting, we undertook a one week deployment of eight sensor nodes at Tungurahua Volcano, Ecuador, in August 2007. Lance was used to manage the bandwidth resources of the sensor network, as described below. Time and budget constraints prevented us from deploying a larger network for longer period of time. An earlier version of Lance was used in this deployment that did not explicitly model energy cost in the download manager. However, due to the short duration of the deployment, we knew that the battery lifetime used would be more than adequate (two D-cell batteries offer a lifetime of approximately 12 days with this platform). Our primary goal was to validate Lance's operation in a field campaign, as well as to identify challenges that only arise in real deployments.

The hardware design was based on one used in a previous volcano sensor network deployment [26]. Each sensor node consisted of a TMote Sky module coupled with a custom 24-bit multichannel ADC board. The network measured seismic signals using 4.5 Hz geophones and infrasonic signals with small electret microphones attached to each node. Data was sampled at 100 Hz per channel. As shown in Figure 12, seven of the nodes were deployed in a three-armed "star" topology radiating away from a central hub node, with two nodes per arm. The eighth node was colocated with the hub and transmitted an unreliable continuous stream of sensor data packets for establishing ground truth. A separate gateway node relayed data (using a FreeWave radio modem) to the base station laptop at the volcano observatory, 8 km from the deployment site. Time synchronization was established using FTSP [19] with a single GPS receiver as the root of the synchronization tree. We experimented with two different summarization functions as well as several different policy modules during the field deployment.

8.1 Overall performance and data yield

The sensor network was operational for a total of 71 hours, out of which the Lance download manager ran for a total of 56 hours. During this time, Lance successfully downloaded 1232 ADUs, or 77 MB of raw data. An additional 308 downloads failed due to timeout or stale summary information, for an overall success rate of 80%. 11012 unique ADU summaries were received from the network, representing an aggregate of 688 MB of sampled data. Lance therefore downloaded approximately 11% of the data produced by the network. Figure 13 summarizes the number of ADUs downloaded and the mean throughput for each node.

Figure 14 shows a breakdown of the packets received at the base station for a representative time period. Fetch download packets consumed the majority of the bandwidth, followed by the continuous sampling packets. The latter is a debugging feature allowing us to visualize the seismic activity from a single node in real time, and is entirely optional. Every node sent a periodic heartbeat to the base station every 10 sec, and a storage summary every 109 sec. As the figure shows, this overhead is a small percentage (less than 5%) of the overall network traffic.

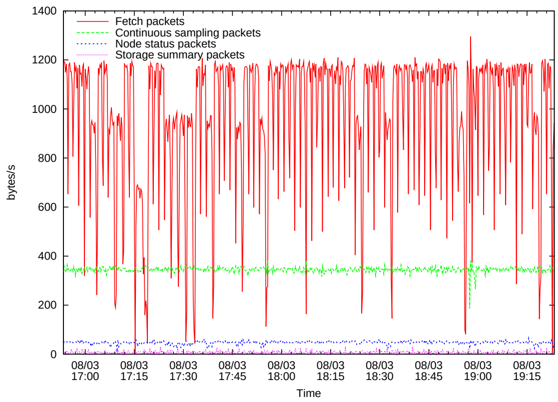


Figure 14: **Breakdown of radio traffic by packet type.** *This figure shows the total number of bytes received at the base station, averaged over 15 sec intervals. Periodic node status messages and storage summaries comprise a small fraction of the overall bandwidth.*

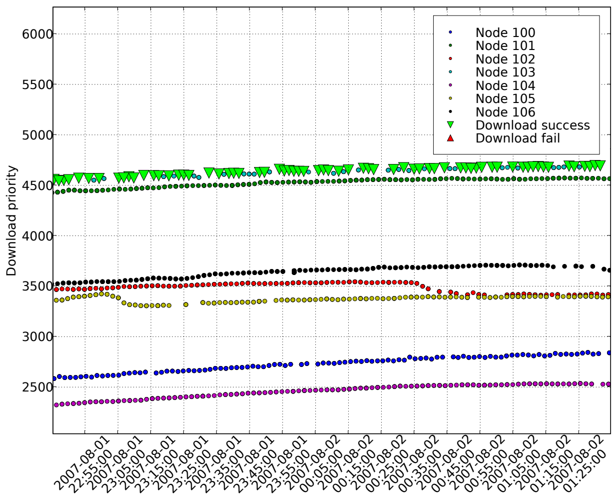


Figure 15: **Effect of DC bias on RSAM summarization function.** *Each point represents the ADU value received at the base station, and the triangles indicate those ADUs that were downloaded by Lance. Since nodes' RSAM values are offset significantly from each other, Lance prefers downloading from the node with the largest positive bias.*

8.2 RSAM-based summarization

The system as initially deployed computed the RSAM [20] as the value for each ADU. This approach was intended to prioritize data based on the overall level of seismic activity. We experienced two problems as soon as the system was fielded. First, the RSAM calculation was sensitive to DC bias in the seismometer signal, causing Lance to generally prefer downloading ADUs from one or two nodes (those with the largest positive bias). Figure 15 shows this effect, with Lance only downloading ADUs from node 103.

This problem was easily corrected, without any node software changes, by introducing a policy module at the base station to process the raw RSAM values received from each node and filter out the DC bias. This was achieved by computing the median RSAM value over each 30-minute window of raw RSAM values on each node, and subtracting the median from the RSAM.

The second problem with the RSAM summarization function was caused by the uncharacteristically low level of seismicity at the volcano throughout the deployment. We observed only about 20 volcano-tectonic earthquakes and *no* clear explosions, whereas the previous week, Tungurahua exhibited dozens of earthquakes each day. As a result, the RSAM summarization function was generally unable to distinguish between actual seismic activity and noise. We corrected this problem by switching to a different summarization function (described below) that was designed to pick out small earthquakes.

To evaluate Lance's behavior with respect to an "optimal" system, we took the 8483 RSAM summaries received during a 16-hour period when the debiasing filter was enabled. Using this information, we compute the set of ADUs that the optimal system would have downloaded, with complete knowledge of all ADUs but limited to the same time duration the original network was operating. We assume the download throughput for a given node is always the mean throughput for that node observed during the deployment (Figure 13). This calculation ignores energy constraints because the deployed system did not consider energy costs.

An optimal system would have downloaded 392 out of the 8483 ADUs, whereas the actual system downloaded 418 ADUs during this time.[1] The total value of ADUs downloaded by the optimal system is 10678, whereas the value of the actual network was 10629, for an optimality of 99.5%. Lance did an exceptional job of extracting the highest-value data from the network using our online heuristic algorithm.

8.3 EWMA-based summarization function

Given the low level of volcanic activity, after the first 25 hours of the deployment we chose to reprogram the network to use a different summarization function that is designed to pick out small earthquakes from background noise. This function computes the maximum ratio of two EWMA filters over the seismic signal; it is similar to that described in [26]. Due to code size limitations on the motes, it was necessary to manually reprogram each node with the new summarization function, which took two teams about 4 hours.

This summarization function reports a high value for an ADU that appears to contain an earthquake or other seismic event. However, there is no guarantee that the event will be centered in the ADU: in the worst case, the earthquake might occur at the very beginning or very end of the ADU, causing the initial seismic P-wave arrival or waveform coda to be stored in adjacent ADUs with low value. To avoid this problem, we made use of the `timespread` policy module that detects ADUs with an elevated value (over a fixed threshold) and assigns the immediately preceding and succeeding ADUs the same value. By dilating the value over time, Lance should download all three of the ADUs and maximize the probability that a given earthquake signal is entirely downloaded.

As with the RSAM-based summarization function, we estimate the optimal set of ADUs that an oracle would have downloaded. During a 25-hour period, the network reported 11012 unique ADU summaries. An optimal system would have downloaded 554 ADUs with total value 577377. The actual network downloaded 518 ADUs with a value of 539115, for an optimality of 93.3%.

As a final evaluation metric, we wish to consider how well Lance, configured in this manner, was able to download seismic signals representing earthquakes. Given the low level of volcanic activity, it turns out that most of the ADUs downloaded by Lance contain no discernible seismic signal. In fact, upon manual inspection of the 518 ADUs downloaded during this period, we identified only

[1]The optimal system would download fewer ADUs than the real system due to the variation in the throughput to each node: the optimal system would download more ADUs from nodes with lower throughput, thereby limiting the total number of ADUs it could download.

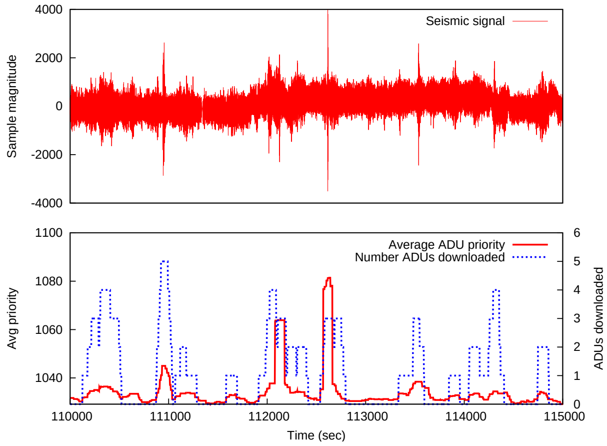


Figure 16: **Lance download behavior overlayed with average ADU value.** *The top plot shows the continuous seismic signal collected by a single node. The lower plot shows the average value of ADUs and the number of ADUs downloaded for each window.*

20 ADUs showing a clear earthquake signal, corresponding to only 9 separate seismic events.[2] Note that we did *not* configure Lance to explicitly download correlated earthquakes as described in Section 5, so we would not expect a high degree of coverage for the same event across multiple nodes.

Figure 16 shows the behavior of Lance during a representative 83-minute period. In the figure, we have broken time into windows of one-half an ADU duration (55 sec in this case), and computed the mean ADU value as well as the number of downloaded ADUs that overlap each time window. As the data shows, elevated seismic activity is well-correlated with an increase in the ADU value from across the network, as well as the number of downloaded ADUs. Moreover, the few cases of clear seismic activity in the trace (at times 111000, 112700, and so forth) tend to have more ADUs downloaded. Of the 9 separate seismic events, a total of 27 ADUs were downloaded, representing a per-event "coverage" of 3 ADUs per event. This represents just under half of the 7 nodes participating in the network.

9. CONCLUSIONS AND FUTURE WORK

Lance is intended to address the limited energy and bandwidth resources in sensor networks by allowing applications to target resource usage at the highest *value* data collected by the network, subject to a lifetime target. We have shown that the Lance architecture permits a wide range of application-specific resource management policies to be constructed atop several simple underlying mechanisms. Our results show that Lance achieves near-optimal data retrieval under a range of energy and bandwidth limitations, as well as varying data distributions. The analysis of our deployment at Tungurahua shows how Lance can be effective in a field setting.

The principles guiding Lance's design also lead to several limitations we hope to address in future work. Lance's linear policy modules are easy to use and compose, although it remains unclear whether more complex interactions between policy modules are needed. Finally, we hope to study the use of more sophisticated node-level data processing, including feature extraction, adaptation to changing energy availability, and data summarization. The complications introduced by these features must be balanced against maintaining the simplicity of our current design.

[2]One seismologist remarked that we "fixed the volcano" by placing our sensors on it.

Acknowledgments

The authors are indebted to Jeffrey B. Johnson of New Mexico Tech and Hugo Yepes of the Instituto Geofísico, Escuela Politécnica Nacional, Ecuador, for their invaluable assistance with the Tungurahua volcano field deployment. We also wish to thank our shepherd, Nirupama Bulusu, for her help with the final version of this paper. This work was supported by the National Science Foundation (grant numbers CNS-0546338 and CNS-0519675) and a generous gift from Microsoft Corporation.

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