Abstract

In this paper, we consider a class of sensor networks where the data is not required in real-time by an observer; for example, a sensor network monitoring a scientific phenomenon for later play back and analysis. In such networks, the data must be stored in the network. Thus, in addition to battery power, storage is a primary resource: the useful lifetime of the network is constrained by its ability to store the generated data samples. We explore the use of collaborative storage technique to efficiently manage data in storage constrained sensor networks. The proposed collaborative storage technique takes advantage of spatial correlation among the data collected by nearby sensors to significantly reduce the size of the data near the data sources. We show that the proposed approach provides significant savings in the size of the stored data vs. local buffering, allowing the network to run for a longer time without running out of storage space and reducing the amount of data that will eventually be relayed to the observer. In addition, collaborative storage performs load balancing of the available storage space if data generation rates are not uniform across sensors (as would be the case in an event driven sensor network), or if the available storage varies across the network.

1 Introduction

Wireless Sensor Networks (WSNs) hold the promise of revolutionizing sensing across a range of civil, scientific, military and industrial applications. However, many battery-operated sensors have constraints such as limited energy, computational ability, and storage capacity, and thus protocols must be designed to deal efficiently with these limited resources.

In this paper, we consider a class of sensor networks where the information collected by the sensors is not collected in real-time. In such applications, the data must be stored, at least temporarily, within the network until it is later collected by an observer (or until it ceases to be useful). Such applications include scientific monitoring: the sensors are deployed to collect detailed information about a phenomenon for later playback and analysis. In addition, some applications have sensors which collect data that may be needed by users of the networks that generate queries dynamically. In such applications, the data must be stored in the network; storage becomes a primary resource which, in addition to energy, determines the useful lifetime of the network. This paper considers the problem of storage management in such networks: how to use limited persistent storage of a sensor to store sampled data effectively. In addition to the applications above, storage can be used to tolerate temporary network partitioning, where the observer is not reachable from the partitioned sen-
sors, without losing potentially valuable data.

One basic storage management approach is to buffer the data locally at the sensors that collect them. However, such an approach does not capitalize on the spatial correlation of data among neighboring sensors to reduce the overall size of the stored data (the property that makes data aggregation possible [7]). Collaborative storage management can provide the following advantages over a simple buffering technique: (1) More efficient storage allows the network to continue storing data for a longer time without exhausting storage space; (2) Load balancing is possible: if the rate of data generation is not uniform at the sensors (e.g., in the case where a localized event causes neighboring sensors to collect data more aggressively), some sensors may run out of storage space while space remains available at others. In such a case, it is important for the sensors to collaborate to achieve load balancing for storage to avoid or delay data loss due to insufficient local storage; and (3) Dynamic, localized reconfiguration of the network (such as adjusting sampling frequencies of sensors based on estimated data redundancy and current resources).

We describe a cluster-based collaborative storage approach and compare it through simulations to a local buffering technique. Our experiments show that collaborative storage makes more efficient use of sensor storage and provides load balancing, especially if a high level of spatial correlation among the data of neighboring sensors is present. The trade-off is that using collaborative storage, data need to be communicated among neighboring nodes, and thus collaborative storage expends more energy than local buffering. However, since data is aggregated using collaborative storage, a smaller amount of data is stored and a smaller amount of data is eventually relayed to the observer, thereby reducing energy dissipation in this phase of operation. We then explore the use of coordination for redundancy control. More specifically, the cluster head can evaluate the amount of redundancy present among neighboring sensors, and use feedback this information back to the sensors to adjust their sampling rate. We exploit coordination in conjunction with local storage as well as collaborative storage and show that it provides desirable properties in both cases.

The remainder of this paper is organized as follows. Section 2 overviews the partitioned sensor network problem and motivates collaborative storage in more detail in the context of this problem. Section 3 provides an overview of related work in this area. Section 4 presents the proposed storage management protocols and discusses the important design tradeoffs. In section 5 we evaluate the storage alternatives under different scenarios. Finally Section 6 presents conclusion and our future research.

2 Motivation

In this section, we describe two different applications which require in-network storage. Zebranet [8], is a sensor network application for wildlife tracking whose goal is to provide more insight into complex issues such as migration patterns, social structures and mobility models of various animal species. In this application, sensors are attached to animals. Scientists (aka observers) collect the data by driving around the monitored habitat receiving information from Zebras as they come in range with them. Data collection is not preplanned: it might be unpredictable and infrequent. The sensors do not have an estimate regarding the observer’s schedule. The observer would like the network to maintain all the new data samples available since the last time the data was collected. Further, we would like the collection time to be small since the observer may not be in range with the zebra for a long time.

The second example application is a Remote Ecological Micro-Sensor Network [12] aimed at remote visual surveillance of federally listed rare and endangered plants. This project aims to provide near-real time monitoring of important events such as visitation by pollinators and consumption by herbivores along with monitoring a number of weather conditions and events. Sensors are placed in different habitats, ranging from scattered low shrubs to dense tropical forests. Environmental conditions can be severe; e.g., some locations frequently freeze. In this appli-
cation, network partitioning (relay nodes becoming unavailable) may occur due to the extreme physical conditions (e.g., deep freeze). Important events that occur during disconnection periods should be recorded and reported once the connection is reestablished. Effective storage management is needed to maximize the partitioning time that can be tolerated.

3 Related Work

Because of the wireless nature of sensors, the primary resource constraint is the limited battery energy available. Energy-awareness permeates all aspects of sensor design and operation, from the physical design of the sensor [1, 3] to the design of its operating system [6], communication protocols and applications [16].

Ratnasamy et al. propose using Data Centric Storage (DCS) to store data by name within a sensor network such that all related data is stored at the same (or nearby) sensor nodes using geographic hashing [11]. Thus, queries for data of a certain type are likely to be satisfied by a small number of nodes, significantly improving the performance of queries. However, this enhanced query performance requires moving related data from its point of generation to its appropriate keeper as determined by geographic hashing. We view this work as a higher level management of data focusing on optimizing queries rather than storage: our approach could compliment DCS by providing more effective storage of the data as it is collected.

Concurrently with us [14], Ganesan et al have explored protocols for storage constrained sensor networks [4]. The work by Ganesan et al considers the same problem and explores some of the solution space we are considering. Our work differs in the following ways: (1) We explore additional approaches to storage management, including those using coordination; (2) we explore issues that arise due to uneven data generation (e.g., due to event driven, or adaptive sampling applications), and non-uniform storage distribution (e.g., due to non-uniform deployment of the sensors). In such applications, effective load balancing is required; and (3) we study some additional characteristics of the storage protocols including coverage and collection time and energy.

4 Storage Management Protocols

A primary objective of storage management protocols is to efficiently utilize the available storage space to continue collecting data for the longest possible time without losing samples in an energy efficient way. Storage management approaches can be classified as:

1. **Local storage**: This is the simplest solution where every sensor stores its data locally. This protocol is energy efficient during the storage phase since it requires no data communication. Even though the storage energy is high (due to all the data being stored), the current state of technology is such that storage costs less than communication. However, this protocol is storage inefficient since the data is not aggregated and redundant data is stored among neighboring nodes. Local storage is unable to load balance if data generation or the available storage varies across sensors.

2. **Collaborative storage**: Collaborative storage refers to any approach where nodes collaborate. Collaboration leads to two benefits: (1) Less data is stored: measurements obtained from nearby sensors are typically correlated. This allows data samples from neighboring sensors to be aggregated; and (2) Load balancing: collaboration among sensors allows them to load balance storage.

It is important to consider the energy implications of collaborative storage relative to local storage. Collaborative storage requires sensors to exchange data, causing them to expend energy during the storage phase. However, because they are able to aggregate data, the energy expended in storing this data to a storage device is reduced. In addition, once connectivity with the observer is established, less energy is needed during the collection stage to relay the stored data to the observer. We note that this holds true.
even if in-network aggregation is carried out for locally buffered data during the reach-back stage due to the following two reasons: (1) Initial communication (first hop) of the locally buffered data will not be aggregated; and (2) Less efficient aggregation: a smaller amount of time and resources is available when near real-time data aggregation is applied during reach-back as compared to aggregation during the storage phase. Aggregating data during reachback is limited because all the data collected during the storage phase is compressed in a short time.

4.1 Collaborative Storage Protocols

Within the space of collaborative storage, a number of protocols are possible. The primary protocol we study is Cluster Based Collaborative Storage (CBCS). CBCS uses collaboration among nearby sensors only: these have the highest likelihood of correlated data and require the least amount of energy for collaboration. We did not consider wider collaboration because the collaboration cost may become prohibitive; the cost of communication is significantly higher than the cost of storage under current technologies. The remainder of this section describes CBCS operation.

In CBCS, clusters are formed in a distributed connectivity-based or geographically-based fashion – almost any one-hop clustering algorithm would suffice. Each sensor sends its observations to the elected Cluster Head (CH) periodically. The CH then aggregates the observations and stores the aggregated data. Only the CH needs to store aggregated data, thereby resulting in low storage. The clusters are rotated periodically to balance the storage load and energy usage. Note that only the CH needs to keep its radio on during its tenure, while a cluster member can turn off its radio except when it has data to send. This results in high energy efficiency: idle power consumes significant energy in the long run if radios are kept on. The reception of unneeded packets while the radio is on also consumes energy.

Operation during CBCS can be viewed as a continuous sequence of rounds until an observer/base station is present and the reach-back stage can begin. Each round consists of two phases: (1) CH Election phase: In this phase, each sensor advertises its resources to its one hop neighbors. Based on this resource information a cluster head (CH) is selected. The remaining nodes then attach themselves to that CH during the data transfer phase; and (2) Data exchange phase: If a node is connected to a CH, it sends its observations to the CH; otherwise, it stores its observations locally.

The CH election approach used in CBCS is based on the characteristics of the sensor nodes such as available storage, available energy or proximity to the “expected” observer location. The criteria for CH selection can be arbitrarily complex; in our experiments we used available storage as the criteria.

There has been considerable research in cluster formation algorithms for MANETs that considered both static and dynamic cluster head election. Our requirements for the clustering algorithm are that it be light-weight and localized – only one-hop clusters. Moreover, we require cluster head rotation for load balancing of energy and storage. This is an idea borrowed from the LEACH protocol [5]. The approach we use is a representative one and there is room for future improvements in this aspect of the protocol.

CH rotation is done by repeating the cluster election phases with every round. The frequency of cluster rotation influences the performance of the protocol. Depending on the cluster formation criteria, there is an overhead for cluster formation due to the exchange of messages.

The cluster election approach above may result in a situation where a node A, selects a neighbor B to be its CH when B itself selects C (which is out of range with A) to be its own CH. This may result in chains of cluster heads leading to ineffective/multi-hop clustering. To eliminate the above problem and restrict clusters to one hop, geographical zoning is used: an idea that is similar to the approach of constructing virtual grids [15]. More specifically, the sensor field is divided into zones such that all nodes within a zone are in range with each other. Cluster selection is then localized to a zone such that a node only considers cluster advertisements occurring in its zone. Only one CH is selected per zone, eliminat-
ing CH chaining as discussed above. We note that this approach requires either pre-configuration of the sensors or the presence of a location discovery mechanism (GPS cards or a distributed localization algorithm \[2\]). In sensor networks, localization is of fundamental importance as the physical context of the reporting sensors must be known in order to interpret the data. We therefore argue that our assumption that sensors know their physical co-ordinates is realistic.

4.2 The Role of Coordination

One idea we explore is coordination among the sensors. Specifically, each sensor has a local view of the phenomenon, but cannot assess the importance of its information given that other sensors may report correlated information. For example, in an application where 3 sensors are sufficient to triangulate a phenomenon, 10 sensors may be in a position to do so and be storing this information locally or sending it to the cluster head for collaborative storage. Through coordination, the cluster head can inform the nodes of the degree of the redundancy allowing the sensors to alternate triangulating the phenomenon. Coordination can be carried out periodically at low frequency, with a small overhead (e.g., with CH election). Similar to CH election, the nodes exchange meta data describing their reporting behavior and we assume that some application specific estimate of redundancy is performed to adjust the sampling rate.

As a result of coordination, it is possible that a significant reduction in the data samples produced by each sensor is achieved. We note that this reduction represents a portion of the reduction that is achieved from aggregation. For example, in a localization application, with 10 nodes in position to detect an intruder, only 3 nodes are needed. Coordination allows the nodes to realize this and adjust their reporting so that only 3 sensors produce data in every period. However, the three samples can still be aggregated into the estimated location of the intruder once the values are combined at the cluster head.

Coordination can be used in conjunction with local storage or collaborative storage. In Coordinated Local Storage (CLS), the sensors coordinate periodically and adjust their sampling schedules to reduce the overall redundancy, thus reducing the amount of data that will be stored. Note that the sensors continue to store their readings locally. Relative to Local Storage (LS), CLS results in a smaller overall storage requirements and savings in energy in storing the data. This also results in a smaller and more energy efficient data collection phase. Similarly, Coordinated Collaborative Storage (CCS) uses coordination to adjust the sampling rate locally. Similar to CBCS, the data is still sent to the cluster head where aggregation is applied. However, as a result of coordination, a sensor can adapt its sampling frequency/data resolution to match the application requirements. In this case, the energy in sending the data to the cluster head is reduced because of the smaller size of the generated data, but the overall size of the data is not reduced. We evaluate CLS and CCS compared to the non-coordinated counterparts, LS and CBCS.

5 Experimental Evaluation

We simulated the proposed storage management protocols using the NS-2 simulator \[10\]. We use a CSMA based MAC layer protocol. A sensor field of $350 \times 350$ meters$^2$ is used with each sensor having a transmission range of 100 meters. We considered three levels of sensor density: 50 sensors, 100 sensors and 150 sensors deployed randomly. We divide the field into 25 zones (each zone is $70 \times 70$ meters$^2$ to ensure that any sensor in the zone is in range with any other sensor). The simulation time for each scenario was set to 500 seconds and each point represents an average over five different topologies. Cluster rotation and coordination are performed every 100 seconds in the appropriate protocols.

We assume sensors have a constant sampling rate (set to one sample per second). Unless otherwise indicated, we set the aggregation ratio to a constant value of 0.5. For the coordination protocols, we used a scenario where the available redundancy was on average 30\% of the data size – this is the percentage of the data that can be eliminated using coordination. We note that this reduction in the data size represents a portion of the reduction possible using aggrega-
tion. With aggregation the full data is available at the cluster head and can be compressed at a higher efficiency. Several sensor nodes that are appearing on the market, including Berkeley MICA nodes [9] have Flash memories. Flash memories have excellent power dissipation properties and small form factor. As a representative we consider a SimpleTech flash memory USB cards [13] with as Transfer Energy/Mbyte $0.055 \text{J}$. In current wireless communication technologies (Radio Frequency based), the cost of communication is high compared to the cost of storage. For example, representative radios following the Zigbee IEEE 802.15.4 standard consume energy at roughly 40 times the cost of the SimpleTech USB card above per unit data. Our energy models in the simulation are based on these two devices. Further, we adjust the radio properties to match those of a Zigbee device.

Note that the possible data aggregation/compression as well as the reduction due to coordination are application as well as topology dependent. Consider a temperature sensing application. For this application a given sensor can collect data from all its neighbors and then simply take the average and store a single value (or maybe minimum, mean and maximum values) as representative. However, if the sensors are sending video data, then such high spatial compression might not be possible. In this paper, instead of considering a specific application, we assume a data aggregation model where the cluster head is able to compress the size of the data by an aggregation ratio $\alpha$. By controlling $\alpha$ we can consider different applications with different levels of available spatial correlation. In this model, the size of the aggregated data grows linearly with the number of available sensors. We consider the implications of this model on collaborative storage and explore other possible models later in this section. We would like to emphasize that we have selected these numbers as just representatives to illustrate the the various tradeoffs. Due to space constraints we can not include the results comparing all these protocols with various values of aggregation ratio.

5.1 Storage and Energy Tradeoffs

Figure 1 shows the average storage used per sensor as a function of the number of sensors (50, 100 and 150 sensors) for the four storage management techniques: (1) local storage (LS); (2) Cluster-Based Collaborative Storage (CBCS); (3) Coordinated Local Storage (CLS); and (4) Coordinated Collaborative Storage (CCS). In the case of CBCS aggregation ratio was set to 0.5. The storage space consumption is independent of the density for LS and is greater than storage space consumption than CBCS and CCS (roughly in proportion to the aggregation ratio). CLS storage requirement is in between the two approaches because it is able to reduce the storage requirement using coordination (we assumed that coordination yields improvement uniformly distributed between 20% and 40%). Note that after data exchange, the storage requirement for CBCS and CCS are roughly the same since aggregation at the cluster head can reduce the data to a minimum size, regardless of whether coordination took place or not.

Surprisingly, in the case of collaborative storage, the storage space consumption decreases slightly as the density increases. While this is counter-intuitive, it is due to higher packet loss observed during the exchange phase as the density increases; as density increases, the probability of collisions increases. These losses are due to the use of a contention based unre-
liable MAC layer protocol: when a node wants to transmit its data to the CH. The negligible difference in the storage space consumption between CBCS and CCS is also an artifact slight difference in the number of collisions observed in the two protocols. The use of a reliable protocol such as that in IEEE 802.11 or a reservation based protocol such as the TDMA based protocol employed by LEACH [5] can be used to reduce or eliminate losses due to collisions (at an increased communication cost). We leave the exploration of these tradeoffs to future work. Packet loss ranged from around 1% for the 50 sensor case to around 10% for the 150 sensor scenarios. Regardless of the effect of collisions, one can clearly see that the collaborative storage achieves significant savings in storage space compared to local storage protocols (in proportion to the aggregation ratio).

Figure 2 shows the consumed energy for the protocols in Joules as a function of network density. The X-axis represents protocols for different network densities: L and C stand for local buffering and CBCS respectively. L-1,L-2,and L-3 represents the results with local buffering technique for network size 50,100 and 150 respectively. The energy bars are broken into two parts: pre-energy, which is the energy consumed during the storage phase, and post-energy, which is the energy consumed during data collection (the relaying of the data to the observer). The energy consumed during storage phase is higher for collaborative storage because of the data communication among neighboring nodes (not present in local storage) and due to the overhead for cluster rotation. CCS spends less energy than CBCS due to reduction in data size that results from coordination. However, CLS has higher expenditure than LS since it requires costly communication for coordination. This cost grows with the density of the network because our coordination implementation has each node broadcasting its update and receiving updates from all other nodes.

For the storage and communication technologies used, the cost of communication dominates that of storage. As a result, the cost of the additional communication during collaborative storage might not be recovered by the reduced energy needed for storage except at very high compression ratios. This tradeoff is a function of the ratio of communication cost to storage cost; if this ratio goes down in the future (for example, due to the use of infra-red communication or ultra-low power RF radios), collaborative storage becomes more energy efficient compared to local storage. Conversely, if the ratio goes up, collaborative storage becomes less efficient.

The data collection model depends on the application and network organization; several models are in use for deployed sensor networks. We use a simple collection model where we only account for the cost of transferring the data one hop. This model is representative of an observer that moves around and gather data from the sensors. Also, in cases where the local buffering approach carries out aggregation at the first hop towards the observer, the size of the data becomes similar in the two approaches and the remainder of the collection cost is the same. However, this is slightly optimistic in favor of local storage because near real-time data aggregation will not in general be able to achieve the same aggregation level during collection as is achieved during collaborative storage. This is due to the fact that collaborative storage can afford to wait for samples and compress them efficiently. Moreover, in collaborative storage, the aggregation is done incrementally over time, requiring fewer resources than aggregation during collection where large amounts of data.

Figure 2: Energy consumption vs. Density
are processed during a short time period. The collaborative storage approaches outperform the local storage ones according to this metric due to their smaller storage size. CLS outperforms LS for the same reason.

Figure 3 shows that with collaborative storage, the collection time is considerably lower than that of local buffering. In addition, CLS outperforms LS. Low collection time and energy are important parameters from a practical standpoint. After exploring the effect of coordination, the remainder of the paper presents results only with the two uncoordinated protocols (LS and CBCS).

5.2 Storage Balancing Effect

In this study, we explore the load-balancing effect of collaborative storage. More specifically, the sensors are started with a limited storage space and the time until this space is exhausted is tracked. We consider an application where a subset of the sensors generates data at twice the rate of the others, for example, in response to higher observed activity close to some of the sensors. To model the data correlation, we assume that sensors within a zone have correlated data. Therefore all the sensors within a zone will report their readings with the same frequency. We randomly select zones with high activity.; sensors within those zones will report twice as often as those sensors within low activity zone.

In Figure 3 the X-axis denotes time (in multiples of 100 seconds), whereas the Y-axis denotes the percentage of sensors that have no storage space left. Using LS, in the even data generation case, all sensors run out of storage space at the same time and all data collected after that is lost. In comparison, CBCS provides longer time without running out of storage because of its more efficient storage.

The uneven data generation case highlights the load-balancing capability of CBCS. Using LS, the sensors that generate data at a high rate exhaust their storage quickly; we observe two subsets of sensors getting their storage exhausted at two different times. In comparison, CBCS has much longer mean sensor storage depletion time due to its load balancing properties, with sensors exhausting their resources gradually, extending the network lifetime much longer than LS.

5.3 Coverage Analysis

Physically co-located sensors have redundant data. For simplicity, we assume that all sensors within a zone have correlated data. In this work we consider two types of coverage, namely, binary coverage and
manifold coverage, defined as follows: (1) Binary Coverage: A given zone $Z_i$ is said to be covered at time $t$ if any one of the sensors $S_1 \ldots S_k$ in $Z_i$ is reporting and storing the reading. Binary coverage can be visualized as a step function; and (2) Manifold Coverage: A given zone $Z_i$ is said to be covered at time $t$ proportional to the number of sensors $j$ ($j < k$) out of its given set of sensors $S_1 \ldots S_k$ that are reporting and storing the reading. This coverage function can be visualized as a monotonically increasing function (which might have diminishing returns after some point). This means that the higher the number of reporting sensors the better the coverage.

Figure 5 shows the Binary Coverage as a function of time. One can see that CBCS has a higher percentage of active zones compared to LS for both data generation models.

Similar trends are seen when considering Manifold Coverage (Figure 5). Each line represents the percentage of zones with some specific coverage level: for example, the line “quarter” represents the percentage of zones where at least 25% of the sensors have storage space left. One can clearly see that, in the case of LS with even data generation (Figure 5(a)), the percentage of zones with full coverage is 100% at 300 seconds, whereas with uneven data generation it reduces to less than 50% within 300 seconds. In CBCS, at the same times, the coverage is around 96% with the even data generation model and with the uneven data model it is around 77%. Note that, A CH stored more data than individual sensor, therefore if the round time is very long, it might happen that the given CH runs out of storage sooner than a sensor storing its data locally. In LS, the percentage of dead zones (zones with all sensors out of storage space) rises in two waves for the uneven data model, reaching up to 30% within 300 seconds and 50% in 500 seconds However, with CBCS, with the uneven data model, the percentage of dead zones rises slowly and is below 30% even at the end of the simulation. In general, from these figures, one can see that the manifold coverage changes are abrupt for local buffering. In contrast, collaborative storage provide smooth degradation of coverage. Moreover, the average coverage is higher for collaborative storage due to the data aggregation and load balancing ability, by transferring data from high activity zones to low activity zones.

5.4 Effect of the Aggregation Model

One limitation of the aggregation model we have used so far is that the required storage size under collaboration grows in direct proportion to the number of sensors in the cluster; that is, the storage consumed in a round is $\alpha N \cdot D$, where $\alpha$ is the aggregation ratio, $N$ is the number of sensors and $D$ is the data sample size. Since the available storage ($N \cdot S$, where $S$ is the available storage per sensor) is also a function of the number of sensors, storage is consumed at a rate ($\frac{\alpha D S}{N}$) which is independent of the number of sensors present in the zone, assuming perfect load balancing. For most applications, this will not be the case: the aggregated data necessary to describe the phenomenon in the zone does not grow strictly proportionately to the number of sensors and we expect storage lifetime to be longer in dense areas than in sparse ones.

To highlight the above effect, we consider the case of a biased deployment where sensors are deployed randomly but with non-uniform density. In addition to the aggregation model considered so far, we con-
sider a case where the CH upon receiving packets from its \( N \) members, just needs to store 1 packet. As an example if the aggregation function is to store the average value of the \( N \) samples (e.g. average temperature reading). Clearly, in the second case, the size of the aggregated data is independent of network density. We now study how these applications with different aggregation functions perform on top of a biased deployment. To model biased deployment, we consider 4 zones with 5,4,3,2 sensors respectively. In these simulations, the round time was set to 10 seconds (CH selection happens every 10 seconds).

In Figure 7, the X-axis shows time (in multiple of 10 seconds), whereas the Y-axis shows the percentage of coverage sensors within a given zone. As described earlier we considered 4 zones for this study and each line in the Figure 7 represents a particular zone. For example line Z-5 stands for a zone with 5 sensors in it and Z-2 denotes the zone with 2 sensors in it and so on. As shown in Figure 7(a) when the aggregation ratio is a constant (0.5), all the zones provide coverage for almost same duration. However, in the second case, as shown if Figure 7(b) coverage is directly proportional to the network density, higher the density, longer the coverage.

The sensor network coverage from a storage management perspective depends on the event generate rate, the aggregation properties as well as the available storage. If the aggregated data size is independent of the number of sensors (or grows slowly with it), the density of the zone correlates with the availability of storage resources. Thus, both the availability of storage resources as well as the consumption of them may vary within a sensor network. This argues for the need of load-balancing across zones to provide long network lifetime and effective coverage. This is a topic of future research.

6 Conclusion and Future Work

In this paper, we considered the problem of storage management in sensor networks where the data is not continuously reported in real-time and must therefore be stored within the network. Collaborative storage is a promising approach for storage management because it enables the use of spatial data aggregation between neighboring sensors to compress the stored data and optimize the storage use. Collaborative storage also allows load balancing of the storage space to allow the network to maximize the time before data loss due to insufficient memory. Collaborative storage results in lower time to transfer the data to the observer during the reach-back stage and better binary and manifold coverage than a simple local buffering approach. Finally, we explored the use of coordination to cut down on redundancy at the source sensors, resulting in an improved version of both local storage and collaborative storage.

While collaborative storage reduces the energy required for storage, it requires additional communication. Using current technologies, collaborative storage requires more energy than local buffering. Network effectiveness is bound both by storage availability (to allow continued storage of collected data) as well as energy. Thus, protocol designers must be careful to balance these constraints: if the network is energy constrained, but has abundant storage, local storage is most efficient from an energy perspective. Alternatively, if the network is storage constrained, collaborative storage is most effective from a storage perspective. When the network is constrained by both, a combination of the two approaches would probably perform best.

As part of our future research, we would like to implement these protocols on real sensor hardware platforms such as the Berkeley motes. Furthermore, in this study we consider all events to be of the same importance, and thus they are stored with the same compression ratio (resolution). In our future research, we will explore the protocol space wherein different events are stored with different resolutions (important events are stored in detail whereas unimportant events are stored with a coarser granularity).

References

[1] G. Asada, M. Dong, T. Lin, F. Newberg, G. Pottie, and W. Kaiser. Wireless integrated network sensors: Low power systems on a chip. In
[2] N. Bulusu, J. Heidemann, and D. Estrin. GPS-less low cost outdoor localization for very small devices. *IEEE Personal Communications Magazine*, Oct. 2000.

[3] A. Chandrakasan, A. Amirtharajah, S. Cho, J. Goodman, G. Konduri, J. Kulik, W. Rabiner, and A. Wang. Design considerations for distributed microsensor systems. In *Proc. of the IEEE 1999 Custom Integrated Circuits Conference (CICC’99)*, May 1999.

[4] D. Ganesan, B. Greenstein, D. Perelyubskiy, D. Estrin, and J. Heidemann. An evaluation of multi-resolution storage for sensor networks. In *Proceedings of the ACM SenSys Conference*, Los Angeles, California, USA, November 2003. ACM.

[5] W. Heinzelman. *Application-Specific Protocol Architectures for Wireless Networks*. PhD thesis, Massachusetts Institute of Technology, 2000.

[6] J. Hill, R. Szewczyk, A. Woo, S. Hollar, D. Culler, and K. Pister. System architecture directions for network sensors. In *Proc. of ASAPLOS 2000*, Nov. 2000.

[7] C. Intanagonwiwat, D. Estrin, R. Govindan, and J. Heidemann. Impact of network density on data aggregation in wireless sensor networks. Technical Report TR-01-750, Univ. of Southern California, Nov. 2001.

[8] P. Juang, H. Oki, Y. Wang, M. Martonosi, L. S. Peh, and D. Rubenstein. Energy-efficient computing for wildlife tracking: design tradeoffs and early experiences with zebranet. In *In Proc. of ASPLOS 2002*. ACM Press, 2002.

[9] Crossbow – smart sensors in silicon (crossbow website), 2003. Commercial product based on Berkeley MICAs [http://www.xbow.com](http://www.xbow.com).

[10] Network Simulator. [http://isi.edu/nsnam/ns](http://isi.edu/nsnam/ns).

[11] S. Ratnasamy, D. Estrin, R. Govindan, B. Karp, S. Shenker, L. Yin, and F. Yu. Data-centric storage in sensornets. In *Proceedings of the First ACM SIGCOMM Workshop on Hot Topics in Networks*, Oct. 2002.

[12] A remote ecological microsensor network, 2000. [http://www.botany.hawaii.edu/pods/overview](http://www.botany.hawaii.edu/pods/overview).

[13] SimpleTech flash memory card datasheet. [http://www.simpletech.com/products/consumer](http://www.simpletech.com/products/consumer).

[14] S. Tilak, N. Abu-Ghazaleh, and W. Heinzelman. Storage management issues for sensor networks. In *Student Posters (ICNP 2003)*, November 2003.

[15] Y. Xu, J. Heidemann, and D. Estrin. Geography-informed energy conservation for ad hoc routing. In *Proceedings of the 7th annual international conference on Mobile computing and networking*. ACM Press, 2001.

[16] Y. Yao and J. Gehrke. The cougar approach to in-network query processing in sensor networks. *SIGMOD Record*, 31(3), Sept. 2002.
(a) LS Manifold Coverage (Even Data Generation)  
(b) CBCS Manifold Coverage (Even Data Generation)  
(c) LS Manifold Coverage (Uneven Data Generation)  
(d) CBCS Manifold Coverage (Uneven Data Generation)

Figure 6: Manifold Coverage
Figure 7: Biased Deployment versus coverage study.

(a) Aggregation ratio = 0.5: Coverage  
(b) Aggregation Ratio = 1/N: Coverage