

Efficient Gathering of Correlated Data in Sensor Networks

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ABSTRACT

In this paper, we design techniques that exploit data correlations in sensor data to minimize communication costs (and hence, energy costs) incurred during data gathering in a sensor network. Our proposed approach is to select a small subset of sensor nodes that may be sufficient to reconstruct data for the entire sensor network. Then, during data gathering only the selected sensors need to be involved in communication. The selected set of sensors must also be connected, since they need to relay data to the data-gathering node. We define the problem of selecting such a set of sensors as the *connected correlation-dominating set* problem, and formulate it in terms of an appropriately defined correlation structure that captures general data correlations in a sensor network.

We develop a set of energy-efficient distributed algorithms and competitive centralized heuristics to select a connected correlation-dominating set of small size. The designed distributed algorithms can be implemented in an asynchronous communication model, and can tolerate message losses. We also design an exponential (but non-exhaustive) centralized approximation algorithm that returns a solution within $O(\log n)$ of the optimal size. Based on the approximation algorithm, we design a class of efficient centralized heuristics that are empirically shown to return near-optimal solutions. Simulation results over randomly generated sensor networks with both artificially and naturally generated data sets demonstrate the efficiency of the designed algorithms and the viability of our technique – even in dynamic conditions.

Categories and Subject Descriptors

C.2.4 [Distributed Systems]: [Distributed Applications]

General Terms

Algorithms, Performance

Keywords

Correlated Data, Topology Control, Energy Efficiency

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1. INTRODUCTION

Sensor nodes in a wireless sensor network must be powered by small batteries, making energy efficiency a critical design goal. In this article, we focus on designing techniques to conserve energy by exploiting existing data correlations, typically that exist in a dense, highly redundant sensor network. Our targeted applications are those that need to sense or sample a signal over the geographic region represented by the sensor network. Such sensor network applications have two types of nodes: *sensing* nodes and *data-gathering* nodes [6]. The data-gathering node gathers periodic snapshots of signal data values measured at the individual sensors and use interpolation to derive the signal value at all points in the geographic region. We exploit the correlations in the sensor data by selecting a small subset of sensor nodes called *connected correlation-dominating set* which forms a connected communication graph and whose signal data values are sufficient to derive the signal value at all points with sufficient accuracy. In this article, we design a correlation structure that captures general data correlation relationships among sensor nodes in a sensor network, and formulate the connected correlation-dominating set problem in terms of a hypergraph describing the correlation structure. We design various distributed and centralized algorithms for computing a small connected correlation-dominating set. Using extensive simulations on artificially and naturally generated data, we show that the energy savings achieved by the above described approach is substantial.

Our work is complementary to the approaches that use compression techniques to exploit correlation in order to reduce the total amount of data transmitted [6, 8, 9, 22, 27]. These techniques still require *all* sensor nodes to transmit their data. Interestingly, [22] shows that compression schemes are of limited use for very dense sensor networks. In particular, [22] shows that any compression scheme is *insufficient* to transport required amount of data for a given accuracy, when the density of the sensor network increases to infinity. A necessary fallout of this thesis is that “oversampling” beyond network capacity is possible for a sufficiently dense sensor network, and the only way to prevent this would be to suppress data transmission by some nodes. This provides credence to approaches such as ours that select only a subset of sensors for data transmission.

The rest of the paper is organized as follows. In the next section, we motivate and formally define the problem of connected correlation-dominating set. In the following two sections, we present the designed distributed and centralized algorithms respectively.

Section 5 presents our simulation results. We end with sections on related work and conclusions.

2. MOTIVATION AND PROBLEM FORMULATION

In this section, we motivate the problem addressed in the article through an application and an example, and give a formal definition of the problem. We start with presenting our sensor network model.

A sensor network consists of a large number of sensors distributed randomly in a geographical region. Each sensor has a unique ID, and a radio interface, which is used to communicate directly with some of the sensors around it. A sensor s is said to be *correlated* to a set of sensors S if the data measured by s can be inferred/computed from the data measured by the sensors of S within an acceptable error bound as defined by the application. Such correlations can be discovered by prior data analysis (as described later).

2.1 Motivating Application and Example

In this article, we focus on data-gathering applications [6], where data-gathering nodes are responsible for gathering periodic snapshots of sensor data of interest. All sensor nodes transmit their measured data of interest to the data-gathering node upon being queried. The focus of this article is to exploit inherent data correlations and reduce the number of sensors that need to transmit data. For example, if a sensor s is correlated to a set of sensors S and each sensor in S is transmitting its data to the data-gathering node, then s need not transmit its data to the data-gathering node. Such suppression of transmissions enables gathering of snapshots with lower communication without compromising much on the data quality.

Our article addresses the following optimization problem (formally defined later) that arises in sensor networks with data correlations. Given a sensor network, select a minimum set of sensors M , called *connected correlation-dominating set*, such that (a) each sensor that is not in M is correlated to a subset of sensors in M , and (b) the selected set of sensors M forms a connected communication graph. The requirement for connectivity in the communication graph is due to the fact that the selected sensor set needs to collectively relay data to the data-gathering node.

It is conceivable that if the sensor data values are rich in correlations, then $|M|$ could be very small compared to n , the total number of nodes in the sensor network. To develop a complete technique based on the above idea, we need to first discover correlations in the sensor data, and then, exploit the data correlations effectively to select a small set of sensors M that forms a connected communication graph and is sufficient to infer data of all the n sensors in the sensor network. The data is relayed to the data-gathering node over a communication tree spanning over M using one message per node per snapshot. Now, if the application is required to gather q snapshots, and D is the total energy cost incurred by a distributed algorithm for computing the set M , then the condition $(D + q|M|) < qn$ would ensure overall energy cost savings. Moreover, a small D (low energy-cost of the distributed algorithm), large q (long running data-gathering queries), and $n \gg |M|$ (high degree of data correlation and good solution quality of the algorithm) will ensure $D \ll q(n - |M|)$ and hence, significant overall energy savings.

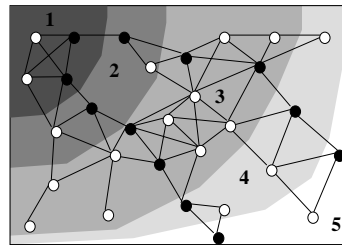


Figure 1: Connected Correlation-Dominating Set Problem.

EXAMPLE 1. Consider the sensor network in Figure 1. The sensor network region has been divided into five regions numbered 1 to 5. Each region is shaded differently and has highly correlated signal values. Thus, sensors in the same region are measuring very similar signal data values. Let us assume that the data correlations between the sensor nodes can be represented by a simple rule: for a given region, any two sensor data values are sufficient to infer the data values of all other sensors in the region. This correlation structure could be represented by a correlation hypergraph where every sensor node s has a hyperedge $((s_i, s_j), s)$ incident on it for every pair of sensors nodes s_i and s_j that belong to the same region as s .

Let M be the set of dark nodes in the figure. Following the above mentioned data correlation rule, it is easy to see that the sensors in M are sufficient to infer the signal data of all the sensors in the sensor network, as M contains at least two nodes from every region. Since, the set M also forms a connected communication graph, it is a connected correlation-dominating set. Note that M contains 4 nodes from region 3 to ensure connectivity even though only 2 are sufficient to infer all others in the region. In this example, the total number of sensors is 30, while the size of the connected correlation-dominating set is only 12. \square

2.2 Formal Problem Definition

We now formally define the connected correlation-dominating set problem addressed in this article. We start with a few definitions.

DEFINITION 1. (Communication Graph; Communication Distance) Given a sensor network consisting of a set of sensors I , the *communication graph* for the sensor network is the undirected graph CG with I as the set of vertices and an edge between any two sensors if they can communicate directly with each other. The *communication subgraph induced* by a set of sensors M is the subgraph of CG involving only the vertices/sensors in M .

The *communication distance* between two sensors I_1 and I_2 is the length of the shortest path between I_1 and I_2 in the communication graph. \square

DEFINITION 2. (Correlation Graph; Correlation Neighbors) Given a sensor network consisting of a set of sensors I , the *correlation graph* over the sensor nodes is a directed hypergraph with I as the set of vertices, and a subset of $(P(I) \times I)$ as the set of directed hyperedges, where $P(I)$ is the power set of I . In other words, the correlation graph is a hypergraph $G(V = I, E \subseteq (P(I) \times I))$. An edge (S, s)

(where $s \notin S$) in the correlation graph signifies that the sensor data of the node s is correlated to the data of the set of sensors S and hence, the data of s can be computed (within some¹ error bound) from the data of the sensors in S . The correlation graph for the sensor network in Example 1 will have a hyperedge $((s_i, s_j), s_k)$ for any three sensors s_i, s_j , and s_k that belong to the same region (1 to 5).

A hyperedge in the correlation graph is also referred to as *correlation edge*. In a correlation edge (S, s) , s is the *sink node*, S is the *source set*, and for any $x \in S$, s and x are called *correlation neighbors*. We assume that in a hyperedge (S, s) , $s \notin S$. \square

DEFINITION 3. (Connected Correlation-Dominating Set) Consider a sensor network consisting of n sensors. Let C be the correlation graph over the sensor nodes in the network. A set of sensors M is called a *connected correlation-dominating set* if the following two conditions hold:

1. For each sensor node $s \notin M$, there is a set of sensors $S \subseteq M$ such that (S, s) is a correlation edge in C .
2. The communication subgraph induced by M is connected.

A set of sensors that satisfies only the first condition is called a *correlation-dominating set* in the network. \square

Connected Correlation-Dominating Set Problem:

Given a sensor network and a correlation graph over the sensors, the connected correlation-dominating set problem is to find the smallest connected correlation-dominating set.

The connected correlation-dominating set problem is NP-hard as the less general minimum dominating set problem is well known to be NP-hard [16]. Constructing a minimum connected correlation-dominating set enables an energy-efficient gathering of sensor data of interest in a sensor network with data correlations.

2.3 Distributed Computation of Correlation Graph

In this subsection, we briefly describe how the correlation graph of a sensor network is constructed by piggybacking additional messages over the normal data-gathering messages, and adding correlation hyperedges. We start with describing when a correlation edge is added, and how are the associated correlation parameters computed.

Computing Correlation Hyperedge Parameters. We use the least squares (LS) approach to determine existence of a hyperedge. In particular, we draw a hyperedge (S, s) from a set of nodes S to a node s , if the data readings of sensor s can be inferred from the readings of sensors in S within a certain bound. Let $x[k]$ and $x'[k]$ denote the actual and predicted values of a sensor x at k^{th} time instant. Let $S = \{s_1, s_2, \dots, s_L\}$. We choose to use a linear predictive model to model the correlation, i.e., we draw a hyperedge

¹The choice of error bound depends on the accuracy and energy-efficiency requirements of the application. If the error bound allowed is higher, the correlation graph will have more number of correlation edges, which will result in a more energy-efficient solution.

(S, s) if $s'[k]$ can be represented as a linear combination of $s_1[k], s_2[k], \dots, s_L[k]$ for all k . More formally,

$$s'[k] = \sum_{i=1}^L \alpha_i s_i[k],$$

where α_i are weighting coefficients. The above equation can be easily generalized to handle temporal correlations as well. A similar model has been used to model correlation in prior work [6]. We use the LS approach to minimize the error between the predicted and actual readings, and draw an hyperedge (S, s) if the minimum error is within a certain application-dependent bound. In particular, the weighted coefficients are chosen to minimize the least square error

$$E(\alpha) = \sum_{k=1}^K (s[k] - s'[k])^2, \quad (1)$$

where K is the number of samples, and the weighted coefficients are given [6, 20] by

$$[\alpha_1, \alpha_2, \dots, \alpha_L]^T = (\mathbf{S}^T \mathbf{S})^{-1} \mathbf{S}^T \mathbf{s}. \quad (2)$$

Here, $\mathbf{s} = [s[1], s[2], \dots, s[K]]^T$ are the actual readings of the node s , and \mathbf{S} is the $K \times L$ ($K > L$) matrix of full rank L representing the actual readings of sensors in S , over time instants 1 to K . Equation (2) can be executed on an individual sensor node within affordable energy cost for reasonable values of K and L , and the energy cost expended in computing Equation (2) is proportional to $K^2 L^6$. For instance, for $L = 3$ and $K = 5$, some profiling shows that the above matrix equation uses around 100,000 CPU instructions on Atmel 128L micro-controller used in Berkeley motes [19]. In addition, from power profiling data in [26], we can estimate that energy used is transmitting a single default-sized (30 bytes) message on TinyOS [10] at the maximum power is the same as that used in computation the above Equation (2) 6 times.

Computing Correlation Graph. Let $N(s, d)$ denote the set of d -hop neighbors of s in the communication graph of the sensor network. To compute *all* the correlation edges a node s is involved in, each node s in the sensor network should collect sufficient samples from nodes in $N(s, d)$, where d is sufficiently large to capture all data correlations. Initially, when the correlation structure is unknown, *all* the network nodes are periodically involved in transmitting data to the data-gathering node using a communication tree. To compute correlation graph, we can collect d -hop neighbors' data at each node by piggybacking over data-gathering messages for d snapshots as follows. Let us assume that each node has collected data from all i -hop neighbors after i snapshots. The inductive step is as follows. During the $(i + 1)^{\text{st}}$ snapshot, when a node v is transmitting the data-gathering message to its parent, it (i) piggybacks the i -hop neighbors' data it has already collected, and (ii) instead of unicast transmission uses a broadcast transmission. Thus, *all* of v 's 1-hop neighbors receive v 's i -hop neighbors' data. Since, the above piggybacking is also done by all the 1-hop neighbors of v during the i^{th} snapshot, the node v would have collected i -hop neighbors' data of all its 1-hop neighbors which is equivalent to data from all its $(i + 1)$ -hop neighbors. As data correlations in sensor networks are spatially local, a low value of d is sufficient to capture all data correlations. Hence, the size of above piggyback messages will be bounded.

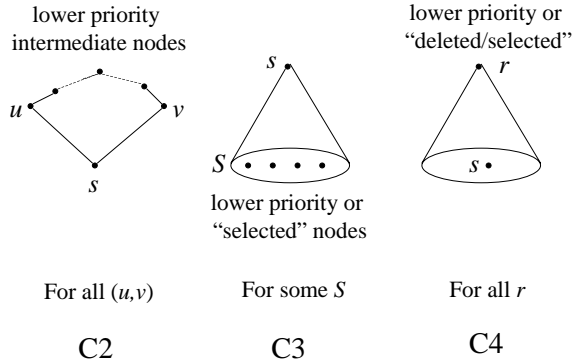


Figure 2: Condition for marking deleted of a node s . The condition C2 involves communication edges, while C3 and C4 involve correlation edges.

3. ENERGY-EFFICIENT DISTRIBUTED ALGORITHM

In this section, we present a set of energy-efficient distributed algorithms to select a connected correlation-dominating set in a sensor network. We start with a description of the basic distributed algorithm. In the later paragraphs, we will optimize the basic algorithm further to develop two distributed algorithms viz. 2-Rounds and Handshake algorithms.

Basic Distributed Algorithm. The basic distributed algorithm works as follows. Initially, each node assigns itself a priority, which could be its own ID or an appropriately chosen number (as described later). Next, each node collects k -hop neighborhood information, i.e., information about communication neighbors of all nodes that are within a communication distance of $k - 1$. Here, k is a small constant; we chose $k = 3$ for our simulations. The neighborhood information can be gathered during the data-gathering process using the piggyback strategy described in the previous section. In the remaining part of the algorithm, each node periodically tests for a set of conditions to be satisfied. If the conditions are satisfied, the node marks itself **deleted** and instructs some of its correlation neighbors to mark themselves **selected**. The **selected** marking on a node signifies that it is being used to infer another node and hence, should not be marked **deleted** in future. The **deleted** or **selected** marking of a node is permanent and in the end, some of the nodes may be left unmarked. If the communication graph of the initial sensor network is connected, the set of nodes that have not been marked **deleted** at any stage form a connected correlation-dominating set. The data-gathering node of the sensor network marks itself as **selected** initially, since it must be part of the connected correlation-dominating set.

Conditions for marking deleted. Informally, a node is marked **deleted** if: (i) it can be inferred (using a correlation edge) from a set of non-**deleted** nodes, and (ii) its deletion preserves the connectivity of the communication subgraph induced over the non-**deleted** nodes. Priorities are used to avoid cyclic dependency of conditions. More formally, a node s with priority $p(s)$ is marked **deleted** if the following conditions are satisfied (see Figure 2):

C1: The node s has not been marked **selected**.

C2: In the communication subgraph induced over the set of non-**deleted** nodes and using only the k -hop neighborhood information, every pair of neighbors (u, v) of s are connected by a communication path wherein all the *intermediate* nodes have a priority less than $p(s)$. This condition ensures that deletion of s will preserve the connectivity of the communication subgraph induced by the set of nodes not marked **deleted**.²

C3: There is a correlation edge (S, s) in the correlation graph, such that every node in the set S is either marked **selected** or has a priority less than $p(s)$.³ This condition selects a set of nodes (S) that can be used to infer s through a correlation edge.

C4: For every correlation edge (R, r) where $s \in R$, either r is marked **deleted** or is marked **selected** or has a priority less than $p(s)$. This condition is to ensure that the set of nodes in R are not being chosen for **selected** markings by the node r at the same time.

When a node s is marked **deleted**, the nodes in a source set S that satisfy the C3 condition are instructed by s to mark themselves **selected**. A node already marked **selected** can be used to infer other nodes without comparison of priorities.

Termination. The **selected** or **deleted** markings of a node are permanent, and hence, the distributed algorithms discussed in this section are guaranteed to terminate. At any intermediate stage of the algorithm, the set of non-**deleted** nodes forms a connected correlation-dominating set. Thus, any intermediate solution is usable by an application, and it may not be critical to explicitly *detect* termination of the algorithm. If required, the algorithm can be considered terminated after sufficient time (message latency times the upper bound on the number of messages) has elapsed. The upper bound on the number of messages is derived later.

Communication Messages. Let d be the maximum communication distance between two correlation neighbors. Initially, each node needs to gather k -hop neighborhood information and priorities of its correlation neighbors, where k is the constant in condition C2. After the initial accumulation of information from close neighbors, additional communication is incurred by the algorithm whenever a node marks itself **deleted** or **selected**. In particular, when a node s is marked **deleted** or **selected**, the following communication steps are executed.

1. Node s informs its *correlation* neighbors of its **deleted** status, so that they could retest their C4 condition. In the *same*⁴ message, node s also instructs nodes of a source set S that satisfies C3 condition to mark themselves **selected**.
2. Node s informs its *communication* neighbors of its **deleted** status, so that they could retest their C2 condition.⁵

²Wu et al. in [28] use a similar condition for computing a connected dominating set.

³Note that by virtue of the next C4 condition, no node in S could be marked **deleted**.

⁴If we use different messages, then we need to worry about the possibility of *only* the **deleted** message reaching a node in S . See proof of Theorem 1.

⁵Note that an unsatisfied C2 condition of a node can become

- Node s informs its *correlation* neighbors of its **selected** status, so that they could retest their C3 and C4 conditions.

In the following theorem, we prove the correctness of the basic distributed algorithm, which is unaffected by message losses. Also, the distributed algorithms designed in this section do not require any synchrony in the underlying communication model and can be easily implemented in an asynchronous system.

THEOREM 1. The above described basic distributed algorithm correctly computes a connected correlation-dominating set, even if there are message losses.

Proof: (sketch) We start with observing that a node s marks itself **deleted** based upon its condition C1-C4 being true at *some* point of time. Below, we will show that irrespective of any additional messages being received, the set of such **deleted** nodes do not disconnect the sensor network, and that each such **deleted** node s can *always* be inferred by a set of non-**deleted** nodes S . Thus, proving the correctness of the algorithm even in the presence of message losses.

First, we show that the removal of nodes that are marked **deleted** does not disconnect the original communication graph of the sensor network. It is easy to see that removal of any single node s that satisfies the C2 condition will definitely maintain the connectivity of the sensor network’s communication graph. Now, note that the satisfaction of C2 condition of s is based upon existence of alternate paths involving nodes with *lower* priority than that of s . **Deleted** marking of a node u in any of the alternate paths of s will result in another alternate path consisting of even lower priority nodes. This is because the node u will also satisfy the C2 condition due to nodes having lower priority than that of u and hence, that of s . Thus, if s satisfies the C2 condition, then there will always exist an alternate path connecting every pair of its neighbors. Thus, removal of s maintains the connectivity of the original communication graph of the sensor network.

Now, we show that the set of nodes that are not marked **deleted** form a correlation dominating set. It is sufficient to show that if a node s is marked **deleted**, then there will always exist a correlation hyperedge (S, s) such that no node in S has been marked **deleted**. Since, the node s satisfied condition C3, there is a hyperedge (S, s) such that each node $x \in S$ is either marked **selected** (and hence, would never be marked **deleted** in future due to condition C1) or has a priority lower than that of s . In the latter case, the node x could mark itself **deleted** *only* when it receives a message about s ’s **deleted** marking (see condition C4). However, as mentioned before, in the *same* message the node x is also instructed by s to mark itself **selected**. Hence, the node x will never mark itself **deleted**. Thus, no node in S is ever marked **deleted** and the node s can always be inferred using the nodes in S . Since the above is true for any node s that has been marked **deleted**, the set of non-**deleted** nodes form a correlation dominating set. ■

true only by **deleted** marking of one of its neighbors. In addition, it can be shown ([28]) that once the C2 condition is satisfied for a node s , the deletion of s will always preserve connectivity in the communication subgraph induced by the non-**deleted** nodes, even if other nodes get marked as **deleted**.

We now present the 2-Rounds and Handshake distributed algorithms, which optimize the basic distributed algorithm further.

2-Rounds Distributed Algorithm. The above described basic algorithm could be improved (in terms of increasing the number of **deleted** nodes) by comparing priorities only between nodes that are contending with each other for marking themselves **deleted**. The 2-Rounds algorithm consists of an initial round before executing the basic algorithm. In the initial round, the priority comparisons in conditions C3 and C4 are made only for nodes that satisfy the C2 condition. More precisely, for the initial round, the conditions C3 and C4 are replaced by the following modified C33 and C34 conditions.

C33: There is a correlation edge (S, s) in the correlation graph, such that no node in the set S is marked **deleted**. In addition, each node in S is either marked **selected** or doesn’t satisfy the C2 condition or has a priority less than $p(s)$.

C44: If there is a correlation edge (R, r) where $s \in R$, then either r is marked **deleted** or marked **selected** or doesn’t satisfy the C2 condition or has a priority less than $p(s)$.

To test the above C33 and C44 conditions, each node should be able to evaluate the C2 condition of its correlation neighbors. Thus, the 2-Rounds algorithms begins with gathering $(d+k)$ -hop neighborhood information, where d is the maximum communication distance between correlation neighbors. After the initial round, the 2-Rounds algorithms behaves exactly as the basic distributed algorithm. In our experiment results, we observed that 2-Rounds algorithm yielded significant improvement in the solution size over the basic distributed algorithm.

Handshake Algorithm. Handshake algorithm is essentially the basic distributed algorithm with the conditions C3 and C4 replaced by the modified conditions C33 and C44, where we compare priorities between only those nodes that satisfy the C2 condition. Thus, we require each node to transmit a “C2-satisfied” message when its C2 condition is satisfied. However, loss of “C2-satisfied” messages may result in neighboring nodes s and \hat{s} both marking themselves **deleted** with s depending on \hat{s} for inference. Thus, to ensure correctness in event of message losses, we need to incorporate additional “handshake” messages. The addition communication steps required in the Handshake Algorithm are:

- Whenever a node’s C2 condition is satisfied, it transmits a ‘C2-satisfied’ message to all its correlation neighbors, so that they have complete information to test their C33 and C44 conditions.
- Before node s marks itself **deleted** (due to satisfaction of conditions C1, C2, C33, and C44), it makes a “handshake” with the nodes in S of condition C33. The handshake involves the node s sending a handshake message to the nodes in S and the nodes in S responding positively or negatively. The node s marks itself **deleted** only if it receives a positive response from all the nodes in S . A node in S sends a positive

response only if it is not marked **deleted** and if it either doesn't satisfy C1 or doesn't satisfy C2 condition or its priority is less than that of s .

3. A node in S of condition C33 marks itself **selected** only after the corresponding node s has conclusively (after positive acknowledgement from all nodes in S) marked itself **deleted**.

Handshake algorithm is expected to select a smaller connected correlation-dominating set compared to the 2-Rounds algorithm. However, the better performance comes at the cost of additional messages for 'C2-satisfied' and handshake messages.

Number of Communication Messages. Let d be the maximum communication distance between correlation neighbors. As mentioned before, the 2-Rounds algorithm needs to gather $(d+k)$ -hop neighborhood information, while the Handshake algorithm collects k -hop neighborhood information. If n is the total number of sensor nodes in the network, l -hop neighborhood information can be gathered using ln messages. However, since the neighborhood information can be gathered during the normal data-gathering process (as described in Section 3), we ignore the communication cost incurred.

Let δ be the average⁶ size of a connected dominating set of the communication subgraph induced by a sensor node and its correlation neighbors. Also, let $|D|$ be the number of nodes that get marked **deleted** and $|S|$ be the number of nodes that get marked **selected** during the entire course of the algorithm. Note that $(|D| + |S|)$ is bounded by n , the size of the sensor network. The total communication cost incurred in each of the distributed algorithms is as follows.

- 2-Rounds Algorithm: $\delta(|D| + |S|) \leq n\delta$.
- Handshake Algorithm: $\delta(|D| + |S|) + \text{'C2-satisfied' messages} + \text{handshake messages} \leq n(\delta + \delta + 2\delta) \leq 4n\delta$.

Assignment of Priorities. Note that we can use different priorities for condition C2 and condition C3-C4. For the C2 condition, we use the inverse of the node's degree as the priority [28]. For the C3-C4 conditions, we assign priority $p(s)$ for a node s as follows. Let S be a source set containing s . If node s satisfies C2 condition initially, we use $p(s) = 1/(\sum_S 1/|S|)$ (since our algorithms favors deletion of higher priority nodes), else we use $p(s) = 1/(30 * NodeDegree(s) \sum_S 1/|S|)$ so that comparison of priorities (in C3, C4) is relevant only for nodes that satisfy the C2 condition.

Handling Dynamic Changes to Correlation Graph. Change in data correlations may result in changes to the correlation graph. Thus, each **deleted** node s periodically checks for validity of the hyperedge (S, s) used in its C3 condition by gathering data from the nodes in S (using the piggyback strategy over normal data-gathering process as described in Section 2.3), recomputing the α parameters (Equation (2)), and checking if the least square error (Equation (1)) is within the given bound. If the least square error is more than the acceptable bound, the hyperedge (S, s) is invalidated, and the node s searches for a still valid hyperedge (S', s) that satisfies its C3 condition and consists of

⁶Average is across all instances when a node has to send a message.

only non-**deleted** nodes in S' . If such a hyperedge exists, the nodes in S' are instructed to mark themselves **selected**. If a node r in S' had to be un-**deleted**, it informs its communication neighbors. If no such hyperedge exists, then the node s marks itself un-**deleted**⁷ itself, and informs its communication neighbors. If a **deleted** neighbor v of either s or r fails to satisfy the C2 condition now due to un-**deletion** of s or r respectively, the node v un-**deletes** itself and informs all its neighbors. The above process continues, and ensures that the connectivity of the non-**deleted** nodes is maintained. To conserve energy, we do not un-**select** a node as it does not affect correctness.

Generalizations. Throughout this article, we have modeled correlation as complete inference of a node from a set of other nodes. However, our distributed and centralized algorithm (next section) can be easily generalized to model the case when a hyperedge (S, s) with a weight b signifies that the node s can save on transmission of b bits, if the data from nodes in S is available. Such a model has been used in [6]. In the above model, higher weighted hyperedges are preferred for use in C3 condition for distributed algorithms. Similarly, weights assigned to sensor nodes to model non-uniform battery energies can be handled by assigning the hyperedge weight as an appropriate function of the sink and source nodes' weights. Centralized algorithms developed in the next section use a notion of benefit of a set of selected nodes – which can also be easily adapted to handle the above generalizations.

4. CENTRALIZED APPROXIMATION ALGORITHM

In this section, we present a centralized approximation algorithm that returns a connected correlation-dominating set that is within an $O(\log n)$ factor of the optimal size. Based on the approximation algorithm, we design a class of efficient polynomial-time heuristics. In Section 5, we will show that even the lower order polynomial-time heuristics deliver near-optimal solutions for spatial sensor networks. The centralized heuristics developed in this section also allow us to ascertain the quality of the solution sizes of the energy-efficient distributed algorithms of previous section by comparing them with the near-optimal centralized heuristics. The centralized heuristics can be implemented in a sensor network by executing the heuristic on one of the special-purpose computationally powerful sensor nodes in the network, after gathering required information from all the nodes in the sensor network. We start with some definitions for a sensor network with a correlation graph.

DEFINITION 4. (Intersection Graph of Source Sets) Let I be the set of nodes in the network, and $\mathcal{I} = \{\{s\} | s \in I\}$. Let \mathcal{S} be the set of source sets in the correlation graph of the network. The *intersection graph of source sets* is the simple graph $G(V = \mathcal{S} \cup \mathcal{I}, E = \{(v_1, v_2) | (v_1 \cap v_2) \neq \phi\})$.⁸ See Figure 3. □

⁷By "un-delete," we mean that it removes its **deleted** marking.

⁸We include the elements of \mathcal{I} in the vertices of graph G , since a node trivially infers itself. Hence, the correlation graph can be thought of to have trivial hyperedges $(\{s\}, s)$ for each node s in the network, but we have precluded presence of these hyperedges in a correlation graph for sake of clarity.

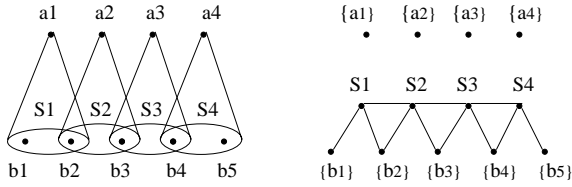


Figure 3: Correlation graph and its intersection graph of source sets.

DEFINITION 5. (Connected Subgraph of Sources; Connected Source Set) A connected subgraph in the intersection graph of source sets is called a *connected subgraph of sources*.⁹ A *connected source set* is a set of nodes corresponding to some connected subgraph of sources, i.e., the union of the sets corresponding to the vertices of a connected subgraph of sources. For example, in Figure 3, S_1, S_2 , and S_3 form a connected subgraph of sources and the corresponding connected source set is $\{b_1, b_2, b_3, b_4\}$. \square

DEFINITION 6. (Inferred Nodes) Given a set of nodes S , the set of inferred nodes for S is denoted by $I(S)$ and is defined as

$$I(S) = S \cup \{x | (Y, x) \text{ is a correlation edge and } Y \subseteq S\}.$$

\square

DEFINITION 7. (Benefit of a Set of Nodes) Benefit of a set S with respect to a set M of nodes M is denoted by $B(S, M)$ and is defined as $B(S, M) = |I(S) - I(M)| / |S - M|$, where $I(S)$ and $I(M)$ are the set of inferred nodes for S and M respectively. \square

Approximation Algorithm. Our proposed approximation algorithm consists of two phases. The first phase is a greedy phase that constructs a near-optimal correlation dominating set. The second phase runs a Steiner tree approximation algorithm [2] to connect the correlation-dominating set constructed in the first phase. The first greedy phase of the algorithm works as follows. Let M denote the set of already selected nodes at any stage. Initially M contains the data-gathering node. At each stage, the algorithm adds to M the connected source set that has the maximum benefit with respect to M at that stage. The phase of the algorithm terminates when M becomes a correlation-dominating set. The second phase of the algorithm builds a communication Steiner tree over the set of nodes in M by adding additional nodes. We build the communication Steiner tree by iteratively connecting the closest pair of connected components, i.e., the pair of components that can be connected by addition of minimum number of nodes.

THEOREM 2. The size of the connected correlation-dominating set returned by the above described centralized algorithm is at most $2d(1 + \log n)|OPT|$, where OPT is the optimal correlation-dominating set, d is the maximum communication distance between two correlation neighbors, and n is the number of nodes in the sensor network.

⁹The notion of “connected” here is in context of the intersection graph of source sets and has nothing to do with the communication graph.

Proof: Whenever a connected source set S is added to M by the greedy first phase of the algorithm, we charge the newly inferred nodes $I(S) - I(M)$ with the number of unselected (not in M) nodes in S , i.e. $|S - M|$. The charge $|S - M|$ is evenly distributed on each of the newly inferred $I(S) - I(M)$ nodes giving each newly inferred node a charge of $|S - M| / |I(S) - I(M)|$.

Let OPT be an optimal correlation-dominating set (not necessarily connected). Consider the subgraph ζ of the intersection graph of source sets induced by the source sets and nodes contained in OPT . Let $\zeta_1, \zeta_2, \dots, \zeta_l$ be the connected components in the induced subgraph ζ . Let S_{ζ_i} be the connected source set corresponding to the component ζ_i . Also, let T_i be the charge accumulated by $I(S_{\zeta_i})$, the set of inferred nodes for S_{ζ_i} , during the entire course of the algorithm. Since, S_{ζ_i} is also considered for selection by the greedy algorithm at each stage, it can be shown ([7]) that T_i is at most $|S_{\zeta_i}|(1 + \log |I(S_{\zeta_i})|)$. Thus, the total charge T accumulated by $I(OPT)$, the set of all nodes inferred by optimal solution OPT , during the course of the algorithm can be bounded as follows.

$$T \leq \sum_{i=1}^l (1 + \log |I(S_{\zeta_i})|) |S_{\zeta_i}|$$

$$T \leq (1 + \log n) \sum_{i=1}^l |S_{\zeta_i}|$$

$$T \leq (1 + \log n) |OPT|.$$

The last equation follows from the fact that the sets of nodes $S_{\zeta_1}, S_{\zeta_2}, \dots, S_{\zeta_l}$ are connected components of the graph ζ , and hence, form a mutually-disjoint *partition* of the optimal set of nodes OPT .¹⁰ Now, since $I(OPT)$ is the set of all nodes in the network, the total charge T accumulated by $I(OPT)$ is the size of the correlation dominating set M returned by the first phase of the algorithm. Thus, we get $|M| \leq (1 + \log n) |OPT|$.

We now show that the second phase of the algorithm adds at most $(2d - 1)|M|$ additional nodes. Consider the connected components M_1, M_2, \dots, M_p in the communication subgraph induced by M . It can be shown by contradiction that there exist two nodes in different connected components M_i and M_j such that the nodes are connected by a communication path of length at most $2d - 1$. Since the above is true for any correlation dominating set, and as $p \leq |M|$, all the connected components of M can be connected together using at most $(2d - 1)|M|$ additional nodes. Thus, the size of the connected correlation-dominating set returned by our approximation algorithm is at most $2d(1 + \log n)|OPT|$. \blacksquare

Gupta [17, 18] has used similar techniques to construct approximation algorithms for a related dual problem of selection of views to materialize in a general data warehouse. The time complexity of the above proposed approximation algorithm is exponential in n , the total number of nodes in the network, since the number of connected source sets considered at each stage of the first phase can be exponential. However, the approximation algorithm is non-exhaustive and may perform better for sensor networks whose intersection graph of source sets has few edges. More importantly, the approximation algorithm gives us an insight and a basis to

¹⁰It is for this reason that the approximation algorithm considers all possible connected source sets at each stage.

design polynomial-time greedy heuristics that restrict the search space by considering only a polynomial number of connected sources sets at each stage. Note that locality of data correlations (within a certain d -hop neighborhood) does not help improve the approximation ratio or the complexity of the above described approximation algorithm.

Polynomial-time Heuristics. Based on the above approximation algorithm, we design the following class of l -hop polynomial-time heuristics. For a given l , the l -hop heuristic works as follows. At each stage, the l -hop heuristic constructs, for *each* source set S , the connected source set $f_l(S)$ (defined in the next paragraph). Then, the algorithm picks the $f_l(S)$ that has the maximum benefit and adds it to the already selected set of nodes M . After M has become a correlation-dominating set, additional nodes are added to construct a communication Steiner tree spanning over M .

The connected source set $f_l(S)$ for a given S is constructed in a greedy manner by merging with S the best source set that is within a distance of at most l from S in the intersection graph of source sets. The greedy construction of $f_l(S)$ stops when its benefit cannot be improved further.

Example. For the correlation graph in Figure 3, in the first stage (when $M = \phi$) of the 1-hop heuristic, $f_1(S_1) = S_1 \cup S_2$ and $f_1(S_2) = S_1 \cup S_2 \cup S_3$. Since, the benefit of $f_1(S_2)$, $B(f_1(S_2), M)$, is the maximum for all $f_1(S_i)$, the 1-hop heuristic sets $M = S_2 \cup S_1 \cup S_3$ in the first stage.

The time complexity of the above described l -hop heuristic is $O(m^2 g^l)$, where m is the total number of correlation edges and g is the maximum degree of a node in the intersection graph of source sets. We expect 1-hop or 2-hop heuristics to perform very well for ad-hoc wireless networks with spatial data correlations where the size of source sets is expected to be small. In fact, using extensive simulations on random sensor networks, we demonstrate that 1-hop heuristic yields a near-optimal connected correlation-dominating set.

5. PERFORMANCE RESULTS

In this section, we present our simulation results that demonstrate the performance and effectiveness of our proposed approach and algorithms. In particular, we compare the size of the connected correlation-dominating set returned by our proposed distributed and centralized algorithms viz. 2-Rounds, Handshake, 0-hop, 1-hop, and 2-hop centralized heuristics. Note that 0-hop is essentially a naive greedy centralized approach. In addition, we compare the communication costs incurred by the two distributed algorithms. We present results from three sets of experiments that elicit various interesting properties of our approaches. In all three cases, the sensor network is randomly generated; however, they differ in how the sensor data is generated and represented. In the first case, the correlation graph itself is generated randomly. In the second set, records of temperature data from 600 US cities is used as the sensor data set. In the third set, the sensor data is generated by simulating the behavior of hypothetical signal sources.

Computation Cost Model. In all our experiments, we estimate energy consumed in computing hyperedge parameters as follows. Using the calculations in Section 2.3, the computation of Equation 2 (for $K=3$ and $L=5$) consumes roughly about 1/25 fraction of energy required to transmit one message on Berkeley notes. Here, we assume message size of 1K bits. Initial computation of the correlation graph re-

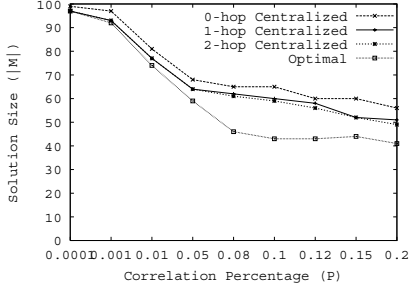
quires each node computing the Equation 2 about 1000 times (number of possible hyperedges in a 2-hop neighborhood size of around 20) for the first (synthetic data) and third (time-varying signals) sets of experiments, and around 100 times (2-hop neighborhood size of around 10) for the temperature data. We have assumed computation of hyperedge parameters at individual nodes, but depending on the resources available the computation could also be done at a powerful central node.

Random Sensor Networks with Synthetic Correlations We generated data for random sensor networks as follows. First, we randomly place 1000 sensors in an area of 40×40 units. Each sensor has a uniform transmission radius of 3 units, and two sensors can communicate with each other if they are located within each other’s transmission radius. We generate the correlation graph over the sensor network as follows. For each node s and a set of nodes S consisting of 1 to 3 sensor nodes that are within a communication distance of at most $d = 2$ from s , we add the hyperedge (S, s) with a probability of $P/100$, where P is a constant less than 100 and is referred to as the *correlation percentage*. We analyze the performance of our algorithms for a sufficiently wide range of P values.

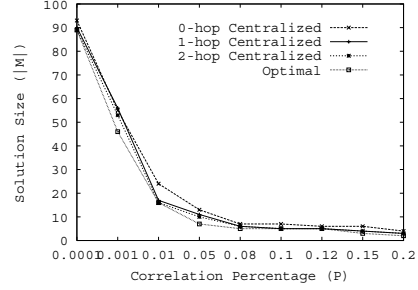
Centralized Heuristics’ Solution Sizes. In Figure 4, we compare the quality of some of the centralized heuristics with the *optimal* (exhaustive search) algorithm for small size sensor networks (100 sensors placed randomly in a 7×7 area) for transmission radius 2 and 4. We notice that the 0-hop, 1-hop, as well as 2-hop centralized heuristic perform quite close to the optimal solution. We observe that the 1-hop heuristic performs quite better than the 0-hop heuristic, while there is no noticeable difference in the solution sizes of 1-hop and 2-hop centralized heuristics. Since, the l -hop heuristics are based on the approximation algorithm that provably returns a near-optimal solution, and increase in l results in increasingly better performance, we conjecture that 1-hop heuristic returns a near-optimal solution for dense sensor networks with rich spatial data correlations involving small source sets. For larger sensor networks (see Figures 5 (a)), we report the solution sizes returned by 0-hop and 1-hop heuristics, and compare them with the solution sizes of the distributed algorithms.

Distributed Algorithms’ Solution Sizes. We observe that the Handshake algorithm returns a smaller solution size than the 2-Rounds algorithm (see Figure 5 (a)). However, the solution size returned by the Handshake algorithm is only marginally better than the 2-Rounds algorithm, which demonstrates the effectiveness of the initial round and the strategy of subsequent assignment of lower priorities to nodes that don’t satisfy the C2 condition in the 2-Rounds algorithm. We also evaluated the delayed-connection versions of the algorithms wherein the algorithms first select a correlation-dominating set and then, connect the selected nodes using a communication Steiner tree. We observed that the delayed-connection versions always performed worse than their counterparts, in terms of both the solution size returned as well as the communication costs incurred. For brevity, we have not discussed the details of the delayed-connection versions here.

Distributed vs. Centralized Solution Sizes. As expected, the solution sizes returned by the centralized heuristics is always better than the solution sizes returned by the distributed

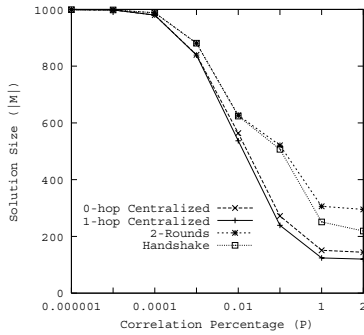


(a) Transmission Radius = 2

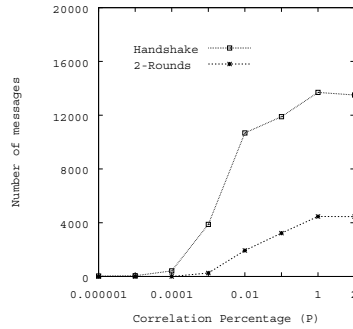


(b) Transmission Radius = 4

Figure 4: Comparison of centralized heuristics with optimal algorithm for small sensor networks (100 sensors in a 7×7 area with synthetically generated correlations).



(a) Solution sizes



(b) Number of messages

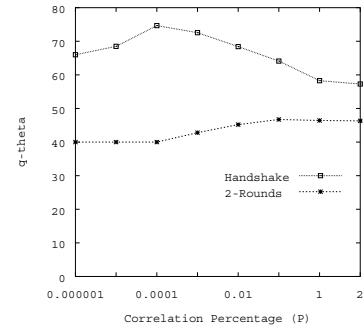
(c) q_θ

Figure 5: Comparison of different centralized and distributed algorithms for large and sparse sensor networks (1000 nodes with transmission radius of 3 units in 40×40 area with synthetically generated correlations).

algorithms (see Figure 5 (a)). This is hardly surprising, since, the centralized heuristics have global information of the sensor network and have time complexities in high order polynomials. In contrast, the distributed algorithms are localized and incur only a linear number of messages. However, we should note that the distributed algorithms still perform impressively close to the near-optimal centralized heuristics.

Number of Messages. The communication cost incurred by the 2-Rounds algorithm is much less than that incurred by the Handshake algorithm (see Figure 5 (b)).¹¹ Since, the solution size returned by the Handshake algorithm is only marginally better than the 2-Rounds algorithm, we can conclusively say that the 2-Rounds algorithm is the best performing distributed algorithm.

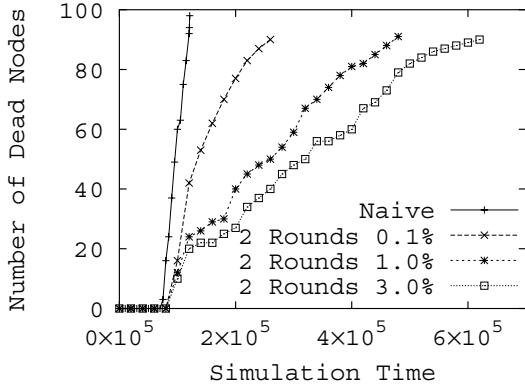
Let D be the the total energy cost incurred by a given distributed algorithm and n be the total number of sensors in the network. As discussed in Section 2.1, as long as the data-gathering query requires more than $q_\theta = \frac{D}{(n-|M|)}$ snapshots the overall energy cost for the data-gathering query using the

¹¹Note that for very low correlation percentages, the 2-Rounds algorithm incurs zero number of messages, because the nodes marked `deleted/selected` in the initial round do not need to transmit as their correlation neighbors can deduce their markings using the $(d+k)$ -hop neighborhood information.

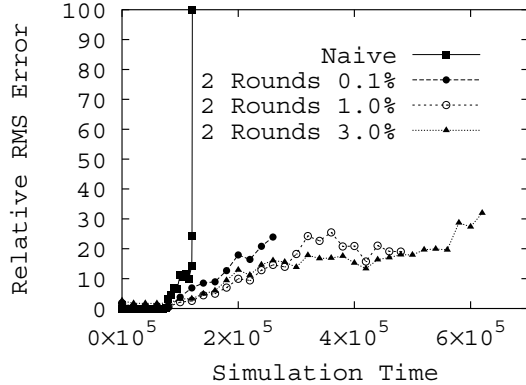
given distributed algorithm is lower than that incurred using the naive approach, wherein all sensor nodes are involved in transmitting data to the data-gathering node. We plot the q_θ value in Figure 5 (c). As estimated before, we have added 40 message transmissions per node for about 1000 computations of Equation 2. We can see that the value of q_θ for the best performing 2-Rounds distributed algorithm is around 50, which is encouraging since data-gathering queries typically gather a much larger number of snapshots.

Simulations on Temperature Data. We gathered monthly average temperature data of over 600 US cities [23] for the last decade. We consider a sensor network formed by placing a sensor node at each of the 600 city locations. We chose a transmission radius of 70 miles for each sensor node, so that each sensor has a good number of communication neighbors. We created a hyperedge (S, s) for a sensor node s and a set of nodes S if the monthly temperature of s can be inferred from S within an error threshold of 5%. Here, S consists of 1 to 3 sensor nodes that are within a communication distance of at most $d = 2$ from s . The experiment results for the city temperature data are shown in Table 1. As estimated before, we have added 4 message transmissions per node for about 100 computations of Equation 2.

Simulations of Dynamic Sensor Networks with Time Varying Data. We have set up a simulation that demonstrates how our distributed algorithms perform in dynamic



(a) Number of Dead Sensors



(b) RMS error in the gathered data

Figure 6: Simulation experiments with dynamic sensor networks (100 nodes with transmission radius of 3 units in a 10×15 area) with time-varying signal data for various error thresholds.

Algorithm	$ M $	Messages	$q\theta$
0-hop	353	-	-
1-hop	320	-	-
2-Rounds	390	3608	20
Handshake	364	7264	35

Table 1: Simulation Results on Temperature Data.

conditions, i.e., when the sensor data and hence, correlation graph changes, and sensor nodes may die after battery depletion. For this experiment, we randomly place 100 sensor nodes, each having a transmission radius of 3, in an area of 10×15 units. We also place a number of signal sources¹² at random locations in this region. The signal intensity at a distance d from the source is assumed to be inversely proportional to d^2 , and the intensity at any point is the sum of the intensities from individual light sources. The sources generate a signal with an intensity chosen randomly between 100 and 200 units. At random intervals (with a mean period of 2000 time units), the signal sources either increase or decrease their intensity by 5% or remain unchanged with equal probability.

Correlation Graph. A correlation hyperedge (S, s) is created for a node s and a set of nodes S , where S consists of 1 to 3 nodes in the 2-hop neighborhood of s , if the least square error (Equation 1) calculated for optimal α parameters (Equation 2) is within a certain error threshold. We run experiments for error threshold values of 0.1, 1, and 3 percentages. Initially, the correlation graph is constructed, and the distributed algorithm executed to compute the connected correlation-dominating set. Over time, invalidation of *used* hyperedges is detected, and the solution incrementally maintained as described in Section 3. Also, just before a sensor node dies, it informs its correlation neighbors who rerun the distributed algorithm.

Battery Consumption. The sensor network is tasked to gather snapshots of the signal intensity levels in the entire region at

¹²The exact nature of the signal is not important for our purposes.

regular intervals of 100 time units. Each sensor is initialized with a battery power chosen randomly between 750-1250 units, where 1 unit of battery power is consumed by every message transmission. Messages are transmitted to compute the hyperedge parameters, to execute the distributed algorithm, and to gather snapshots from the connected correlation-dominating set. As estimated before, each node consumes about 40 units of battery energy for about 1000 computations of Equation 2.

Performance. We compare the performance of our distributed algorithms with a Naive approach, wherein all sensors in the network report data for each data gathering snapshot. We use the root mean square (RMS) approach to quantify the error in the gathered data. Note that the gathered data may have inaccuracies because of the following two reasons. In our approach of gathering data only from a connected correlation-dominating set, bounded errors are introduced when data for other sensors is inferred. Also, for both approaches (Naive and ours), data for dead sensors is “recovered” at the data-gathering node by using an available hyperedge involving alive source nodes. If no such hyperedge exists, then we take an average of the data from 2 of its nearest alive neighbors.

Figure 6(a) and (b) plot the number of dead sensors and the RMS error in the gathered data for the 2-rounds algorithm and the Naive approach, for various choices of error threshold values. We have only shown 2-rounds algorithm in the figure, as 2-Rounds consistently outperformed Handshake for the used parameter values. Note that there is no error in the beginning for the naive approach. However, there is a very sharp rise in the error when the nodes start dying, and the nodes are all dead soon after 100,000 time units. In contrast, the 2-rounds algorithm incurs some error throughout and the error gradually increases when the nodes start dying. We notice better performance for higher error thresholds. In particular, we observe that the RMS error remains at a reasonable level for upto 600,000 time units for 3% error threshold. These simulations demonstrate the effectiveness of our approach in increasing the useful lifetime of a sensor network.

Summary. Based on the above described simulation re-

sults, we can conclude that the 2-Rounds algorithm is the best performing algorithm among all the designed distributed algorithms, in terms of the size of the connected correlation-dominating set selected, the number of messages incurred, and RMS error introduced in the gathering data. Also, 2-Rounds algorithms returns a solution whose size is quite close to that returned by the 1-hop heuristic, which seems to return a near-optimal solution for spatially correlated dense sensor networks. Based on the total number of messages incurred and the savings achieved, we conclude that the approach of constructing a connected correlation-dominating set using the 2-Rounds algorithm will result in substantial energy savings.

6. RELATED WORK

The problem of efficient gathering of correlated data in a sensor network has been recently addressed by Rickenbach et al. [27], Chou et al. [6], and Cristescu et al. [8,9], where the focus is on reducing the total number of bits transmitted to the data-gathering node using coding techniques. In particular, authors in [27] focus on single-input coding strategies (i.e., simple correlation edges). They consider two coding schemes viz. foreign-coding and self-coding, and present algorithms to construct optimal (minimum weighted number of bit transmissions) and near-optimal data-gathering trees for foreign-coding and self-coding respectively. In [6], the savings are achieved by having the data-gathering node track the correlation structure among nodes and then, use this information to inform the sensor nodes the number of bits they should use for encoding their measurements. However, they assume a fixed correlation structure and a “star” topology, and do not address the optimization problem of minimizing the number of bit transmissions. Lastly, [8] considers a coding strategy based upon Slepian-Wolf model and design efficient distributed approximation algorithms optimizing the transmission structure and the rate allocation at the nodes. In all of the above methods, *all* sensors are engaged in data transmission albeit with reduced number of bit transmissions. As noted before, the model and techniques developed in this article can also be extended to optimize total number of bit transmissions.

Similar to the idea proposed in our paper, Yoon and Shababi [32] propose a mechanism (called CAG) that reduces the number of transmissions and provides approximate results to aggregate queries by utilizing the spatial correlation of sensor data. Like our approach, they also select only a select of nodes for transmission of data to the sink node. However, their formulation of the problem is a simpler version of our problem wherein correlation graph consists of only simple edges (connecting a node to its ancestor in the data gathering tree). They select a set of clusterheads (which actually form a correlation dominating set in our terminology) using a simple localized scheme during the query propagation phase. Due to connectivity requirement, each node that has at least one descendant as clusterhead is involved in transmission. The main shortcomings of the above approach is that it uses a very simple notion of correlation, and uses *only* the edges of the forwarding tree (typically the shortest path tree) for selection of clusterheads and connecting nodes.

The problem of constructing an efficient *aggregation* tree to reduce the total bits of transmitted in the network have also been addressed recently [14,15]. In particular, Goel et

al. [15] look at the problem of finding efficient trees to send aggregated information to a sink, where information can be aggregated at intermediate nodes. They present a randomized tree construction algorithm, which is a good approximation simultaneously for all concave non-decreasing aggregate functions. In [14], authors analyze a simple randomized tree construction algorithm that achieves a constant factor approximation of the optimal tree for grid network topologies. Both of the above works assume data compression models specific to aggregation, wherein *any* k data values can be compressed into a data value of appropriately defined size. In contrast, the correlation model considered in our article is more general, wherein only the given set (which can be arbitrary) of data values can be compressed depending on the correlation structure present in the network.

Recently, Marco et al. [22] analyzed the data transport capacity of a dense sensor network in data-gathering applications. In their model, all sensors in the network encode/compress their measured samples and transmit them to a single data-gathering node. They show that as the density of a sensor network increases to infinity, then the total number of bits required to attain a given quality of reconstructed field also increases to infinity under *any* compressing scheme. Thus, the only way to limit the total amount of data transmitted below the network’s transport capacity would be to suppress transmission from some sensors to prevent “oversampling.” In [25], authors show that if data can be encoded *en route* – for example, at the tree nodes – then the capability of the dense sensor network and the correlation structure of a typical random field are sufficient to permit data gathering by any nodes within any given distortion value. However, an appropriate routing technique must still be devised, which remains an open question. Our work proposes an alternate efficient approach to reduce data communication in data-gathering applications by minimizing the number of sensors that are involved transmitting their data to the data-gathering node. In other related work, Patten et al. [24] analyze the performance of various routing with lossless compression schemes, and show that near-optimal performance can be achieved using a static clustering scheme for the case of 1D and 2D array of sensor nodes for a wide range of spatial correlations.

There has been a significant amount of work on the related problem of computing a minimum connected dominating set [13,16] in a distributed manner. A connected dominating set (CDS) is used for efficient broadcasting of a message in a mobile ad hoc network, since only the nodes in CDS need to forward the message to its neighbors. The work in wireless network research community ([1,5,11,12,21,28,29]) has primarily focussed on developing energy-efficient distributed algorithms to construct a good connected dominating set. The connected dominating set problem is a special case of the connected correlation-dominating set problem wherein the correlation graph consists of undirected simple edges and is the same as the communication graph.

In other related works, GAF [30], SPAN [4], PEAS [31], and ASCENT [3] develop distributed algorithms to identify nodes that are similar in routing perspectives so that other nodes can be turned off to conserve energy. None of these works use any notion of a data correlation structure.

7. CONCLUSIONS

In this article, we have considered the connected correlation-

dominating set problem that helps in minimizing communication costs in data-gathering sensor network applications. Taking advantage of the existing data correlations in the sensor network, our proposed approach is to select a small set of sensors called the connected correlation-dominating set that form a connected communication graph and are sufficient to infer data of the remaining unselected sensors. The problem is defined in terms of a correlation structure (hypergraph) that captures general data correlations. To select a connected correlation-dominating set of small size, we have designed a set of energy-efficient distributed algorithms, and a class of efficient centralized heuristics that are based on a provably competitive approximation algorithm. Our simulation results show that the designed distributed algorithms and the centralized heuristics return small size solutions and the communication cost incurred by the best performing distributed algorithm (2-Rounds) is small enough to considerably increase the useful lifetime of a sensor network.

Acknowledgments

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